UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Managerial Use of Generative AI

Enablers and Constraints in a Consulting Context

Axel Wikner | Gustav Bårdén

Master's thesis in Innovation and Industrial Management

Graduate School
Spring 2025

Thesis Supervisor
Marouane Bousfiha

Executive Summary

Generative AI tools like ChatGPT can transform how managers make decisions, yet adoption at the managerial level remains limited. Why? Through interviews with nine managers at Rejlers and validation from a generative AI transformation specialist, we identified three key constraining areas. Trust develops through domain expertise, creating a paradox where knowledge enables verification of generative AI outputs while simultaneously making managers more critical of them. Managers with stronger expertise feel confident using AI because they can evaluate accuracy, yet this heightens their scrutiny of AI-generated content. Boundaries are established based on contextual understanding. Managers readily delegate routine tasks to generative AI while reserving complex, relationship-sensitive decisions for human judgment. AI's lack of organization-specific context limits its utility for company-specific challenges. Practical barriers impede adoption, including insufficient integration with existing systems, established work habits, and limited awareness of generative AI capabilities. These factors often prevent adoption even when managers recognize potential benefits.

From these insights, we developed the Managerial AI Interaction Framework illustrating how managers progress through four stages: awareness and experimentation, competence building, workflow integration, and boundary-aware collaboration. Our research suggests that effective human-AI collaboration requires addressing trust dynamics, establishing appropriate task boundaries, and overcoming practical integration barriers rather than focusing solely on technical capabilities.

Acknowledgement

We are deeply grateful to our supervisor Marouane Bousfiha, whose contagious enthusiasm transformed this thesis from a mere academic undertaking into a genuinely enjoyable experience. Equally important was Simon Broomé at Rejlers, who encouraged our ideas, allowed us to pursue the direction we found most interesting, and helped us recruit participants for our study. Our sincere appreciation goes to the nine Rejlers managers who generously shared their time and AI experiences despite their hectic consulting schedules. Finally, thank you to our supervision group colleagues whose dedication and valuable feedback enriched this work from start to finish.

Gustav Bårdén

Axel Wikner

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1. Introduction

Imagine managers having access to a digital assistant that cuts their work time by 40%, improves output quality by 18%, and saves them over four hours every week. These aren't hypothetical benefits but documented productivity gains when professionals use generative artificial intelligence (AI) tools like ChatGPT (Noy & Zhang, 2023; Bick et al., 2025). Yet despite this significant efficiency potential, most managers aren't integrating these tools into their daily decision-making. This productivity paradox defines the current state of generative AI in business: powerful systems that can analyze data, draft documents, and reason through complex problems remain largely underutilized in practice. The numbers prove this disconnect, while 94% of executives consider generative AI a top priority and 91% believe it gives them a competitive advantage, only 1% of companies report advanced AI deployment in practice (Mayer et al., 2025; Riverbed, 2024). This implementation gap matters not just for organizations investing in generative AI, but also for system developers who create impressive features without understanding real-world human needs. Meanwhile, academic research has focused more on organizational adoption than on how managers experience and use these systems. As generative AI capabilities continue advancing rapidly, we risk developing increasingly sophisticated tools that look impressive in demos but sit unused in practice. Without deeper insight into how managers interact with, trust, and use AI in their decisions, this productivity potential may remain largely untapped.

1.1 Research Aim and Question

This study aims to bridge multiple gaps in our understanding of how humans and generative AI models work together in management settings. First, we examine how managers use these tools in everyday decision-making, addressing the disconnect between generative AI strategies and practical implementation. Second, we contribute to academic theory by exploring how existing models of technology adoption apply to the unique characteristics of generative AI. Third, we provide insights for generative AI developers who need to understand the human factors that determine whether their systems will be used effectively in real-world professional settings. Through a case study at Rejlers, a multinational engineering consulting firm, we investigate how managers interact with generative AI, and what enables or constrains its use across three key functions: reasoning, analysis, and knowledge acquisition. This practical focus leads to our central research question:

"What factors enable and constrain managers' use of generative AI for decision-making?"

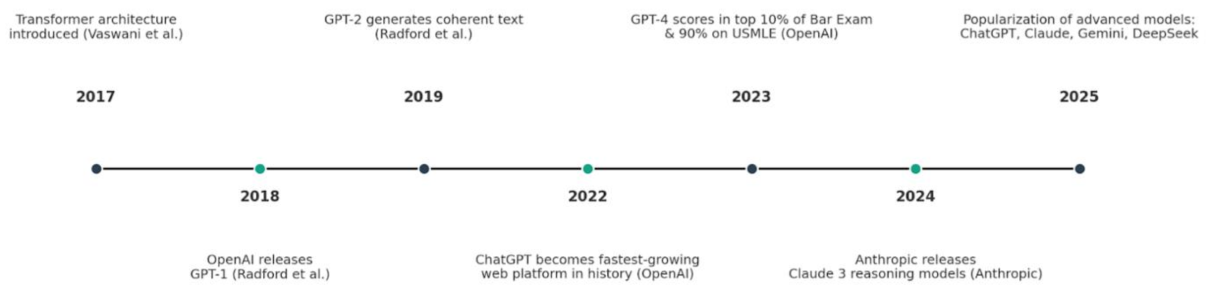
By answering this question, we aim to provide practical insights that help organizations use generative AI more effectively, contribute to academic understanding of how humans and AI work together, and help developers create systems that better fit managerial work patterns and decision processes.

1.2 Background: Relevance and Urgency

AI has developed considerably from its original applications in automation, classification, and forecasting. Now, it has a much wider role in decision-making, problem-solving, and even creative processes (Singla et al., 2024). Previously, AI was mainly used for organized, predictable tasks like analytics and process automation. Today, however, its increasing ability to create new content and work through complex situations is changing how businesses operate. Generative AI, especially, is helping organizations move beyond simple efficiency gains to improve strategic insights and creativity in their workflows.

The rapid advancement of generative AI capabilities has been driven by breakthrough developments in reasoning models. New models like OpenAI's o3 represent significant leaps in analytical capability compared to their predecessors (OpenAI, 2025). The timeline of these developments (see Figure 1) illustrates how successive innovations in model design and training approaches have progressively enhanced AI's capacity for complex reasoning and strategic thinking.

Figure 1: Timeline displays introductions to new reasoning models



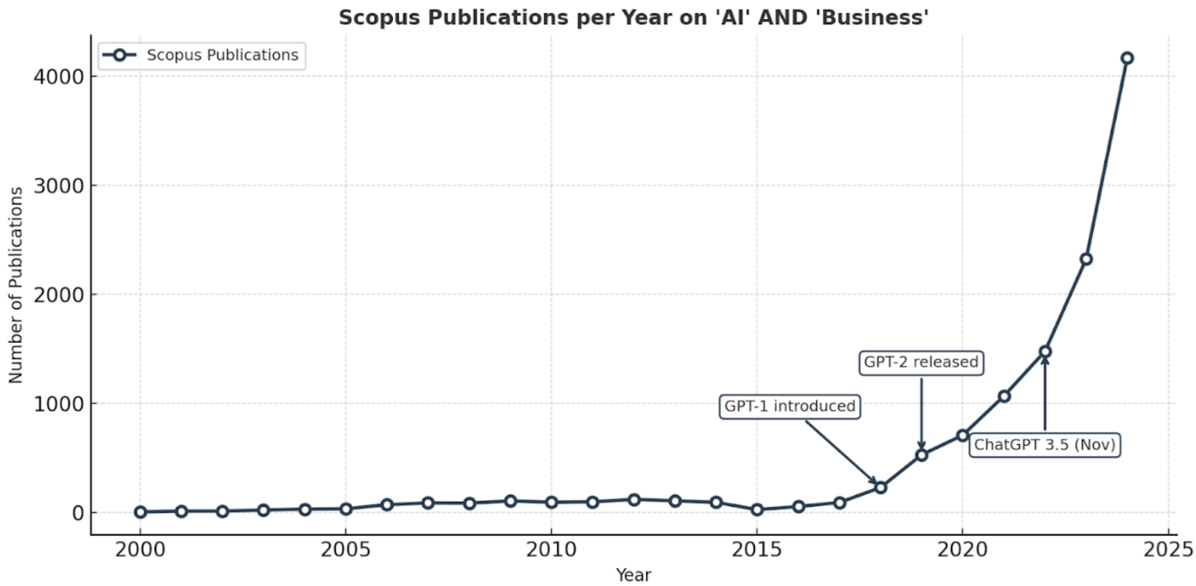
This increase in reasoning ability is an important development for how businesses can use generative AI. Instead of just finding and summarizing information, advanced reasoning models can now perform step-by-step reasoning, create organized plans, and function as true thought partners for decision-makers. Companies can also adjust these models with their own industry knowledge, allowing them to provide more accurate and useful insights (OpenAI, 2024).

1.2.1 Current State of AI Adoption

Driven by increased practical use as previously stated, companies are investing heavily in generative AI. Amazon has invested $8 billion in Anthropic, Microsoft over $13 billion in OpenAI, and Google is committed to investing $75 billion in AI initiatives such as their Gemini model lineup (Amazon Staff, 2024; Microsoft, 2024; Li & Chan, 2025). Overall, AI infrastructure spending by major tech firms is up 40% year-on-year, projected to hit $325 billion in 2025 (The Economic Times, 2025).

The rising investment signals more than corporate commitment, it reflects broader societal interest in AI's potential. Businesses, employees, and even the general public are becoming more interested in AI's capabilities. This is clear in rising search trends and publications for generative AI and AI adoption in business (figure 2), showing a growing demand for knowledge and practical guidance on using AI.

Figure 2: Number of publications on 'AI' and 'Business' per year, including the release dates of ChatGPT models



Despite all this interest, only 1% of executives say their companies are truly advanced in AI deployment. Many organizations are still in early testing stages, finding it difficult to scale AI effectively (Riverbed, 2024). While 94% of surveyed executives say generative AI is a top priority at the C-suite level, only 37% of companies feel they are ready to implement these technologies (Mayer et al., 2025; Riverbed, 2024).

One of the main obstacles to adoption of generative AI is not employees at the operational level, according to Relyea et al. (2024). Rather, it is managers and leaders who are uncertain or have not been able to include generative AI into their own workflows. While AI has been easier to integrate into structured, process-driven operational roles, managerial workflows are much more complicated. Managers often handle strategic thinking, reasoning, and problem-solving, areas that AI has traditionally found challenging. Unlike operations, which usually follow set processes that can be automated, managerial tasks are more context-based and require flexibility. However, newer models like o3, Sonnet 4.0, and Gemini 2.5 Pro now support advanced reasoning, making AI more useful for managerial decision-making (OpenAI, 2025; Anthropic, 2025; Kavukcuoglu, 2025).

This convergence of AI's developing capabilities, the complex nature of managerial decision-making, and the unprecedented levels of investment in AI proves this the right moment to study generative AI adoption and usage at a managerial level.

1.2.2 Consulting Industry Context

The consulting industry is well-suited for studying managerial use of generative AI due to its demand for complex, fast-paced decision-making. Mid-level managers must analyze incomplete information, solve ambiguous problems, and generate creative, tailored solutions which require strategic reasoning and innovation (Kubr, 2002; Christensen et al., 2013). At the same time, consulting operates in a competitive environment with tight margins and pricing pressure (Appelbaum & Fewster, 2003). Managers must balance resources, timelines, and budgets, making efficient analysis and decision-making crucial to maintaining value and profitability.

It is this combination of demands that makes the consulting industry worthwhile for studying Generative AI adoption. Tools like ChatGPT can overlap directly with these core activities. For example, they might help in accelerating initial research, examining complex data more quickly, creating preliminary ideas, or helping organize strategic thoughts and reports (Brynjolfsson et al., 2023; Lebovitz et al., 2023). Studying how managers use or avoid using generative AI for these tasks, under these specific pressures, can provide important insights into the human-AI interaction in professional settings.

Within this industry context, Rejlers AB serves as our case company. Despite strong digital competence and a focus on learning, generative AI use in managerial work is still emerging and uneven, reflecting the broader adoption trends. This makes Rejlers a relevant case for studying how generative AI is adopted in real time, rather than retrospectively, offering valuable insight into the enablers and constraints shaping its role in managerial decision-making within consulting.

1.3 Scope, Delimitation, and Definitions

Generative AI refers to a type of artificial intelligence designed to create content, including text, images, code, and even music, by analyzing large amounts of data. Unlike traditional AI, which mainly focuses on classifying information and making predictions, generative AI produces new content that imitates human creativity and reasoning (Caballar, 2024). Large Language Models (LLMs) like ChatGPT use deep learning techniques based on transformer architectures, trained on extensive datasets to generate outputs that resemble human-generated content (Marr, 2024).

While other generative AI systems may relate to image creation and audio models for music generation, this thesis focuses specifically on LLMs. Text-based interaction aligns well with how managers already work with reports, emails, memos, and analyses, making LLMs naturally suited for managerial reasoning, communication, and decision-making tasks.

Table 1: Differences between traditional AI and generative AI.

Traditional AI	Comparison	Generative AI
Structured task execution based on defined inputs	**Primary Function**	Synthesis of novel data from learned distributions
Rule-based or supervised learning framework	**Learning Paradigm**	Large-scale unsupervised neural network training
Decisions, clarifications, or predictions	**Output Type**	Autonomously generated text, images, video, audio, or code
Precision tasks, automated decisions systems, repetitive workflows	**Ideal Applications**	Creative exploration, content development, complex reasoning

This technological landscape is changing rapidly. Some models and interfaces now combine multiple modalities, and the line between model types is blurring. This introduces a limitation: some parts of this thesis may become outdated as these technologies evolve into more general systems.

Given these capabilities and limitations, the academic literature presents different models for human-AI interaction, including automation, hybrid, and augmentation approaches. This study focuses on augmented human-AI interplay, as it is widely recognized as the most effective setup for strategic and knowledge-intensive decisions (Leoni et al., 2024; Shrestha et al., 2019).

In augmented interactions, AI supports human work by allocating tasks to the respective strengths of each party. This iterative process fits well in knowledge-driven environments, where AI's analytical capabilities and human judgment must be balanced. AI becomes a partner rather than a replacement, helping managers benefit from AI-generated insights while maintaining human control over strategic choices that require expertise and contextual awareness (Leoni et al., 2024).

1.4 Disposition

The thesis is structured into six chapters. The first chapter introduces the background, outlines the problem statement, and presents the purpose and research question. The second chapter reviews relevant literature and introduces the theoretical framework, explaining how it connects to both previous research and the study's empirical findings. The third chapter describes the methodological approach, including research design, data collection, analysis methods, limitations, ethical considerations, and quality measures. The fourth chapter presents the empirical findings and analysis based on interviews with nine managers and one expert informant with extensive cross-industry AI-implementation experience. The fifth chapter discusses the findings in relation to the literature, leading to the development of the Managerial AI Interaction Framework. The final chapter concludes the thesis by summarizing the results, highlighting contributions to theory and practice, and suggesting areas for future research.

> **Summary Chapter 1: Introduction**
> - Generative AI boosts managers' productivity but is still under-used in practice.
> - Our study targets the gap between generative AI's promise and real-world managerial adoption.
> - Case company = Rejlers; focus on managers' reasoning, analysis & knowledge-acquisition tasks.
> - Central research question: *What enables or constrains managers' use of generative AI?*

2. Literature Review

This chapter reviews relevant theories and empirical studies to frame the adoption and use of generative AI in managerial decision-making. It begins with established frameworks for technology acceptance and human-AI collaboration, including both traditional and AI-specific models. It then outlines key factors that enable or hinder AI adoption, categorized into individual, social, organizational, and technological dimensions. Recent developments in the application of generative AI for managerial tasks, especially reasoning, analysis, and knowledge acquisition, are also explored. The chapter further connects these AI capabilities to established theories of decision-making, such as bounded rationality and Simon's decision-making framework. Together, these perspectives form the theoretical foundation for understanding how managers interact with AI tools like ChatGPT in their daily work.

2.1 Theoretical Frameworks for AI Adoption and Human-AI Interaction

Understanding how managers accept and work with AI systems requires a foundation in technology adoption theories. Two key models in this area are the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), hereafter referred to as the acceptance framework and the technology use framework, respectively.

The acceptance framework suggests that a person's intention to use new technology mainly depends on two factors: perceived usefulness (how much they think the technology will improve their job performance) and perceived ease of use (how much effort they think using it will take) (Davis, 1989). Simply put, if managers find an AI tool helpful for their work and not complicated to use, they are more likely to include it in their decision processes.

The technology use framework combines several earlier models (including the acceptance framework) and adds other factors that affect adoption such as performance expectancy (similar to usefulness), effort expectancy (similar to ease of use), social influence (how much colleagues and bosses affect one's use of the technology), and facilitating conditions (the organizational and technical support available) (Venkatesh et al., 2003). The technology use framework acknowledges that a manager's social environment and organizational context matter alongside personal views in technology acceptance.

Both acceptance and technology use frameworks have been widely applied to explain how new technologies spread in organizations, and they offer a useful starting point for studying AI adoption. However, these models were created for traditional information systems and might not fully address the complications of AI adoption, which often involves issues like unclear algorithms, trust, and automation concerns (Liang & Xue, 2009).

Recent studies have tried to expand or adjust these theories for generative AI and human-AI collaboration. One important contribution is the Human-AI Collaboration and Adaptation Framework (HACAF) developed by Russo (2024), which was specifically created to understand generative AI adoption in software engineering. Hereafter, HACAF will be referred to as the adoption framework. The adoption framework builds on the acceptance framework, technology use framework, Diffusion of Innovation (DOI) and Social Cognitive Theory (SCT), combining their main concepts while adding new aspects discovered in qualitative research by Russo.

For example, Russo's (2024) framework keeps perceptions of the technology (usefulness, ease of use, and relative advantage, similar to the acceptance framework) and shows that practitioners judge AI tools, like ChatGPT, mainly by their practical benefits and time savings. The adoption framework also stresses compatibility (from DOI theory), as in how well the AI fits with current workflows, values, and needs. In practice, early adopters of generative AI said that workflow compatibility was a key factor: tools that matched their existing processes were adopted much more readily (Russo 2024).

Additionally, the adoption framework includes social influences and personal factors. In line with technology use framework, social approval (like wanting to appear advanced) and the user's comfort with technology were found to affect adoption behavior (Russo, 2024). Personal differences, such as one's openness to trying new technologies, also proved important. Lastly, the adoption framework considers organizational context (similar to facilitating conditions): organizational support, through resources or an encouraging environment for AI use, can significantly impact adoption (Russo, 2024). In short, models like the adoption framework expand on classic models by adding trust, transparency, and situation-specific factors to better explain human-AI collaboration, although in a software engineering context. While acceptance and technology use frameworks point out general factors (usefulness, ease, social influence), newer models recognize that trust in AI, perceived risk, and fit with work practices are crucial in adopting AI decision tools (Marocco et al., 2024).

For instance, Russo's (2024) adoption framework identified job security concerns as a significant barrier, with 25% of software engineers expressing fear that AI could "automate a lot of tasks and make most of my work obsolete." This research shows that perceived threats to job security can create resistance to AI adoption, and that emotional reactions can override logical cost-benefit analysis when deciding whether to use AI (Marocco et al., 2024).

Overall, a mix of traditional and AI-specific frameworks is needed to understand the complex human-AI interaction in management settings, where both the practical value of AI and human aspects (trust, perceived threat, social norms) determine how technology and managers work together in decision-making.

Summary Chapter 2.1: Theoretical Frameworks for AI Adoption and Human-AI Interaction

- Traditional technology adoption models look at usefulness and ease of use when explaining why people use new tools
- Newer models add things like trust, transparency, and workflow fit as important factors.
- Managers may avoid AI systems if they seem threatening or can't be understood, even if they are useful.

2.2 Facilitating and Inhibiting Conditions for AI Adoption in Management

When bringing generative AI into managerial decision processes, several factors can either help acceptance or create barriers. These can be grouped into individual, social, organizational, and technological factors, each affecting a manager's ability to adopt AI support.

2.2.1 Individual Factors

At the personal level, a manager's trust and view of AI is essential. Research on algorithm aversion shows that managers often avoid relying on AI-generated insights, especially if they cannot understand how the AI works (Dietvorst et al., 2015). Transparency is therefore crucial. When AI systems give clear explanations or show fairness and accountability, users trust them more (Shin, 2021). For example, Shin (2021) found that perceptions of an AI's fairness, accountability, and transparency directly build trust and acceptance. On the other hand, managers tend to reject algorithms they cannot interpret, which happen often with complex AI models (Marocco et al., 2024).

A manager's comfort and confidence with technology also affects adoption. Those familiar with digital tools feel less anxious and are more willing to try AI (Russo, 2024). In contrast, people who fear technology may see greater risk in using AI, viewing it as stressful rather than helpful (Marocco et al., 2024). Perceived ease of use reflects this idea that difficult or mentally demanding AI tools will limit adoption. Personal traits like openness to new things also matter, managers who like trying new technologies are more likely to use AI in their work (Russo, 2024).

2.2.2 Social Factors

Adoption does not happen in isolation, social and cultural influences greatly affect a manager's decision to use AI. Within organizations, peer usage and norms create pressure or encouragement. If respected colleagues are successfully using generative AI, managers may feel motivated to do the same. Russo's (2024) study showed that developers valued being seen as modern by peers, which drove AI adoption. This matches the technology use framework social influence concept and what Mahmud et al. (2022) found: social influence can positively affect AI acceptance in organizations.

On the other hand, organizational cultures may create social barriers. If using AI is seen negatively, perhaps viewed as showing weak expertise, adoption may be held back. Tradition can be a limiting social factor; one study noted "image barriers" where managers worried that using algorithms could make them seem less capable or less in control (Mahmud et al., 2023). Also, the need for human interaction can restrict AI uptake. Managers often prefer discussing decisions with colleagues; replacing that with AI might seem impersonal. A recent review found that some managers hesitate to accept algorithmic advice in areas like finance or HR because they value human intuition and personal aspects of decision-making (Booyse & Scheepers, 2023).

2.2.3 Organizational Factors

Organizational setting often determines how well new technologies are adopted. Leadership support is crucial. When top management backs AI initiatives by sharing a clear vision and providing resources, managers at lower levels are more likely to use these tools. Organizational readiness and digital maturity are also essential factors. Companies with good IT infrastructure, available data, and in-house AI expertise make it easier for managers to include AI in decision workflows (Nguyen Van Phuoc, 2022). Lada et al. (2023) found that organizational readiness, including infrastructure and skilled staff, is linked to higher AI adoption rates among managers.

The level of digital transformation in a company also affects attitudes toward new tech. Organizations further along with their digital transformation tend to have cultures that welcome experimentation and value data. Managers in these firms see AI tools as more useful and easier to use, showing greater intention to use them (Rodríguez-Espíndola et al., 2022). In contrast, organizations lacking technical infrastructure or data management present practical obstacles to AI use.

Organizational culture and norms set the tone, companies that support innovation and accept smart failures create environments where managers feel free to try AI tools. Another factor is training and change management: giving managers proper training on how to use and interpret AI outputs can reduce fears and build skills, helping adoption (Booyse & Scheepers, 2023). Clear ethics and governance policies can either encourage or limit AI use. Guidelines on acceptable AI use, data privacy, and accountability give managers confidence to use tools properly, while unclear or strict rules limit use (Booyse & Scheepers, 2023).

2.2.4 Technological Factors

Features of the AI technology itself affect adoption. Usability is essential, an AI tool must have an easy-to-use interface and fit well into existing workflows. This connects to perceived ease of use in Davis's (1979) acceptance framework. A well-designed generative AI assistant that feels natural will lower barriers to entry. Reliability and accuracy are equally as important. Users need to trust that the AI's outputs are accurate enough to consider. Studies show that if users see algorithms make mistakes, they often stop using them even if they perform better on average than humans (Dietvorst et al., 2015; Marocco et al., 2024).

Transparency and explainability are technical factors that increase user trust and willingness to rely on AI systems (Shin, 2021). Also, compatibility and integration help adoption, if AI tools easily connect with data sources and software managers already use, they become more valuable. If they require exporting data or switching between programs, they may be seen as more trouble than they are worth. Lastly, security and privacy features matter, organizations and managers are reluctant to use AI tools that might leak sensitive information or break compliance rules (Shin, 2021).

By understanding these conditions across individual, social, organizational, and technical areas, companies can better plan for successful human-AI collaboration. To encourage adoption, they should build trust through transparency, develop a culture that supports innovation, ensure leadership backing, invest in training, and select AI tools that match users' needs and workflows. Ignoring any of these areas could mean even powerful generative AI decision-support remain unused or face resistance, showing that effective human-AI interaction needs both technological readiness and human readiness.

Summary Chapter 2.2: Facilitating and Inhibiting Conditions for AI Adoption in Management

- Individual factors like trust, understanding of AI, and technology-comfort affect whether professionals adopt AI
- Social influence such as what colleagues think, and organizational culture can encourage or discourage AI use.
- Technical aspects like accuracy and fit with workflows determine if professionals continue using AI tools.

2.3 Generative AI in Managerial Decision-Making: Recent Developments

In just the past 1-2 years, generative AI (particularly LLMs like OpenAI's ChatGPT) has quickly shifted from a novelty to a practical tool in management settings. This section looks at recent studies on how professionals are using generative AI and what benefits have been discovered.

Surveys show that generative AI use in the workplace has become more common and is growing quickly. McKinsey's "Global State of AI" survey from early 2025 (reporting on 2024 data) found that 71% of organizations surveyed reported using generative AI regularly in at least one business function, a big increase from previous years. Also, 53% of C-suite executives reported personally using generative AI tools for work tasks, showing that even top leaders are actively using tools like ChatGPT (McKinsey, 2025). Executives also largely expect generative AI to change their industry, with most reporting their companies increased AI investments partly because of recent generative AI advances (McKinsey, 2024). Another survey found that 70% of hiring managers have used generative AI in their work (Flynn, 2023), for instance to help write job descriptions or screen candidates. These findings highlight that professional use of ChatGPT and similar tools are increasing in use across many sectors. By 2024-2025, many companies moved beyond testing into developing rules around AI use, while expanding high-impact applications in areas like marketing content, customer service, and decision support (McKinsey, 2025).

This widespread adoption is supported by emerging research on productivity benefits. An important experiment by Noy and Zhang (2023) gave 444 professionals real-world writing tasks and allowed half to use ChatGPT. The results were notable, ChatGPT increased productivity by cutting task time by about 40% while improving output quality by 18% on average (Noy & Zhang, 2023). More recent studies continue to show significant time savings; for example, an analysis based on late 2024 data found workers using generative AI saved over four hours per week on average (Bick et al., 2025). This suggests that for many knowledge-based tasks, generative AI can improve both efficiency and effectiveness, potentially leading to better-informed decisions.

Beyond productivity gains, these tools also enhance creative capabilities. Urban et al. (2024) found that students using ChatGPT achieved better creative performance by generating more ideas and more original solutions. Notably, using ChatGPT improved participants' confidence in problem-solving, with solutions rated as more detailed and creative (Urban et al., 2024). Participants also found the task easier with AI help. Supporting this, a study in Nature Human Behavior by Lee & Chung (2024) had business professionals create creative ideas with either ChatGPT, Google search, or no help; ideas created with ChatGPT were judged most creative on average, as the AI could combine different concepts coherently (Lee & Chung, 2024). Generative AI thus seems to be a good enhancer of human creativity by adding fresh perspectives and knowledge that managers alone might not have, leading to more innovative decision options.

Summary Chapter 2.3: Generative AI in Managerial Decision-Making: Recent Developments

- Generative AI is now widely used in workplaces, with 71% of organizations using it in at least one area.
- Studies show these tools can cut task time by 40% while improving quality by 18% on average.
- Managers find AI especially helpful for creative problem-solving, where it helps generate more and better ideas.

2.4 Managerial Decision-making Theories

To better understand how AI affects managerial decision-making, it helps to review how decision-making is viewed in management theory. Traditional decision-making models show us the thinking processes and tasks involved when managers make choices, which helps clarify where AI can provide support. Key theoretical perspectives include the rational decision-making model and bounded rationality approaches.

2.4.1 Rational and Bounded Rationality Approaches

The rational decision-making model describes decision-making as an organized and logical process: identify the problem, collect information, develop options, evaluate options using criteria, and select the best solution (Simon, 1956). This ideal model assumes decision-makers have complete information and perfect logic. Managers often try to follow this rational ideal, using tools like decision matrices, cost-benefit analysis, or forecasting models to reach the "best" decision. However, in reality, business decisions are limited by uncertainty, incomplete information, and human thinking limitations. This is where bounded rationality (Simon, 1956) becomes relevant, recognizing that managers settle for good enough rather than perfect solutions. They use shortcuts (rules of thumb) to make decisions that are acceptable given their limited time and information. Simon's perspective and later behavioral decision theory (such as Kahneman & Tversky's (1974) work on shortcuts and biases) show that managers rely on simplified mental models and past experiences, which can lead to biases like overconfidence, anchoring, or fear of loss. These biases mean that real-world decisions often differ from the purely rational solution (Tversky & Kahneman, 1974).

In knowledge-intensive fields like management consulting or strategic planning, decision-making combines both art and science (Jacobson et al., 2005). It involves analytical reasoning, breaking down complex problems, analyzing data, predicting outcomes, as well as experience-based intuition. All of it using tacit knowledge and gut feeling for what might work (Kahneman, 2011). Current theories of managerial decision-making, such as dual-process theory, suggest that managers switch between System 1 thinking (quick, intuitive, emotional) and System 2 thinking (slow, careful, logical). Good decision-makers know when to trust their instincts and when to use detailed analysis. For example, in an important strategic decision, a manager might first use intuition to reduce the number of possible options, then switch to analytical thinking to carefully compare those options (Kahneman, 2011).

2.4.2 Simon's Framework for Decision-Making

Simon's (1977) intelligence-design-choice model provides a helpful framework for understanding how decision functions. Intelligence involves searching for information and identifying the problem or opportunity, Design involves developing and analyzing possible solutions, and Choice is selecting among alternatives (Simon, 1977). In management terms, we can map these to functions:

- Knowledge acquisition (intelligence gathering, finding information and insights)
- Analysis and reasoning (designing solutions, applying logic, number analysis, and structured thinking to assess options)
- Judgment/decision (choice, applying values, preferences, and judgment to select an option and implement it)

Importantly, the first two functions are where much managerial work happens and are areas that generative AI, like ChatGPT, can significantly support. The final choice (judgment/decision) is typically kept for the manager themselves.

With this theoretical background, reasoning, analysis, and knowledge acquisition represent core parts of managerial decision-making that can be improved by AI capabilities. Current generative AI tools offer specific technical features that match these areas. For knowledge acquisition, generative AI tools provide information retrieval through their training, but also through direct internet search and the ability to review uploaded documents and data files (OpenAI, 2025). This varied approach to information gathering greatly expands access to both general and specific knowledge sources. For reasoning and analysis, the newest models like ChatGPT-4o and Claude 4.0 Sonnet include advanced reasoning abilities that support structured thinking, complex problem-solving, and data analysis (Open AI, 2025; Anthropic, 2025). These models have extended reasoning modes that allow for deeper, more methodical thinking on complex problems, enabling more reliable analytical support for managerial decisions.

Managerial decision theory emphasizes both rational analysis and human judgment, with AI potentially supporting specific aspects of the decision process. The following section explores how current generative AI capabilities align with these decision support needs across reasoning, analysis, and knowledge acquisition functions.

Summary Chapter 2.4: Generative AI in Managerial Decision-Making: Recent Developments

- Decision-making is shaped by both rational analysis and human limitations like bias and intuition.
- Simon's model (intelligence, design, choice) helps map where AI can assist, mainly in knowledge, analysis and reasoning.
- Generative AI tools align well with early decision stages, supporting information gathering and structured reasoning.

2.5 AI for Reasoning, Analysis, and Knowledge Acquisition

A key theme in studying human-AI interaction is understanding how AI can enhance specific thinking functions of managers. In decision-making, the three functional areas central to managerial work derived from the sections above are: Reasoning, Analysis, and Knowledge Acquisition. Generative AI like ChatGPT can work as a tool in each area, effectively serving as a thinking assistant. Below, we review research and technical capabilities for each function:

Generative AI offers distinct capabilities that support managers across all three functional areas. For knowledge acquisition, generative AI tools such as ChatGPT can search the internet in real-time, providing access to current information beyond their knowledge cutoff dates (OpenAI, 2025; Anthropic, 2024). They can also process uploaded documents like PDFs, spreadsheets, and presentations, allowing managers to quickly extract insights from business reports without manual review (OpenAI, 2025). A manager can upload quarterly reports and get synthesized performance trends within seconds rather than spending hours reviewing documents manually.

In the reasoning domain, recent improvements represent a major step forward in AI support for managerial thinking. The newest models like Claude 4.0 Sonnet have specific reasoning modes that enable deeper, more methodical thinking on complex problems (Anthropic, 2025). Creative problem-solving is another area where AI shows particular strength. Urban et al. (2024) found that people using ChatGPT created more original solutions compared to those working without AI help. This expands the range of options considered and helps managers avoid settling too quickly on familiar but suboptimal solutions.

The increasing reasoning capability of generative AI is also evident in standardized test benchmarks. For instance, GPT-3.5 scored in the 70th percentile on SAT math and the 87th on SAT verbal, indicating strong general knowledge and language skills (OpenAI, 2023). Its successor, ChatGPT-4, performs at a much higher level, ranking in the top 10% of test takers on the U.S. Bar Exam and answering 90% of questions on the Medical Licensing Examination (OpenAI, 2024). These scores imply that generative AI now possess reasoning abilities comparable to university-educated professionals, strengthening their suitability for supporting complex managerial tasks.

For analysis tasks, generative AI systems offer sophisticated data processing capabilities that were previously available only through specialized analytics tools. The latest models can interpret structured data from spreadsheets and databases, then generate insights based on patterns in that data (OpenAI, 2025). Advanced systems can also create appropriate visualizations, helping managers quickly spot trends, outliers, and relationships that might be missed in table formats (Anthropic, 2024). Systems like ChatGPT-4o even offer code execution capabilities, bridging the gap between managerial questions and technical implementation (OpenAI, 2025).

Despite these advances, important limitations exist across all functional areas. AI systems may sometimes generate incorrect information or misinterpret complex documents (IBM, 2023). They also struggle with highly specialized domain knowledge and can show many of the same thinking biases as humans (Chen et al., 2025). These limitations create verification needs that affect practical usefulness, especially for high-stakes decisions where accuracy is crucial.

While the technical potential of AI in managerial settings is clear from the literature, questions remain about how managers actually engage with these tools in practice, specifically generative AI, and what barriers they encounter, as well as what conditions enable effective collaboration. To investigate these questions and understand the human side of AI adoption in managerial contexts, we now turn to our methodology, which outlines our approach to studying how managers interact with generative AI in real-world decision-making scenarios.

Summary Chapter 2.5: AI for Reasoning, Analysis, and Knowledge Acquisition

- Generative AI can support all key managerial thinking tasks: reasoning, analysis, and knowledge gathering.
- ChatGPT helps managers explore ideas, analyze data, and extract insights from documents quickly and efficiently.
- Despite strong capabilities, limitations like hallucinations, bias, and lack of domain knowledge require human verification.
- The gap between technical potential and real-world use highlights the need to study how managers actually adopt and work with AI tools.

3. Methodology

This chapter explains how the study was performed. It describes the research strategy, how the data was collected, and how it was analyzed. The goal is to understand the process we used to analyze generative AI in managerial decision-making. A qualitative approach was chosen due to the complexity of the topic and that generative AI in the managerial context is evolving. The chapter also explains why case study design was used, how participants were selected, how the interviews were structured, and how we ensure quality.

3.1 Research Strategy

This study uses a qualitative research strategy to explore the use of generative AI in managerial decision-making processes. The choice is based on the need to understand a new and complex phenomenon that is not yet fully captured by existing theories. While there are models that look at AI in general, few focus on how managers interact with generative AI. Building on missing literature, a qualitative approach allows for in-depth exploration of phenomena that are not fully captured by existing frameworks (Bell et al., 2022; Timmermans & Tavory, 2012). The study also follows an abductive approach, meaning we move back and forth between theory and data. This is useful when researching areas that are not well understood, especially when asking "what" or "how" questions (Bell et al., 2022; Yin, 2009). It allows us to adjust our understanding as we learn more from the data.

In contrast to the adoption of a natural scientific model in quantitative research, the primary focus is to understand the social world through examination of managers. This position of research is described as interpretivist, where the goal is to understand the contextual setting by its participants (Bell et al., 2022). We are interested in how meaning is created through interactions, shaped by social, technological and organizational settings. Because of this, we use a constructionist view, where knowledge is seen as something built through human experience and interpretation (Bell et al., 2022).

The negative aspect of conducting a qualitative study is that observations are empirical findings which cannot be statistically quantifiable (Bell et al., 2022). However, abductive reasoning views findings as temporary and open to change as theory and data influence each other (Dubois & Gadde, 2002). The theory development from this research could, however, be tested in different contextual situations to further improve or adjust the theory to make it more generalizable.

3.2 Research Design

This study explores how managers interact with generative AI in decision-making, focusing on what enables or hinders effective use. A case study approach is suitable because it allows detailed investigation within a real-world context (Bell et al., 2022). Given the evolving and context-specific nature of generative AI, this method helps capture the interplay between technology, organizational practices, and human behavior. It is especially useful for examining key factors like trust, reasoning, and boundary-setting, and for generating insights that can complement existing theory (Bell et al., 2022).

Looking at how managers use generative AI in decision-making through a case study lets us explore practices we do not yet fully understand, with the flexibility needed to see new things beyond initial knowledge (Bell et al., 2022). With the awareness that a case study might limit how widely our findings apply, studying decision-making and the use of AI is better done through detailed, context specific examples than broad perspectives. The narrow focus on managers with varying levels of experience with generative AI yet operating in the same environment and making similar decisions, helps us identify patterns in how AI is used in management.

Like all research designs, case studies have both negative and positive aspects. Siggelkow (2007) points out the small sample size and limited scope, which essentially means that the conclusion is drawn from a single social setting, resulting in the finding to potentially not be generalized. However, Flyvbjerg (2006) finds this narrow focus to give deep, detailed insights, which helps in new areas like generative AI in managerial decision-making. By using an approach that closely ties findings to the specific social setting being studied, raises our chance to understand the human-AI relationship.

3.3 Data Collection

Primary data were collected through ten semi-structured interviews: nine with Rejlers managers and one key-informant interview with an external AI-transformation specialist. The semi-structured interviews are structured around three areas: knowledge acquisition, reasoning, and analysis. This helped focus the conversation while allowing for open answers. All interviews were recorded, transcribed, and used as the main data source. The key-informant interview served as theoretical triangulation, providing an external lens on the dimensions that emerged from the managerial sample. Participants were chosen through purposive sampling to capture different roles and experiences with generative AI.

3.3.1 Semi-structured Interviews

Semi-structured interviews were chosen as the main method for collecting primary data as it offers a balance between structure and flexibility (Bell et al., 2022). These interviews let the researcher start with a clear set of questions but also allow room for exploring new topics that participants bring up. This flexibility is essential when studying the human-AI relationship, as managers' experiences and knowledge are varying. Using this method helps ensure that the data collected is detailed and reflects the realities of participants' work environments. As Bell et al., (2022) suggest, interviews are particularly effective in capturing the complexity of organizational issues and providing context-specific insights. Being able to capture the complexity is crucial when doing research within a specific setting, as managers practical challenges will vary across the organization.

Semi-structured interviews also enable a deeper exploration of subjective opinions, which is essential for understanding complex phenomena (Bell et al., 2022). Unlike surveys that limit answers to set choices, semi-structured interviews provide opportunities for follow-up questions and clarifications. This helps avoid misunderstandings and makes sure the data reflects what participants think and have experienced, rather than being constrained by the researcher's assumptions, helping the research meet quality standards (Bell et al., 2022).

A considerable limitation is the possibility of interviewer bias, where the way questions are asked, or the interviewer's behavior might unintentionally influence how participants respond. To reduce this risk, it is essential to create a clear and consistent interview guide and train the interview before the first proper interview. Gioia et al. (2013) explain that using consistent question techniques and reflecting on the process can help limit bias and make the data more reliable.

3.3.2 Interview Design

The design of the interview guide is a critical step in the process to ensure that the data collection is relevant and useful. The guide was divided into five sections:

- Introduction & General Experience
- Knowledge-acquisition
- Reasoning
- Analysis
- Overall Adoption

The three functional areas of knowledge-acquisition, reasoning, and analysis represent the core dimensions of managerial decision-making where generative AI may play a role. Each category captures distinct interaction types and reflects how AI supports managers in tasks ranging from gathering external information to structuring decisions or engaging in cognitive work. This structure allowed us to systematically explore the how manager use generative AI and identify both enabling and constraining factors.

To establish a common ground for conversation during the interviews, we sent out a practice case to all interviewees in advance. The purpose was to create a shared starting point for discussion and provide concrete examples related to our three focus areas: analysis, reasoning, and knowledge-acquisition. This approach ensured that managers had a fresh experience with generative AI to reflect upon during our conversation, rather than trying to recall past interactions or speak in hypotheticals. All managers were expected to read, understand, and use ChatGPT to solve the case prior to the interview. We provided simple guidance on potential prompts they might use, such as asking ChatGPT to analyze customer data, reason through strategic options, or gather industry information. The case itself was based on a real consulting scenario that the managers could recognize, both in terms of the general assignment and the decision-making procedures they encounter in their daily work. This familiarity helped participants engage more authentically with the AI tool in a context relevant to their actual responsibilities.

This interview structure enabled discussions around the three focus areas regardless of each participant's prior experience with generative AI. Initially, our intention was for managers to work through the case during the interview, allowing us to assess their process and final decision. However, after the first interview, we decided to pivot: the manager did not have enough time to complete and familiarize with the case within the allocated interview slot. As a result, we adapted the interview process, by sending the case out in advance for managers to go through before the interview started, an approach that proved more effective for both the researchers' goals and the managers' time constraints. While the degree to which managers engaged with the case beforehand somewhat varied, we were prepared to adapt our interview questions accordingly. The case ended up fulfilling its purpose very well as a concrete reference point for discussion.

Semi-structured interviews allowed for open-ended questions, which enable participants to provide detailed responses about their experiences with generative AI. This approach is key to capturing the full complexity of managers' perspectives and practices. As Gioia et al. (2013) argue, open-ended questions are essential in qualitative research because they enable participants to raise ideas that might not emerge with closed questions. However, as Robinson (2023) notes, open-ended questions can also lead participants to introduce information that is not directly relevant unless guided by effective probing. This highlights the importance of carefully guiding the conversation while maintaining flexibility to ensure the data collected remains focused and meaningful.

Additionally, the researchers are aware that discussions about AI can sometimes be sensitive for employees. Participants are informed that their responses will remain confidential and will not be shared with colleagues, supervisors, or anyone else in the organization. This reassurance aims to create a safe environment where participants feel they can speak openly without fear of consequences.

3.3.3 Sampling

Given the qualitative nature of this study and its aim to explore the interplay between generative AI and managerial decision-making processes, a purposive sampling approach has been adopted. In addition, a single expert informant with extensive cross-industry AI-implementation experience was purposefully selected to validate and challenge emerging dimensions. This approach will help gain different perspectives and keep the research focus primary attention (Bell et al., 2022).

Criterion sampling involves selecting participants who meet a predetermined set of characteristics essential to the research question (Patton, 2002). In this case, the criteria include managers who have, at some point, engaged with generative AI tools and have decision-making in their normal work setting. This ensures that all selected participants possess relevant experience and insight.

The participating managers included in this study vary in both age and gender, ensuring a broad range of perspectives and experiences. Interviews were conducted between March 20 and April 24, 2025. The age of the participating managers ranged from below 30 to 60 years, with a gender distribution of 55% male and 45% female. The sampling aimed to reflect diversity across age, gender, managerial level, and AI experience, dimensions that literature identifies as influencing AI use and trust (Shin, 2021; Russo, 2024). Including varied backgrounds helps explore how different cognitive, social, and experience levels affect the use of generative AI.

The sample consists of managers in two roles: business unit managers (who lead business units operating within a specific area) and business area managers (who oversee entire business areas comprising multiple business units). This mix of managerial roles provides a broad view of decision-making, encompassing strategic, personnel-related, low-stakes, and high-stakes decisions. To better understand each respondent's relationship to generative AI, we have categorized their experience into three levels:

- Limited: minimal or no experience integrating generative AI into tasks.
- Intermediate: familiar with common applications and uses generative AI for specific tasks.
- Proficient: understands its capabilities and limitations, uses generative AI widely.

Table 2: Interview participants

Respondent	Position	Duration	Language	Generative AI Experience
1	Business Area Manager	58 min	Swedish	Intermediate
2	Business Unit Manager	38 min	Swedish	Limited
3	Business Unit Manager	50 min	Swedish	Proficient
4	Business Area Manager	52 min	Swedish	Intermediate
5	Business Unit Manager	60 min	Swedish	Proficient
6	Business Area Manager	43 min	Swedish	Intermediate
7	Business Area Manager	56 min	Swedish	Limited
8	Business Unit Manager	39 min	Swedish	Limited
9	Business Unit Manager	50 min	Swedish	Intermediate

3.3.4 Key-informant Interview

Consistent with case-study guidance on informant triangulation (Bell et al., 2022), we conducted one additional semi-structured interview with an external AI-transformation specialist Trent Gillespie (former head of Alexa Privacy Compliance at Amazon, and currently the CEO of Stellis AI) after coding was finished. It is not included in under interview participants because it falls outside the Rejlers managerial sample. The interview material served to validate or critically assess our findings and emergent themes. Notably, it did not influence the initial coding of the nine interviews.

3.3.5 Literature Review

The literature review in this study serves a dual purpose. First, it provides a foundation of existing knowledge about the interaction with new technology and managerial decision-making. Second, it guides the abductive analysis by offering theoretical insights without restricting researchers' natural view of the topic. In line with an abductive research strategy, prior literature is not used to test a hypothesis, but rather to inform and enrich the interpretation of empirical data (Dubois & Gadde, 2002). The review looks at research about AI use and adoption, and how current theoretical frameworks apply to decision-making processes. These frameworks help place our findings within wider academic discussion, while letting us stay open to patterns we see in the data.

The approach to our literature review is built on relevance to our research topic. Initial key words for the search in Scopus were *decision-making* and *generative AI*.

After identifying one relevant article, we used its reference list to discover additional sources, employing a cumulative approach to build a solid understanding of technology adoption frameworks and the managerial decision-making models on which explain how managers base their decisions. This approach on gathering relevant literature is preferred over systematic reviews since the researcher avoids reading articles that are not necessary for the research area. The cumulative approach used captures fundamental and relevant literature for our research area, touching upon older management theory and newer technology adoption factors.

Summary Chapter 3.3: Data Collection

- Nine Rejlers managers and one external AI expert were interviewed using a semi-structured format focused on knowledge, reasoning, and analysis.
- A practice case was sent out beforehand to ground the discussion in real decision scenarios.
- Sampling was purposive, aiming for variation in AI experience, role, age, and gender.
- The expert interview was used for triangulation and reflection but not included in primary coding

3.4 Data Analysis

To analyze the qualitative data, we adopted a grounded theory approach, combining data-driven analysis with insights from existing literature (Bell et al., 2022). This method is particularly well-suited for our research objective: to develop a novel understanding of how managers engage with generative AI in their decision-making processes, while grounding our insights into both empirical data and relevant theoretical frameworks.

The analysis followed the key principles of grounded theory outlined by the Gioia methodology, including first order concepts, second-order themes, and aggregated dimensions (Magnani & Gioia, 2022). The aggregate dimensions were developed from the nine managerial transcripts while the expert transcript was consulted only to confirm, challenge, or illustrate those dimensions. The first-order concepts were identified by using participants' own terms and expressions to stay close to actual experiences. These concepts were then grouped into second-order themes through an iterative comparison process between the theory and the insights from the data. Finally, we developed aggregated dimensions by combining data patterns and theoretical constructs through an abductive reasoning process. This structured and systematic approach enabled us to construct a data structure that clearly demonstrates the link between empirical findings and theoretical interpretation, consistent with the principles of the Gioia Methodology (Magnani & Gioia, 2022).

3.5 Quality Measures

Case studies, as presented above, are often small-scale and context specific. Bell et al. (2022) emphasize that their detailed nature can provide context-dependent insights valuable in understanding broader trends. For instance, examining managers' interplay with generative AI might help other engineering consultancies understand similar issues and apply these insights effectively. In-depth cases can provide the basis for concrete context-dependent knowledge, the only thing social science can reliably produce (Bell et al., 2022). To ensure our aim of high quality of this study, the criteria of credibility, dependability, confirmability, and transferability are applied. These criteria are more appropriate in qualitative, interpretivist research than the traditional criteria of validity, reliability, and replicability found in most of the quantitative research (Bell et al., 2022).

3.5.1 Credibility, dependability, confirmability, transferability

Credibility refers to the internal validity of the findings that correctly reflect the participants' views and experiences (Bell et al., 2022). To ensure accurate credibility, the interviews will be recorded and transcribed. Due to the interviewing structure, a follow-up question and clarifications will be used to increase trustworthiness and understanding. To ensure the credibility of the study the sampling is crucial. The selection of participants covers all levels of experience with generative AI, to not achieve skewed data. The semi-structured interview will help lower the bias of the data collection process by following the script and not deviate considerably, this essentially means that the analysis can be more reliable. The balance between structure and flexibility during the data collection is, therefore, vital. Thus, too much structure can result in not enough deep data to find the underlying reasons for the usage of generative AI in decision-making.

To complement credibility, dependability addresses the consistency and traceability of the research process (Bell et al., 2022). To address this concern, all steps of the data collection and analysis will be documented, and a structured yet flexible interview guide will be used. The research process, including sampling logic and coding procedures will be documented to enable others to follow our thoughts in the research process. The documentation of the process, data collection, and analysis will enable other researchers to evaluate the study design.

Closely related to dependability, confirmability refers to the extent to which the findings are shaped by the participants' input rather than researcher bias, aligning with the traditional criterion of objectivity (Bell et al., 2022). Since it is recognized that complete objectivity is not feasible, an effort will be made to ensure the least number of biases possible. Reflective activities were performed to keep the awareness of assumptions and influence on interpretation. Finally, transferability relates to whether findings can be applied in other contexts (Bell et al., 2022). While this study focuses on a single case, a detailed description of the organization context, participants, and decision-making processes are provided, allowing the reader to assess the relevance of the findings in other settings.

3.5.2 Validity in Relation to Interview Structure

Although the term "validity" is not commonly used in interpretivist research, it remains important that there is internal consistency between the research question, data collection, and analysis (Bell et al., 2022). In this study, validity is strengthened by the alignment between the interview guide and the core research question. Each interview was structured around our three functional areas and had the case as a common conversation starter. This ensured that collected data addressed the intended aspects of human-AI collaboration in decision-making.

Questions under knowledge-acquisition targeted the manager's ability to judge and use AI-generated information and facts, directly linking to how generative AI influences information search and trust. Reasoning-related prompts captured how managers brainstorm or problem-frame with ChatGPT, addressing AI's role in cognitive collaboration. Finally, analysis, questions explored how managers interpret quantitative output, seek confirmation, and potentially revise decisions, linking directly to decisional behavior.

4. Findings

This chapter presents our empirical findings from nine managerial interviews conducted at Rejlers, addressing our research question: "*What factors enable and constrain managers' use of generative AI for decision-making?*" Our analysis reveals foundational contextual findings about manager awareness and adoption behaviors (section 4.1), followed by three core dimensions that directly answer our research question: Knowledge-Dependent Trust (section 4.2), Contextual Intelligence Boundaries (section 4.3), and Organizational & Behavioral Barriers (section 4.4). These findings are further supported and nuanced by insights from our interview with Trent Gillespie, former head of Alexa Privacy Compliance at Amazon and currently CEO of Stellis AI. Together, these findings reveal the key factors that shape managers' ability to effectively collaborate with generative AI in decision-making contexts.

4.1 Manager Awareness and Adoption Behaviors

A general finding across interviews was managers' limited awareness of generative AI capabilities, even for features that have been available for longer periods. Although the depth of awareness varied from manager to manager, it was clear that for most participants, this gap created a significant barrier to effective utilization, as expressed by one manager:

(R8) *"I haven't known how to do it (make presentations), or I didn't even know it was possible"*

This quote reflects a fundamental unawareness that such functionality exists. The pattern continued with managers expressing similar unawareness of generative AI capabilities:

(R7) *"Yes, there's probably a lot more I could use it for, if I had really... thought it through, knew more, or maybe had it explained to me how I could use it specifically in my role."*

(R2) *"I still don't know exactly how to do it - for example, how it's supposed to extract data from PX"*

These statements reveal that managers recognize their awareness limitations and anticipate untapped potential yet lack the foundational knowledge to explore these possibilities independently. This awareness gap exists despite managers' technical backgrounds and overall digital literacy, suggesting that even technically proficient professionals require specific orientation to generative AI capabilities. It is also important to note that the time demands of managerial roles, particularly in consulting, reduce the capacity for internal business development.

Importantly, this uneven awareness and large gaps often mirrors organizational direction leadership. As external AI-transformation expert Trent observed, "*you have to have alignment with your leadership team as to what you're going to do about AI… even if you've got pockets of people who are figuring out how to use it in their role, if the senior team, doesn't have that agreement, you're not going anywhere material*." Without a clear sense of ownership from senior leadership, isolated experiments remain just that, and overall awareness stays low.

Connected to this knowledge gap is how managers approach experimentation with generative AI. Instead of systematic exploration, they typically try simple, low-risk tasks in an opportunistic manner. This cautious approach was often linked to uncertainty about when generative AI is truly helpful:

(R6) *"I think it's about just getting started – understanding when I can use it and when it actually helps me."*

(R9) *"So far, I do it the fastest myself. But maybe it could be even more efficient if I knew how to do it with ChatGPT"*

Without sufficient knowledge of capabilities or clear use cases, managers default to established methods even when recognizing AI's potential benefits.

(R3) *"If I don't have prior knowledge, I usually Google it instead of using ChatGPT."*

(R3) *"I think you could use it to a very large extent. But it also depends on what you're used to."*

This pattern tells a story of how awareness alone does not drive adoption. Managers need both knowledge, confidence, and clear leadership signals to break existing habits, creating a significant threshold they must cross before incorporating generative AI into their decision-making processes.

Another important general finding in our interviews was that social stigma or embarrassment around using AI does not seem to be a major barrier to adoption at Rejlers. Managers generally felt comfortable with colleagues knowing they used AI and were open about trying it out. The few social barriers that did appear were more specific to context and situations, namely two areas: customer-facing interactions, and knowledge sharing gaps.

For example, regarding custom facing interaction, managers expressed reservations about using generative AI in direct customer communications due to authenticity concerns rather than embarrassment:

(R5) *"Well, one risk I can see is if I start using ChatGPT in conversations with customers, since building relationships with our customers is really important. So that's a concern - I don't want it to get to the point where the customer feels unseen."*

Similarly, when it comes to knowledge sharing gaps, knowledge about AI capabilities was not systematically shared across teams despite individual experimentation. This created isolated pockets of adoption rather than organization-wide integration. Respondent three highlighted a simple potential solution:

(R3) *"It would be enough if everyone just shared how they use it in some forum."*

These two findings point to a clear distinction in how managers view generative AI adoption. Namely, they are more willing to experiment internally but remain cautious in external contexts.

This suggests their decisions are driven by practical concerns rather than general resistance to technology. Together, these general findings reveal that effective usage of generative AI depends on both individual knowledge development and supportive organizational structures. Managers need specific examples and guidance rather than general capability overviews, as implied by one manager:

(R9) *"You need to see the benefit of using ChatGPT for it to actually happen"*

These initial barriers must be addressed before the more complex dimensions of factors that enable and constrain generative AI use in decision-making can fully develop. In the following sections, we keep these overarching and general findings in mind as we begin to explore the deeper patterns of interactions between managers and AI that we group into three main dimensions.

Summary Chapter 4.1: Manager Awareness and Adoption Behaviors

- Most managers had limited awareness of what generative AI can do, despite technical backgrounds.
- Experimentation was cautious and unsystematic, often limited to low-risk tasks.
- Adoption depends on leadership signals, clear use cases, and shared practices, not just interest or access.

4.2 Dimension One: Knowledge Dependent Trust

The first major dimension that emerged from our analysis of factors that enable and constrain AI use in managerial decision-making is what we term "*Knowledge-Dependent Trust*". This dimension captures how managers' willingness to engage with and trust generative AI outputs is directly proportional to their domain knowledge in the relevant area. Essentially, managers were more willing to engage with and trust ChatGPT when they had sufficient background knowledge to evaluate its suggestions. Without this knowledge, the interviewees expressed hesitation and tended to use the tool only for simple or exploratory tasks. Two of the 2nd order themes that significantly contributed to the dimension of *Knowledge-Dependent Trust* were *Trust Through Verification* and *Expert Knowledge as Validators*. These 2nd order themes connect back to our general findings about knowledge gaps but reveal a deeper pattern. Even as managers gain awareness and begin experimenting with AI, their trust remains conditional upon their ability to verify and validate outputs using their own expertise.

What these two 2nd order themes illustrate is the essentialness of sufficient knowledge. Managers generally limit their use of generative AI to simpler tasks and lower-stakes decisions due to the need for ownership and a complete understanding when the stakes are high. Managers rely on their expertise to evaluate the output and determine what is usable. The lack of transparency in AI's reasoning creates a trust challenge, which managers navigate by using their judgment to assess and validate the generated content.

Table 3: Coding of Dimension One: Knowledge Dependent Trust

1st Order Concept	2nd Order Theme	Aggregated Dimension
Need for fact-checking		
Source transparency issues	Trust Through Verification	
Trust building over time		
Need to understand reasoning		Knowledge Dependent Trust
Questioning AI assumptions		
Expert judgment requirements	Expert Knowledge as Validator	
Knowledge-based evaluation		

In the following two sections, we will explore *Trust Through Verification* and *Expert Knowledge as Validators* more in depth, examining how they manifest in practice and what they reveal about the conditions that enable or constrain effective use of generative AI.

4.2.1 Trust Through Verification: The Need to Confirm AI Outputs

Building on our understanding of *Knowledge-Dependent Trust*, we found that managers consistently exhibit what we call *Trust Through Verification*. This is a pattern where they feel compelled to verify AI outputs before accepting them, particularly for important decisions. This verification behavior reveals how the human-AI interplay in decision-making involves a validation step.

The need to verify the output of AI-generated material was apparent across all identified areas of analysis, knowledge-acquisition, and reasoning. This behavior is rooted in managerial habits; across all managers' activities, seeking verification or a second opinion was consistently observed before using the material in higher-stakes decisions. As a manager explained through a familiar analogy:

(R4) *"I think it's a bit like when we hire someone – the interview might feel great, but you still want to check references. You turn to another source to get confirmation."*

This quote highlights that managers' normal working behavior includes verification, and that they are not unique to AI interactions but rather reflects managers' standard operating procedure. Even when impressed by AI outputs, managers apply their verification processes to anything they plan to use in their work:

(R4) "We felt a clear need to fact-check what you got from ChatGPT. We would never submit anything unless we truly believed in it."

This need for verification applied consistently across different types of AI use, whether for analytical tasks, information gathering, or reasoning. The verification step represents a critical point in the human-AI collaboration where managers assert final control over the decision-making process. Particularly noteworthy is how some managers still place greater trust in human confirmation than in AI systems:

(R1) *"But if I know that someone is really skilled in their field, and I compare that to an answer from ChatGPT - then there's still something more reassuring about checking with a colleague."*

This quote illustrates that even as AI tools become more capable, the human element in verification remains crucial, especially when managers lack complete confidence in their own domain knowledge. An overarching insight is that trust to human conformation is still significantly higher than for LLMs such as ChatGPT.

4.2.2 Expert Knowledge as Validator: Using Knowledge to Evaluate AI

Closely related to verification is *Expert Knowledge as Validator*, which describes how managers use their existing knowledge as a validation filter for AI outputs. This 2nd order theme, which supports the main dimension of *Knowledge-Dependent Trust*, highlights how personal expertise becomes the lens through which managers evaluate AI suggestions before incorporating them into decisions.

Managers with strong knowledge in a domain act as validators of AI's logic and conclusions. Without sufficient expertise, managers hesitated to trust output, especially in high-stakes settings. This validation process functions as a critical filter through which all AI outputs must pass before being used in important decisions, regardless of whether they relate to analysis, knowledge acquisition, or reasoning. For example, this filtering process manifests in managers' desire to understand AI's reasoning process:

(R4) *"I want to know what data was used and how it was interpreted."*

(R6) *"And then you'd really like to know more specifically how it arrived at that conclusion"*

These statements reveal how managers rely on their domain expertise to assess not just what AI tells them, but how it reached its conclusions. This represents a sophisticated level of human-AI interplay where managers don't simply accept or reject outputs but engage critically with the reasoning process itself. The desire for transparency in AI reasoning was repeatedly mentioned as an enabling factor that would increase trust and usage:

(R1) *"So you get some kind of audit trail of how ChatGPT made the decision."*

Together, these findings on verification and domain expertise as validation mechanisms show how trust in the human-AI relationship is not given automatically but earned through a process that heavily depends on managers' knowledge and established verification habits. This insight helps explain why even technically advanced generative AI tools may face use-and adoption challenges in knowledge-intensive management contexts.

> **Summary Chapter 4.2: Dimension One: Knowledge Dependent Trust**
> - Managers with strong knowledge in a field feel more confident using AI because they can spot mistakes.
> - Trust builds when managers verify AI outputs rather than accepting them automatically
> - Managers use their expertise as a filter to judge whether AI suggestions are useful or misleading

4.3 Dimension Two: Contextual Intelligence Boundaries

While our first dimension explored how managers' knowledge affects trust in AI, our second dimension examines how organizational context influences which tasks managers consider suitable for AI involvement. *"Contextual Intelligence Boundaries*" describes how managers determine the appropriate scope for AI assistance, particularly in environments requiring organizational insights that AI typically lacks.

This dimension emerged strongly in relation to task complexity, cultural and social nuances, and the criticality of decisions. Managers repeatedly mentioned that ChatGPT lacks understanding of how Rejlers operates. ChatGPT doesn't have access to, for example, Rejlers' internal workflows, strategic priorities, and client sensitivities that shape decision-making in practice. These contextual factors are vital not only for informed reasoning but for making analysis and knowledge acquisition relevant to Rejlers' specific organizational setting. The higher the stakes of a decision, the more essential the contextual setting becomes.

The boundaries of contextual intelligence are partly shaped by the 2nd order themes of the *Business Context Limitations* and *Selective Task Application*, both of which relate to the challenges posed by generative AI's lack of contextual understanding in specific tasks and settings.

Table 4: Coding of Dimension two: Contextual Intelligence Boundaries

1st Order Concept	2nd Order Theme	Aggregated Dimension
Prompt clarity challenges		
Spotting irrelevant outputs	Business Context Limitations	
Industry-specific limitations		
Simple vs. complex task sorting		Contextual Intelligence Boundaries
Experience level differences	Selective Task Application	
Selective use cases		
Risk-based decisions		

4.3.1 Business Context Limitations: AI's Limited Organizational Understanding

The first 2nd order theme of *Contextual Intelligence Boundaries* relates to how managers consistently identified a significant "contextual gap" in AI systems. This gap represents AI's inability to understand organization-specific information that humans naturally incorporate into their decision-making. We chose to call this theme *Business Context Limitations*.

Managers consistently pointed out that ChatGPT is not trained or have access to organizational or contextual data needed for more complex decisions. The interviewees noted that effective use requires human insights to bridge the context that ChatGPT initially lacks. This limitation was especially noted in analysis tasks, where financial or strategic decisions require an understanding of organizational operations, history, and dynamics that are not accessible to AI. The contextual gap that most of the interviewees noted is crucial to understanding barriers to increased use of generative AI tools. Below are key quotes that support the construction of the 2nd order theme of *Business Context Limitations*:

(R7) *"Sometimes the question you ask the AI might be too broad - 'Connected Energy' could be confused with unrelated topics that have nothing to do with remote grid control. It's the context that's missing."*

(R2) *"It was too general. It didn't align with what we actually do."*

These quotes show how ChatGPT sometimes fails to fit the specific organizational context. This leads to managers using ChatGPT less when tasks require adjustments to make outputs relevant to their situation. There is also another reason for this gap: sensitive client information that cannot be freely shared with AI systems. In complex business cases and for security reasons, managers do not feel comfortable specifying or explaining the entire business context, which results in a contextual mismatch.

(R7) *"So it was more an example of the content lacking context, that it was copied directly and therefore became too general"*

The quote presented above is another example showcasing that the generated output is too broad to be used in specific or complex business cases, highlighting the intelligence gap between the AI model and the demands of specific business contexts. This contextual gap limits generative AI's utility in areas such as reasoning or complex analysis, where context dictates how to interpret results and what is most essential to focus on. In contrast, for pure knowledge-acquisition tasks that require less organizational context, managers found the tool more effective.

4.3.2 Selective Task Application: Matching Tools to Tasks

The next 2nd order theme that contributes to the dimension of *Contextual Intelligence Boundaries* reveals how managers develop nuanced perspectives on which tasks are suitable for AI assistance. We chose to call this 2nd order theme *Selective Task Application,* and it represents managers' evolving understanding of generative AI's strengths and limitations within their organizational context.

Managers hinted on which tasks they thought were appropriate for generative AI use. Routine, low-risk, or technical tasks were commonly delegated to ChatGPT, while strategic, high-impact decisions remained human-led. The concept relates directly to reasoning and analysis. AI was accepted for supporting reasoning in structured, predictable domains where managers had high levels of expertise, but less so for unstructured or context-specific analysis. The ability to assess relevance and implications within a specific business setting is something managers did not believe ChatGPT could replicate without sufficient data. Below are quotes that support the construction of 2nd order theme of *Selective Task Application*:

(R3) *"In simpler cases yes, I would use AI."*

(R6) *"When it comes to risks, calculations, and similar matters, I want to understand the data much more thoroughly. And if it becomes more complex, which it often does, experience plays a key role."*

These quotes strengthen the 2nd order theme of *Selective Task Application* because they directly illustrate how managers differentiate between when generative AI is suitable and when human expertise is necessary.

(R7) *"For simpler tasks, I think it works quite well as is. Sometimes even better than what I would have done myself - it condenses what's important in a clear way."*

(R3) *"It's repetitive, and in that area I think AI is ten times better than we are."*

Managers develop nuanced perspectives on when and how to leverage generative AI tools based on task complexity and criticality, reinforced by the quotes presented above. AI is seen as valuable for routine, structured tasks but less suitable for complex, critical decisions. This selective utilization pattern reveals how managers mentally categorize tasks as 'AI-appropriate' or 'human-required' based on risk assessment and complexity of the case.

Together, the *Business Context Limitations* and *task-appropriate utilization* patterns show how organizational context shapes the enabling and constraining factors of effective generative AI use in managerial decision-making. These findings directly reveal how managers draw lines around where generative AI can effectively support their decision-making. The contextual boundaries managers establish aren't arbitrary but emerge from their practical experience with AI's limitations in understanding organization-specific knowledge. As we'll see in the next section covering dimension number three, these contextual factors interact with broader organizational structures and individual behavioral patterns to create additional barriers to effective AI use in managerial contexts.

Summary Chapter 4.3: Contextual Intelligence Boundaries

- AI tools lack understanding of specific company context, making them less useful for complex decisions.
- Managers give AI lower-risk tasks while keeping strategic or relationship-based decisions for themselves.
- The more a task requires organizational context, the less managers trust the AI.

4.4 Dimension Three: Organizational & Behavioral Barriers

Moving from contextual boundaries to broader structural challenges, our third dimension examines how organizational systems, and individual behaviors constrain human-AI collaboration. Despite recognizing generative AI's potential benefits, managers encounter significant barriers when attempting to implement these tools in their decision-making processes. Our analysis revealed a complex interplay of organizational structures and individual behavioral patterns that constrain effective AI use. These problems exist at many levels, from system integration issues to ingrained personal habits, and significantly affect how managers interact with AI.

This dimension builds on our earlier findings about knowledge and context by examining the practical, day-to-day factors that determine whether managers incorporate AI into their workflows. While the previous dimension focused on cognitive aspects (trust and contextual understanding), this dimension addresses the operational realities that managers face when attempting to use AI tools.

Table 5: Coding of the third aggregated dimension: Organizational and Behavioral Barriers

1st Order Concept	2nd Order Theme	Aggregated Dimension
Workflow fit requirements		
Resistance to change routines	Workflow Integration Needs	
Ease of access importance		
Familiar tool preference		
Potential vs. practice gap	Resistance to Change Habits	Organizational & Behavioral Barriers
Sticking to routines		
Incomplete information concerns		
Data connection difficulties		
System compatibility problems	Organizational Data Barriers	
Data security limits		

4.4.1 Workflow Integration Needs: The Need for Seamless Integration into Routines

A critical organizational barrier we identified is the integration of AI tools into existing workflows and systems. Managers expressed unwillingness to change established practices unless AI tools seamlessly fit into their current technological ecosystem. This integration challenge directly influences how generative AI use for managers manifests in practice, if the interaction requires extra effort, it often does not happen at all. A participant articulates this integration need:

(R1) *“An important prerequisite is that the AI is integrated into the application. I want it to be available right there, not something I have to leave what I’m doing to log in somewhere else for.”*

This highlights how convenience and workflow compatibility often trump abstract potential benefits. The same participant further explains:

(R1) *“It’s more that I have a way of working that works. It’s hard to change that unless you truly see the benefit. You almost need to ‘see it to believe it’ - then change can happen.”*

This barrier emerges not from opposition to generative AI but from practical considerations about efficiency and effort. Even when benefits are recognized, transition costs can be prohibitive. This finding reveals an important factor that constrains effective collaboration: the AI tool must integrate into existing workflows rather than requiring managers to adapt their processes around the technology.

4.4.2 Resistance to Change Habits: The Power of Established Routines

Beyond organizational systems, individual habits create powerful behavioral barriers to generative AI use. Managers develop work routines that persist even when alternatives might offer improvements. This behavioral aspect of human-AI interplay shows how psychological factors can override rational adoption decisions. We chose to name this 2nd order theme *Resistance to Change Habits*. These habits which lead to the use of familiar tools occurs despite recognition of generative AI's potential. This quote describes how existing habits inhibit AI use:

(R5) *"I think you could use it to a very large extent. But it also depends on what you're used to."*

Similar patterns appeared across participants, noting how established work habits create collaboration barriers:

(R2) *"I go to the person I usually go to. It's more of a habit. I just haven't gotten around to trying ChatGPT for that kind of question."*

This type of behavioral resistance appears common beyond our case organization. An alignment can be seen between our findings and the experiences of Trent, he explained: "*The third step in my SPRINT framework is Rally, and it's called Rally because you've got to get people to want to use it. Because most people don't want to. You've got to give them some reasons to want to.*" His account and methodology reflect a similar observation: that even when generative AI is accessible and potentially useful, uptake is often limited by default behaviors and a general lack of intrinsic motivation to engage with the tool.

These patterns reveal that generative AI usage is not merely a rational decision but is significantly influenced by psychological factors and established cognitive patterns. This finding connects to our overarching and general findings about managers' experimentation patterns. Even after initial awareness and trials, habitual behaviors often reassert themselves unless consciously redirected.

4.4.3 Organizational Data Barriers: Managing Organizational Knowledge

A significant system-level constraint emerges from the disconnect between organizational information ecosystems and generative AI tools. This third 2nd order theme is called *Organizational Data Barriers* and is the third theme contributing to the dimension of *Organizational and Behavioral Barriers.* This theme also relates directly to the *contextual intelligence boundaries* discussed earlier. However, this concept focuses specifically on the practical challenges of connecting generative AI to organizational knowledge systems.

Managers struggle with determining what information to input, balancing comprehensiveness with security concerns, and effectively connecting disparate data sources. One interviewee articulates this challenge:

(R7) *"It's about the fact that a lot of information is needed to make the right decision. You have to be careful to include all relevant data."*

This highlights the rigor required to ensure AI has sufficient context for meaningful outputs. The same participant identifies security concerns:

(R7) *"There's definitely a risk with entering sensitive information."*

These challenges point to a broader organizational constraint: the lack of systematic approaches for integrating generative AI tools with existing information systems. One participant envisions potential solutions:

(R5) *"You could have a version that only pulls data from Rejlers so that you can easily see what internal competencies we have, our average prices, margins, and so on."*

Similar observations appear to have emerged in other organizational contexts. Trent, described the same issue in broader terms: "*AI is not a project, it's an operational change. And you've got to look at it that way. It's not a one-time thing. It's not you just give it out to your employees and all of a sudden it's done.*" His remarks align with the view that generative AI cannot be separated from the organizational data landscape it depends on. Both our participants and Trent point to the same core issue: without structural integration of knowledge systems, generative AI tools remain disconnected from the operational realities in which managers work.

Together, these three themes of *Organizational and Behavioral Barrier*s (*Workflow integration Needs, Resistance to Change Habits*, and *Organizational Data Barriers*) reveal why generative AI usage and adoption often lags its technical potential in managerial decision-making. Rather than simple resistance to change, managers face genuine workflow challenges, deeply ingrained habits, and information integration issues that directly constrain how generative AI usage manifests in practice. These findings accurately identify specific factors that constrain and enable effective collaboration between managers and AI. The barriers are not primarily about technological limitations but about the human and organizational environment in which the technology operates. Addressing these organizational and behavioral barriers appears essential for realizing the full collaborative potential between managers and AI systems.

Summary Chapter 4.4: Organizational & Behavioral Barriers

- Managers avoid using AI if it does not fit smoothly into their existing processes and systems
- Strong habits and familiar routines prevent managers from changing how they work, even when they see AI's benefit.
- Connecting AI to company data securely while maintaining privacy creates a technical barrier.

4.5 Boundaries of Findings

The results from this study mainly apply to managers working in the consulting industry, especially in engineering consultancy firms where projects are complex, and knowledge driven. Since the research was based on one case company the findings should be understood in that specific setting. Some of the patterns we observed may also be relevant to other professional services, but the usefulness of the results may vary depending on the type of organization, its way of working, or how far along it is in using digital tools. Because of this, the findings should be seen as connected to the case context rather than as something that can be assumed to work everywhere.

5. Discussion

This chapter synthesizes our empirical findings with existing theory to address our research question: *"What factors enable and constrain managers' use of generative AI for decision-making?"* We examine how managers at Rejlers interact with generative AI tools, focusing on trust dynamics, contextual boundaries, and adoption barriers. By connecting our findings to established theoretical frameworks, we offer both theoretical contributions and practical insights for organizations seeking to implement generative AI in managerial contexts.

5.1 Trust Development Through Domain Knowledge and Verification

Our research reveals that managers develop trust in generative AI through an interactive process fundamentally shaped by their domain expertise and verification behaviors. This section examines how managers' knowledge creates both opportunities and barriers to effective AI collaboration and use, as well as how verification practices become essential to enabling productive human-AI teamwork in decision-making.

5.1.1 Strong Domain Knowledge both enables, and limits trust in AI

Our research shows an interesting contrast in how managers build trust with generative AI tools like ChatGPT. The more domain knowledge managers have, the better they can trust AI outputs. However, at the same time, this knowledge makes them more critical of AI-generated content. This creates what we call the "domain knowledge trust paradox", where expertise both enables and limits trust.

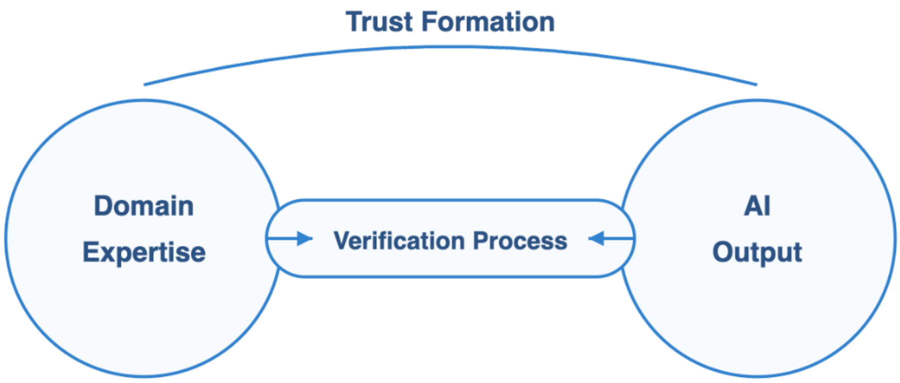
The managers at Rejlers showed that their willingness to use material from AI tools like ChatGPT for decisions depends on their ability to verify that content. Extensive field expertise acts as a verification filter for outputs from AIs. Importantly, we found that domain knowledge also affects what tasks managers feel okay using generative AI for. Managers with strong field expertise were willing to use ChatGPT for more complex, high-stakes tasks because they could confidently check the outputs. In contrast, those with limited domain knowledge stuck to simpler, lower-risk tasks where mistakes would have small consequences. This creates a clear link between expertise and the range of possible AI uses in managerial work.

This finding connects to the theoretical frameworks discussed in our literature review. The acceptance framework focuses on perceived usefulness and ease of use as main factors in technology adoption (Davis, 1989). However, our research suggests these factors come after basic awareness and are affected by domain knowledge. Many managers saw that generative AI tools like ChatGPT could be valuable but did not know how to use them in their specific roles, indicating that an awareness gap exists. This gap precedes the stage at which managers can meaningfully evaluate a tool's usefulness or ease of use.

UTAUT, or how we refer to it as the technology use framework, highlights performance expectancy as a key adoption factor (Venkatesh et al., 2003), but our findings show that performance assessment itself depends on domain expertise. Managers need enough knowledge to recognize whether the AI's output is helpful or possibly misleading.

More recent frameworks like the adoption framework for software engineers proposed by Russo (2024) recognized that trust and transparency affect adoption of generative AI. Our findings add to this by showing the same holds true for managers, but that trust is not fixed but grows through a knowledge-dependent verification process. The ability to verify generative AI outputs becomes the link between domain expertise and trust formation.

Figure 3: Trust-formation model. Source: Authors



The trust-formation model in Figure 3 illustrates how managers develop confidence in AI-generated outputs through an iterative verification process. Domain expertise serves as the foundation for evaluating AI output quality and accuracy. The bidirectional arrows between these elements represent the continuous back-and-forth process managers engage in when checking generative AI responses against their professional knowledge. This verification cycle either strengthens or weakens trust formation, shown by the overarching curve. The model captures the dynamic nature of human-AI collaboration, where trust isn't binary but develops through repeated interactions and successful verification experiences. Managers with stronger domain expertise can engage in more rigorous verification, leading to more nuanced trust relationships with generative AI tools.

This process relates to algorithm aversion as described by Dietvorst et al. (2015) in our literature review. Interestingly, our findings both confirm and refine research on algorithm aversion. While their work showed managers often hesitate to rely on AI-generated insights they cannot understand, our research shows that this aversion depends on knowledge. When managers have strong domain knowledge, their initial doubt turns into a productive verification process rather than outright rejection.

This knowledge-dependent trust dynamic shows up differently across the functional areas of our study. For knowledge gathering and analysis tasks, domain expertise was crucial as managers needed to check the accuracy of information or calculations. However, for reasoning tasks like brainstorming, the importance of domain knowledge and trust was less important. When using ChatGPT simply to generate ideas rather than factual answers, managers were less worried about perfect accuracy and more willing to use the output as inspiration regardless of their expertise level.

The domain knowledge trust paradox creates both opportunities and challenges for effective human-AI teamwork. While expertise enables more meaningful use of generative AI, organizations must consider how to help managers with varying levels of domain knowledge to develop appropriate trust relationships with these increasingly powerful language models.

5.1.2 Verifying AI Output is the Foundation of Trust

Our findings show that verification serves as the main way trust in generative AI develops. Unlike older technologies where trust might build through repeated use or social pressure, trust in generative AI like ChatGPT comes through active verification processes that depend on both manager expertise and situation factors.

Managers at Rejlers described verification routines they developed to validate outputs from generative AI before using them in decisions. This verification behavior exists across all functional areas but gets stronger in high-stakes decisions, due to that high-stakes decisions carry significant consequences for the organization. The need to verify the generated output also helps managers to navigate uncertainty, defend their choices, and lead effectively under critical moments. This trust through verification pattern matches with Shin's (2021) research on fairness, accountability, and transparency in AI systems. As noted in our literature review, views of an AI's fairness, accountability, and transparency directly build trust and acceptance. Our findings add to this by showing that transparency works through verification, managers need to understand not just that the AI works, but how it reaches its conclusions.

Recent changes in generative AI models have started addressing this need for transparency. Newer versions of these systems include features that show sources of information and explain reasoning steps. However, our research shows an important gap: some managers have limited knowledge that these features exist. During our interviews it came apparent that some managers' limited interaction time with generative AI show an awareness gap that continues to limit the effectiveness of even well-designed transparency features in generative AI tools.

Interestingly, the verification processes described by managers reflect what Kahneman (2011) called "System 2 thinking." Slow, careful, logical thought processes. While generative AI might speed up the generation of options (supporting System 1's quick processing), managers use System 2 thinking during verification. This observation adds to our understanding of dual-process theory in human-AI teamwork, suggesting that good partnerships use both systems: AI's speed and pattern recognition abilities combined with human verification and context judgment.

The implications of trust through verification are important for organizational adoption strategies. Traditional adoption models like the acceptance and technology use framework might suggest improving perceived usefulness through showing generative AI capabilities is enough to establish trust. However, our findings indicate that building trust requires more than that. Two examples would be transparency features that explain how the AI reaches conclusions, and clear ways for managers to check and validate AI-generated information. Furthermore, training that helps managers better understand what they are looking at differs from the "black box" nature of many AI systems that our literature review identified as problematic (Dietvorst et al., 2015). Our research suggests that for generative AI in managerial decision-making, increased transparency and explainability are not just preferences but requirements for trust formation.

The importance of verification also connects to Simon’s (1977) intelligence-design-choice phase model of decision-making. Verification spans all three phases but especially strengthens the “intelligence” phase (gathering information/knowledge-acquisition) and “design” phase (analyzing/reasoning). Generative AI can speed up these phases, but verification ensures their quality and reliability.

Our findings on trust through verification go beyond existing literature by showing how trust in generative AI emerges not from the technology’s inherent properties but through an interactive process of questioning, testing, and validation. This dynamic trust formation process highlights the fundamentally cooperative nature of effective human-AI interactions in managerial contexts.

> **Summary Chapter 5.1: Trust Development Through Domain Knowledge and Verification**
>
> - Manager expertise creates a paradox: more knowledge helps check the AI but also makes managers more critical.
> - Trust in AI develops from verification, not just from AI features or reputation.
> - Different tasks require different levels of trust, where managers are more willing to try AI for tasks like idea generation.

5.2 How Managers Draw Boundaries Around AI Use in Decision-Making

Building on our findings about trust development, we now examine how managers establish practical boundaries for generative AI use in their work. While trust mechanisms determine how managers evaluate AI outputs, boundary-setting determines which tasks they believe are appropriate for AI use in the first place. This section explores the contextual limitations of generative AI and the resulting patterns in task distribution. This offers insights into how managers strategically allocate responsibilities between themselves and AI tools.

5.2.1 AI systems lack Organization-Specific Context

Our research showed a basic limitation of generative AI tools like ChatGPT that greatly shapes how managers use them: their inability to understand organization-specific context. This *Business Context Limitation* theme emerged as a key factor in managers’ decisions about when to use generative AI and when to rely on human judgment.

Managers at Rejlers identified that while generative AI have impressive general knowledge, they lack understanding of the company’s specific workflows, client relationships, and organizational history. These observations during our interviews highlight a critical limitation of current generative AI models: they lack the organizational integration and knowledge needed for many complex managerial decisions. This finding connects to Simon’s (1956) theory of bounded rationality discussed in our literature review. Simon described how decision-makers operate with limited information, time, and cognitive resources. What our research reveals is that generative AI models face their own form of bounded rationality. They lack access to the organization-specific context that shapes managerial decisions. While humans develop bounded rationality through lived experience within an organization, generative AI remains bounded by its training data and inability to directly experience organizational life.

Figure 4: AI-bounded rationality model. Source: Authors

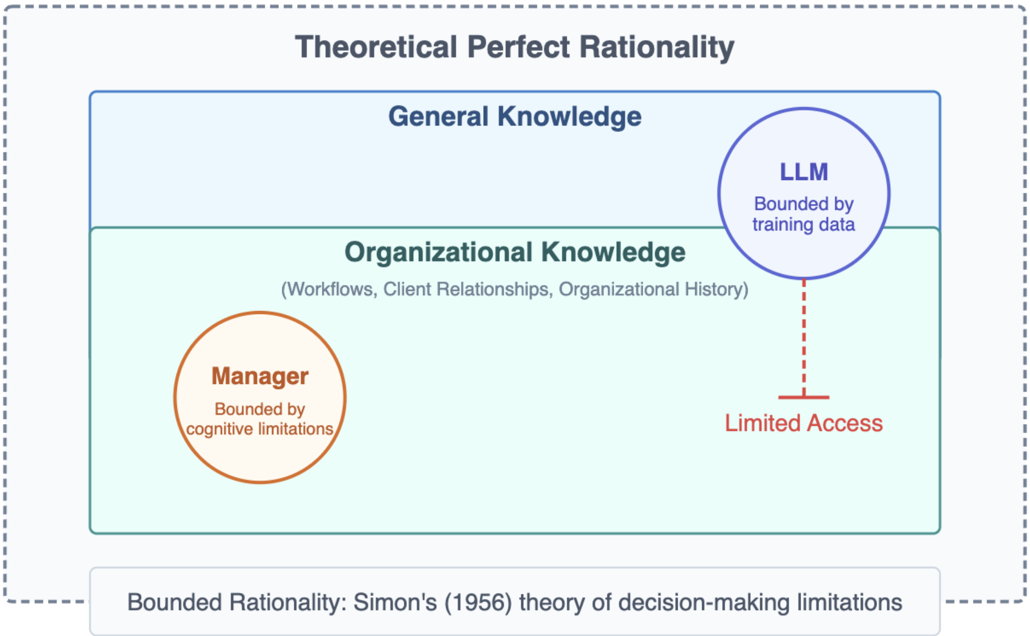


Figure 4 illustrates how both managers and generative AI such as ChatGPT (LLMs) operate within bounded rationality, constrained by different limitations within the broader framework of theoretical perfect rationality. The model shows two knowledge layers: general knowledge and organizational knowledge, both encompassed within the ideal of perfect rationality that Simon (1956) described as theoretically possible but practically unattainable. While generative AI have extensive access to general knowledge from their training data, they face limited access to organizational knowledge, represented by the red dotted line barrier. Managers, conversely, are bounded by cognitive limitations but have deep access to organizational context through direct experience. This creates complementary but misaligned knowledge boundaries, where neither party can achieve perfect rationality, but each possesses different pieces of the complete knowledge puzzle. This explains why effective collaboration requires bridging these knowledge gaps, which is what our theme of *Business Context Limitations* is capturing.

The theme *Business Context Limitations* appears in the human-AI interplay in several distinct ways. First, generative AI tools have trouble with organization-specific terminology and concepts. Terms that have specific meanings within Rejlers (like “Connected Energy”) may be understood differently by generative AI models trained on general data. Second, these interactive tools lack understanding of unwritten rules, cultural norms, and power dynamics that affect decision-making. Third, they cannot access the practical knowledge that experienced managers gather through years of working within a specific organization.

Some technology solutions are starting to address this contextual gap. Tools like Microsoft Copilot and integrated local language models that connect to company databases represent attempts to bridge this divide by giving AI access to organization-specific information. A few participants mentioned experiences with such integrated tools, finding them more contextually aware than standalone models such as ChatGPT. However, these solutions create their own challenges related to data security, privacy concerns, and the difficulty of managing organizational knowledge in a way that generative AI can effectively access.

We found that only a small minority of managers (one or two participants) actively tried to bridge the contextual gap by providing background information when prompting ChatGPT, basically trying to "teach" it about relevant organizational context. Most participants were not aware of this possibility or lacked the skills to effectively implement it. Instead, the majority simply used outputs from ChatGPT as starting points that they would then modify based on their contextual knowledge. This translation role emerged as a critical human function in the back-and-forth collaboration with generative AI.

The *Business Context Limitations* varied in importance across different functional areas. For knowledge acquisition on general topics, the gap was less problematic. Managers could use ChatGPT and similar tools to gather information from public domains without needing deep organizational context. For analysis of company-specific data, the gap became more significant, as interpretation required organizational understanding. For reasoning about complex organizational problems with multiple stakeholders, the contextual gap became most critical, often making assistance from the AI limited without extensive human guidance.

This finding adds to current understanding of generative AI limitations in decision support. While previous research has noted technical limitations of traditional AI systems, our findings highlight a more fundamental boundary for interactive, generative AI. Namely that these types of generative AI models operate outside the social and organizational context that gives meaning to managerial decisions. This insight has important implications for how organizations approach the integration of generative AI tools, suggesting that effective implementation requires ways to bridge this contextual gap rather than expecting AI models to function on their own in organization-specific domains.

5.2.2 Managers strategically divide tasks between themselves and AI

While the *Business Context Limitations* shows what generative AI systems struggle to understand, managers' responses to this limitation reveal more about generative AI use in decision-making. Rather than abandoning generative AI tools entirely, managers developed approaches to dividing tasks between themselves and AI, creating partnerships that leverage each party's strengths. Rather than purely random or unplanned delegation, managers developed intuitive judgments about "AI-appropriate" versus "human-required" tasks. These boundaries were not based on strict mental models but emerged through experience and intuition as managers dealt with different decision scenarios.

The clearest pattern appeared around task structure and routine. Managers consistently gave well-defined, routine tasks to generative AI while keeping ill-structured, novel problems for human judgment. This task-appropriate use reveals managers' practical understanding of where Generative AI currently add most value. Our research revealed that while managers readily used generative AI for structured tasks, many also used these tools for creative functions like brainstorming and idea generation. This suggests that the interactive, conversational nature of generative AI makes it suitable for certain creative tasks, even while managers maintain control over which ideas to actually pursue.

The task separation also aligned with Simon's (1977) intelligence-design-choice phase model. Generative AI tools were most often used in the intelligence phase (gathering information) and parts of the design phase (developing options). However, as expected, managers consistently kept the choice phase (making final decisions) for human judgment. This maintains human accountability while using the conversational AI's ability to process large amounts of information and generate alternatives.

Risk assessment emerged as another key factor in task boundaries. For low-risk decisions, managers were comfortable with significant involvement from generative AI. However, for high-stakes decisions with significant consequences, managers insisted on greater human oversight, as the need to understand and interpret the output becomes more essential the higher the stakes of the project or decision. This risk-based boundary setting shows managers' sense of responsibility and accountability for consequential decisions.

This pattern connects to dual-process theory described by Kahneman (2011). Interactive AI tools effectively support System 1 thinking (fast, intuitive, pattern-matching) by rapidly generating options and processing information. However, managers retain System 2 thinking (slow, deliberate, logical) for evaluating AI outputs and making final judgments. The back-and-forth collaboration between AI's rapid processing and human deliberation creates a potentially strong decision-making partnership that combines speed with judgment.

Interestingly, our findings showed that task boundaries were shaped not only by technical capabilities but also by social and relational considerations. Managers were particularly hesitant to use generative AI for customer-facing communications that involved relationship building. Similarly, participants expressed reluctance to apply generative AI to sensitive personnel matters within the organization. These boundaries highlight how organizational norms and relationships influence perceptions of appropriate use for generative AI tools.

These findings go beyond prior research by revealing not just which tasks managers delegate to generative AI, but the underlying logic of their boundary-setting process. While previous studies have examined technical capability matches with traditional AI systems, our research identifies factors related to contextual intelligence, risk assessment, and social factors combine into an intuitive model of appropriate human-AI task division.

The patterns identified suggest that an important enabler for effective generative AI use among managers is thoughtful task alignment rather than blanket application. Organizations seeking to implement generative AI tools in managerial contexts should focus on matching these tools to appropriate tasks rather than attempting to apply them across all decisional activities. This targeted implementation approach acknowledges both the strengths of generative AI in structured information processing and creative ideation, and their limitations in contextual understanding and relationship management. The boundary-setting behaviors we observed represent a key factor that enables effective collaboration when managers understand which tasks benefit most from AI involvement and which require primarily human judgment.

> **Summary Chapter 5.2: How Managers Draw Boundaries Around AI Use in Decision-Making**
>
> - AI's lack of understanding of specific company context severely limits its usefulness for organization specific decisions.
> - The boundaries managers set for tasks they give to AI does not follow a systematic pattern.
> - These boundaries reflect practical experience with AI limitations rather than resistance to technology.

5.3 Barriers to Effective AI Adoption in Managerial Work

Having examined how managers develop trust in generative AI and establish boundaries for its use, we now turn to the more practical challenges that prevent effective integration of these tools into daily work. While our previous sections focused on cognitive and decision-making aspects of generative AI use, this section addresses the organizational and behavioral factors that constrain daily usage. We also highlight practical approaches to overcome these challenges.

5.3.1 The Need for Seamless Organizational Integration

Our research showed that organizational factors significantly impact whether managers successfully use generative AI tools. These structural barriers often prevent even interested managers from effectively integrating generative AI into their workflows.

The most notable organizational barrier we identified was the lack of smooth integration between generative AI and existing work systems. Managers expressed reluctance to adopt AI when doing so required leaving their established workflows and applications. Participants emphasized that generative AI tools need to be embedded directly into existing applications, rather than requiring users to switch platforms or interrupt their workflows. This integration challenge reflects a basic gap between the standalone nature of many generative AI tools and the interconnected systems managers use daily.

This finding connects to the concept of “workflow compatibility” highlighted in Russo’s (2024) adoption framework discussed in our literature review. The adoption framework emphasizes that, for software engineers, AI tools that fit well with existing workflows are much more readily adopted. Our research confirms this factor is particularly crucial for generative AI adoption in managerial contexts too, as the perceived switching cost of moving between systems creates significant friction that prevents regular use.

These challenges align with organizational readiness identified by Nguyen Van Phuoc (2022) and Lada et al. (2023). They found that IT infrastructure and data readiness relate to higher AI adoption rates. Our findings add to this understanding for generative AI specifically, where the disconnection between organizational information systems and generative AI tools creates a significant adoption barrier despite managers’ interest.

The concept of “digital maturity” mentioned in our literature review also appears relevant. Organizations further along in their digital transformation journey typically have more integrated systems and data-sharing capabilities that could potentially handle generative AI integration. Participants envisioned, for example, that a generative AI trained on company data could help gather information on the internal expertise the company already has, the hourly rates Rejlers charges, and the typical margins a certain project yields for the organization. This suggests that organizational readiness for generative AI requires not just technical infrastructure but specifically integrated data systems.

Current approaches to addressing these integration barriers remain ad hoc and incomplete. A minority of managers created workarounds, manually transferring information between systems. Others limited their use of generative AI to standalone tasks that did not require deep integration with organizational data. The most successful adopters in this context were those who worked in areas where their organizations had implemented specialized integrated solutions like Microsoft Copilot that directly connected generative AI capabilities with existing workflows.

These findings highlight that organizational readiness for generative AI adoption goes beyond general digital infrastructure. Organizational readiness also includes specific integration capabilities that allow generative AI to function within existing workflows and access relevant organizational data. This represents a significant challenge but also points toward clear implementation priorities for organizations seeking to enhance generative AI adoption.

5.3.2 Overcoming Individual Behavioral Barriers

While organizational factors create structural barriers to generative AI usage, our research revealed equally powerful individual psychological and behavioral barriers. These personal factors often persist even when organizational barriers are minimal, creating a complex adoption landscape that operates at multiple levels.

The most common individual barrier we identified, captured by our dimension of “*Organizational and Behavioral Barriers*”, is the tendency to stick with established work routines even when alternatives might offer improvements. This pattern appeared consistently across participants, with one manager explaining that, instead of using ChatGPT to search for information, the convenience and habitual use of Google outweighed the benefits of using ChatGPT. This gap between recognized potential and actual behavior highlights how deeply ingrained work habits limit adoption.

This tendency to stick with established work routines connects to the concept of “personal innovativeness” identified in Russo’s (2024) adoption framework. Our research confirms that individual willingness to experiment with new technologies significantly impacts generative AI adoption. However, we add to this understanding by showing that habitual patterns can override even positive attitudes toward innovation. Another participant described relying on familiar colleagues out of habit, this suggests that breaking established patterns requires more than just openness to innovation, it demands conscious effort to disrupt comfortable routines.

A second significant individual constraint was managers' uncertainty about their ability to effectively use generative AI. This manifested as hesitation about prompt crafting and output evaluation. This uncertainty creates a psychological barrier where managers default to familiar approaches even when recognizing potential benefits from generative AI. This finding relates to the concept of the user's comfort with technology mentioned in our literature review. Russo's (2024) research found that users' confidence in their ability to effectively use technology shaped adoption behavior. Our findings add to this by highlighting how the unique interaction mode of generative AI creates specific competence uncertainties different from traditional software. Unlike menu-driven applications, generative AI require managers to formulate effective prompts, a skill many found challenging to develop.

A third individual barrier that emerged was mental effort required to use generative AI effectively. One participant described the "invisible mental labor" behind seemingly effortless AI use, explaining that formulating a prompt often requires careful thought about how to phrase it to receive a useful response. This mental investment creates resistance, particularly when managers perceive the AI's output might require significant verification or modification. These observations aligned with the experiences of Gillespie, whose findings across multiple organizations reflects a similar behavioral pattern, where even access to useful tools does not guarantee usage unless users are motivated to change.

Interestingly, we found minimal evidence of the job security concerns identified in Russo's (2024) adoption framework. None of the managers expressed concerns about job displacement or status loss from generative AI adoption. One possible explanation could be limited awareness of AI's current capabilities and rapid development trajectory. Managers generally viewed generative AI as something to adapt to and learn to work with, reflecting an acceptance of technological change rather than resistance.

This pattern is consistent with experiences reported in other organizational contexts. As Gillespie explained, technical roles such as IT and business intelligence teams tend to show the strongest resistance: "*The most resistant force was exactly that - the IT team and the business intelligence team*". He suggested that perceived job threat may be a factor: "*I think there is the job fear [in IT and BI] because you can see that it's doing things better. And I think outside of the IT group, most people are still really unaware of the impacts that are coming.*"

This supports our hypothesis that awareness level may shape whether job security concerns emerge at all. In our case, low perceived threat may stem not only from role differences but also from limited understanding of generative AI's full potential and implications. This suggests that managers in general may not perceive generative AI as a significant job security threat. Instead, barriers focused on practical concerns about effort and effectiveness. This aligns with Russo's (2024) findings in software engineering contexts, where resistance was noted among technical professionals. It's possible that managers in thinking-oriented, problem-solving, and creative roles feel less threatened than professionals in more repetitive, technical tasks where AI automation appears more directly applicable.

Overall, our analysis suggests that addressing individual adoption barriers requires a multi-part approach that:

1. Helps managers break habitual patterns through specific use cases and examples
2. Builds competence and confidence through guided practice with clear feedback
3. Reduces cognitive load through prompt templates and simplified interfaces
4. Raises awareness through targeted education about capabilities and applications

These findings add to existing literature by highlighting the behavioral and psychological aspects of generative AI adoption that go beyond traditional technology acceptance models. While perceived usefulness and ease of use remain relevant, our research suggests that habitual patterns, competence uncertainty, and cognitive load create distinct barriers for generative AI tools that require specialized interventions. By identifying both organizational and individual barriers to AI usage, our research provides important insights into the conditions that constrain effective human-AI collaboration in managerial decision-making. These barriers help explain why, despite significant technical advances in generative AI capabilities, usage and adoption in managerial contexts remains uneven and often superficial.

Summary Chapter 5.3: Barriers to Effective AI Adoption in Managerial Work

- Generative AI tools are often underused because they don’t integrate smoothly into existing workflows.
- Personal habits, low confidence in prompting, and the mental effort of using AI create major behavioral barriers.
- Adoption requires both technical integration and targeted support to break routines and build user competence

5.4 The Managerial AI Interaction Framework

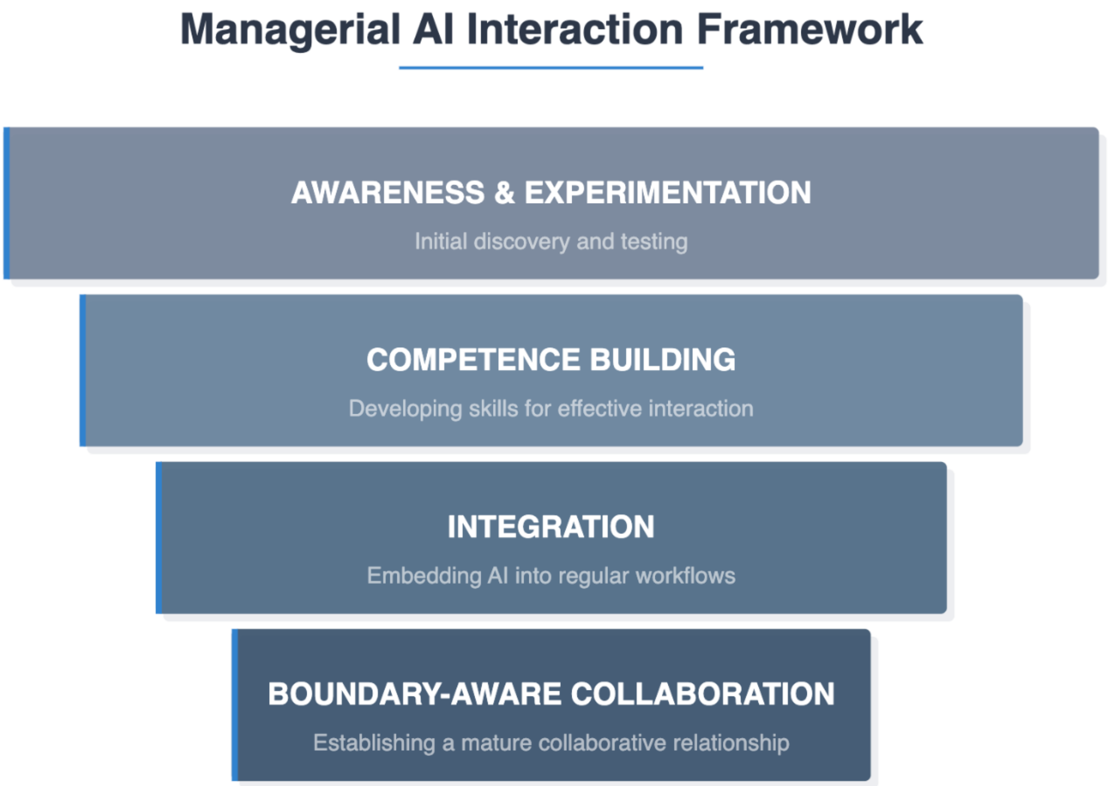
Building on our analysis of trust development, boundary setting, and adoption barriers, we now propose an integrated framework that helps organizations understand and support how their managers develop relationships with generative AI tools. This Managerial AI Interaction Framework serves as both a diagnostic tool and implementation guide for organizations seeking to accelerate effective AI adoption among their management teams.

The framework addresses a key organizational challenge: how to move managers from little or no awareness of AI tools to productive collaboration. Our research revealed that this journey follows predictable patterns. Without understanding where managers are on their adoption journey, organizations will struggle to provide appropriate support or measure progress effectively.

Our framework presents a reverse pyramid structure with four distinct stages that managers may find themselves in when it comes to adopting and using generative AI tools:

- **Awareness & Experimentation**: Initial discovery and testing
- **Competence Building:** Developing skills for effective interaction
- **Integration:** Embedding AI into regular workflows
- **Boundary-Aware Collaboration:** Establishing a mature collaborative relationship with defined boundaries

Figure 5: The Managerial AI Interaction Framework



The reverse pyramid shape reflects both the foundational nature of each stage, and the reality organizations face when implementing AI initiatives. Awareness and experimentation form the largest foundation because it's the prerequisite for everything else. Managers cannot build competence without first discovering what is possible, they cannot integrate tools without understanding their capabilities, and they cannot establish collaborative boundaries without basic interaction experience. This foundational stage also represents where most managers currently are, making it the largest group requiring organizational attention. As managers progress through more sophisticated stages, fewer reach each advanced level without targeted organizational support. This creates the narrowing effect: competence building requires more intensive intervention than basic awareness, integration demands even more systematic support, and boundary-aware collaboration emerges only with comprehensive organizational backing. Each stage builds on the previous one through practical experience with generative AI's capabilities and limitations, requiring different organizational responses.

The framework emerged naturally from our research data, reflecting consistent patterns in how managers described their AI adoption and usage patterns. By interviewing nine managers with varying levels of AI experience, this allowed us to capture the full spectrum of usage experiences and identify clear patterns across different experience levels. Managers at Rejlers demonstrated clear progression markers: those stuck at awareness expressed frustration about not knowing applications, those building competence focused on things like prompt effectiveness and technical features, those integrating worried about workflow disruption, and those collaborating discussed strategic task boundaries. By analyzing these distinct experience profiles, we could map the logical progression that managers follow, providing organizations with insights that would typically require years of longitudinal observation. These patterns enable organizations to identify where their managers are and what support they need next.

Organizations can use this framework in three ways. First, as a diagnostic tool to assess the current distribution of managers across stages and identify where most support is needed. Second, as an implementation guide to design stage-specific interventions that address the right barriers at the right time. Third, as a progress tracking system to measure how effectively organizational initiatives move managers toward productive AI collaboration.

This model provides organizations with practical guidance for managing generative AI usage systematically rather than hoping individual managers will figure it out independently. Each stage represents a distinct phase with specific characteristics, challenges, and enablers that organizations must address for successful progression.

5.4.1 Framework Foundations and Connection to Existing Adoption Models

Our Managerial AI Interaction Framework builds upon existing technology adoption theories while offering new insights specific to the unique nature of generative AI tools. Unlike traditional technologies that follow relatively straightforward adoption paths, generative AI requires a progressive relationship development that unfolds over time.

The framework's foundation connects to the acceptance framework (TAM) (Davis, 1989). The adoption framework emphasizes perceived usefulness and ease of use as primary adoption drivers. Our research confirms these factors matter for generative AI adoption, but reveals they operate differently across framework stages. In early stages, managers can only guess about AI's usefulness based on what they have heard rather than direct experience. Later, as managers gain experience, they judge usefulness based on concrete results they have personally achieved, making their assessment more refined and task specific.

Similarly, our framework adds to the technology use framework (UTAUT) described in our literature review (Venkatesh et al., 2003). The technology use framework highlights additional adoption factors like social influence and facilitating conditions. Our research shows social influence is more powerful in early stages when managers have limited personal experience with generative AI, implying that knowledge-sharing would help find relevant use cases where generative AI would augment managers' workflow. This knowledge sharing helps overcome initial awareness barriers. In contrast, facilitating conditions like technical infrastructure become crucial during Integration when managers need AI tools to work smoothly with existing systems.

The closest connection exists with Russo's (2024) adoption framework (HACAF), which was developed in the context of software engineers adopting generative AI. As discussed in our literature review, the framework incorporates aspects like workflow compatibility and personal innovation. Our Managerial AI Interaction Framework adds to Russo's framework by including a progression dimension, showing how different adoption factors emerge and change depending on the stage, rather than operating all at once.

What makes our framework different is its specific focus on the developmental stages of generative AI usage in managerial contexts. While previous models explain why adoption occurs, our framework captures how the relationship manifests, recognizing that effective collaboration with generative AI tools requires moving through distinct phases of interaction maturity. The framework integrates and explains the three core aggregated dimensions we identified in our research:

First, it shows how trust development evolves across stages. From basic experimentation with low-risk tasks to sophisticated verification practices based on domain knowledge. As managers progress through the stages, their trust mechanisms become more nuanced and efficient, enabling more complex collaborations. Second, it demonstrates how understanding of contextual boundaries matures as familiarity and usage increases. As managers gain experience, they develop clearer judgment about which tasks are appropriate for AI versus human handling. This boundary understanding becomes more sophisticated and task-specific in later stages. Third, it illustrates how adoption constraints are progressively addressed. Both technical integration challenges and behavioral habits become less problematic as managers advance through the stages. Early barriers like awareness gaps give way to different challenges related to workflow integration and boundary management.

This shows how our framework captures the overall managerial experience when using generative AI tools, providing both theoretical insights and practical guidance for organizational implementation.

5.4.2 Barriers and Implementation Strategies for the Managerial AI Interaction Framework

Our framework reveals how managers progress through distinct stages when adopting generative AI tools, each with unique challenges and opportunities. Understanding the various stages and level of usage provides organizations with practical guidance for supporting managers throughout their adoption journey. The initial Awareness & Experimentation stage involves managers discovering what generative AI tools can do through simple testing with low-risk tasks. Many managers remain stuck at this early phase, aware of the technology but uncertain how to apply it meaningfully to their work.

Organizations can accelerate progression through this initial stage by providing specific work examples demonstrating generative AI solving actual managerial problems. Creating low-pressure environments for first-time experimentation helps overcome hesitation, while clear leadership directives can establish expectations for regular generative AI use in specific tasks. Sharing ready-to-use starter prompts for common activities like meeting summaries could significantly lower entry barriers.

These implementation strategies are further supported by experiences shared by Gillespie, in his work with organizations on generative AI adoption challenges. When reflecting on the reluctance many employees have toward trying generative AI, he noted: "*You've got to give them some reasons to want to [use it]. And there's training, but there's also incentives, there's support, there's future opportunity.*" His account shows that awareness alone is not sufficient, motivational factors and structural support play a critical role in helping managers move beyond hesitation and begin experimenting meaningfully.

Table 6: Awareness & Experimentation Stage

Primary Barriers	Implementation Strategies
Limited awareness of what's possible	Provide specific work-relevant examples
Sticking to familiar tools out of habit	Create low-pressure experimentation environments
Uncertainty about where to start	Issue clear leadership directives for AI use
Familiar tool preference	Share ready-to-use starter prompts

As managers advance to the Competence Building stage, they begin learning how to effectively communicate with generative AI systems, developing skills in writing clear prompts and evaluating responses. This stage requires effort but starts producing valuable results. Barriers and constraints at this stage shift from basic awareness to practical skill development. Managers express lack of confidence in their AI interaction abilities. The mental effort required to formulate effective prompts also emerges as a challenge, alongside uncertainty about output trustworthiness.

To support this competence-building phase, organizations should identify and educate managers on high-value applications with clear benefits, such as document summarization, spreadsheet analysis, or presentation feedback. Teaching managers to recognize common generative AI pitfalls like hallucinations and overconfident incorrect answers also helps build critical evaluation skills. This stage connects directly to our findings about *Trust Through Verification*, as structured approaches to verification can accelerate skill development and confidence.

Table 7: Competence Building Stage

Primary Barriers	Implementation Strategies
Lack of confidence in AI interaction skills	Identify high-value applications
Mental effort required for effective prompting	Offer hands-on practical workshops
Uncertainty about output trustworthiness	Teach recognition of AI pitfalls
	Provide verification frameworks

The third stage, Integration, represents a significant transition as managers incorporate generative AI tools into their regular work routines rather than treating them as occasional resources. They begin developing consistent patterns of use, with focus shifting from learning the tool to making it a part of daily workflow. Our research identified several key constraints at this stage, particularly the disruptive workflow jumps between systems. Managers also faced challenges connecting generative AI to company data sources and systems, often lacking consistent support from IT or leadership.

Organizations can facilitate integration by developing plugins or integrations with existing software ecosystems, connecting generative AI tools to company data sources to eliminate manual information transfer, and tracking specific productivity gains to reinforce usage. This stage connects directly to the organizational readiness factors highlighted in our literature review, particularly the importance of technical infrastructure and data governance. It also reflects our findings about *Workflow Integration Needs*, where convenience and workflow compatibility often determine whether generative AI tools become regularly used.

The importance of sustained support for this stage is emphasized by Gillespie. He describes integration as an ongoing process rather than a one-time effort in order to overcome these barriers successfully: "*[integration] is not something you can do just once. You've got to start and then you've got to support it. Everything from role guidelines to information sharing, to prompt libraries, to newsletters…it becomes an ongoing thing. So that's how you integrate it.*" His shared experiences highlight that these implementation strategies for successful integration are not purely technical. They rely on continuous support through internal structures that sustain integration over time.

Table 8: Integration Stage

Primary Barriers	**Implementation Strategies**
Disruptive workflow jumps between systems	Develop software integrations
Challenges connecting to company data	Connect to company data sources
Inconsistent organizational support	Track and highlight productivity gains
Time costs of system switching	Streamline authentication and access processes

In the final Boundary-Aware Collaboration stage, managers develop a mature working relationship with generative AI tools based on experience with both successes and limitations. They establish clear boundaries about when to use AI and when human judgment is preferable, developing efficient verification methods for important decisions. At this advanced stage, generative AI becomes a trusted but carefully managed resource. Usage constraints shift toward more sophisticated challenges: establishing reliable verification methods for critical decisions, addressing generative AI's limited understanding of company-specific context and finding the optimal balance between AI speed and human oversight.

Supporting this advanced stage requires more sophisticated organizational approaches: creating holistic AI knowledge systems that integrate company policies, employee expertise, client relationships, and market context; establishing clear guidelines about which decisions can be AI-supported versus human-led; and building feedback loops that improve AI's contextual understanding over time. This stage connects to our findings about *Contextual Intelligence*

Boundaries, highlighting how effective collaboration requires understanding both AI capabilities and limitations. It also relates to Simon's (1977) intelligence-design-choice model, with managers strategically involving generative AI in different decision phases based on contextual understanding.

Table 9: Boundary-Aware Collaboration Stage

Primary Barriers	**Implementation Strategies**
Verification needs for important decisions	Create holistic AI knowledge systems
AI's limited understanding of company-specific context	Establish AI-appropriate decision guidelines
Balancing AI speed with human oversight	Build contextual feedback loops for AI improvement
Risk assessment for AI-supported decisions	Develop organizational verification protocols

This progression model provides organizations with a practical roadmap for supporting managers through the adoption process. It addresses stage-specific constraints and enablers to enable effective human-AI collaboration in managerial decision-making. By understanding the various stages of generative AI-usage and adoption, organizations can develop targeted actions that accelerate effective generative AI use while ensuring appropriate boundaries around AI in managerial contexts.

Summary Chapter 5.4: The Managerial AI Interaction Framework

- Our Managerial AI Interaction Framework shows 4 stages in how managers develop relationship with AI tools.
- Each stage has specific barriers and requires different organizational support to help managers advance.
- The framework help explain why adoption happens unevenly and offers practical guidance for implementation.

5.5 Theoretical Contributions and Implications

Having established the Managerial AI Interaction Framework as a model for understanding adoption progression, we now turn to the broader implications of our research. Our findings offer significant insights for organizations implementing generative AI tools, developers creating these systems, and researchers studying human-AI collaboration in management contexts.

This study contributes to our understanding of how managers interact with generative AI in decision-making, and what enables or constrains effective use. It refines several theories by showing that trust in AI tools like ChatGPT is not automatic. It is earned through a process of domain expertise and verification. We highlight a trust paradox: managers with more knowledge are better at checking generative AI outputs but are also more critical. This dynamic, shaped by task type and context, is not fully captured by traditional models like the acceptance or the technology use framework. Our findings expand on models like adoption framework by showing that trust and tool use vary depending on whether tasks are exploratory, high-stakes, or require deep contextual understanding.

These insights carry several practical implications and contributions for three different stakeholders. First, for organizations and managers, our findings emphasize the need for targeted training in practical generative AI use, particularly prompt formulation and output verification. Companies should develop structured guidelines and verification checklists for different decision types. To address generative AI's lack of organizational understanding, firms should prioritize connecting AI tools to internal data and workflows. When direct integration is not possible, managers need clear processes for adapting generalized AI outputs to their specific context.

Second, for generative AI developers, our research shows the need for flexible, transparent systems. Managers must be able to understand how outputs were generated, especially in critical tasks. Systems should adjust explanation depth to fit task complexity. Generative AI tools also need to fit seamlessly into existing systems and workflows in order to reduce switching costs and friction. These improvements will make tools more usable in real professional settings.

Third, for academic researchers, our Managerial AI Interaction Framework offers a structured way to understand adoption progression that should be tested in other sectors and over time. The framework offers a structured way to understand adoption and usage but needs validation across contexts and time. Researchers should also revisit bounded rationality, as decision-making now involves limitations from both human cognition and generative AI systems. Human decision-makers rely on shortcuts and limited information when under pressure. Similarly, generative AI tools may produce plausible but incorrect answers due to limitations in reasoning, context awareness, or training data. Understanding how these bounded rationalities interact is essential for improving AI-supported decision processes.

Summary Chapter 5.5: Theoretical Contributions and Implications

- Organizations need to focus on practical training and connecting AI to their data.
- AI developers need to improve transparency, communicate use-cases, and provide better system integration.
- Researchers should track how managers progress through stages over time to identify where bottlenecks occur.
- Traditional theories of bounded rationality need updating to account for how human AI limitations interact.

6. Conclusion

Finally, building on the theoretical and practical implications outlined above, we now summarize our key findings and contributions to this these. This study set out to answer the research question: "*What factors enable and constrain managers' use of generative AI for decision-making?"*

The findings show that human-AI interplay is shaped by a mix of personal confidence, task characteristics, and organizational context. Managers build trust in generative AI gradually and verifying outputs in areas where they already have expertise. As a result, generative AI is mostly used for exploratory or low-stakes tasks. In contrast, complex or high-stakes decisions remain in human hands, as managers need a deeper understanding of both the context and the AI outputs when the consequences are greater. In these cases, confidence in judgment and the ability to critically assess AI input become essential.

The study also finds that effective collaboration between humans and generative AI depends on more than technical capability. Organizational support, knowledge-sharing, and workflow integration are key enablers. When these are missing, even useful tools are underused. Constraints like limited awareness, resistance to habit change, and lack of system integration reduce the chances of successful adoption and use.

To better understand this interaction, the thesis introduces the Managerial AI Interaction Framework. It outlines four stages of generative AI adoption, from exploration to integration, with specific constraints and enablers at each step. This model helps organizations and researchers identify where managers are in their generative AI journey and what support they need to move forward.

In general terms, this thesis concludes that human-AI collaboration in management is real but conditional. Generative AI can support decision-making, especially in tasks involving information search, early-stage reasoning, and data interpretation. However, managers remain cautious and largely uninformed on and use-cases of generative AI. Usage depends not only on the tool's capabilities, but also on the managers own awareness, whether it fits the task, aligns with workflows, and earns trust through transparent output and consistent performance.

While our findings offer valuable insights, the study is limited to one organization and relies on self-reported behavior. While our findings have been triangulated through theory and one industry expert, they may still not fully capture actual usage patterns. Future research should test the framework in other organizational contexts with different industry dynamics and maturity levels of AI adoption. Longitudinal studies could also examine how manager behavior and trust in generative AI evolve over time, especially as tools become more integrated and workplace norms shift.

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Appendix

Semi-Structured Interview Guide

Objective & Interviewer Notes

Research Objective: Understand how managers interact with generative AI across three functional areas (knowledge acquisition, reasoning, analysis) to identify adoption patterns, barriers, and enabling conditions.

Key Reminders:

- Assess engagement with practice case early. Adapt questions accordingly
- Probe for specific examples rather than general opinions
- Allow natural flow between functional areas
- Remind them about recording procedure, and that they remain anonymous.

Section 1: Introduction & General Experience

Q1: Can you describe your role and the types of decisions you make regularly?

Q2: What's your experience with AI tools like ChatGPT, and how did the practice case go for you?

Section 2: Knowledge Acquisition

Q3: How do you typically find and gather information for your decisions?

Q4: Have you used AI to help gather or summarize information? What was that experience like?

Q5: When AI provides you with information, how do you verify or check it?

Q6: What concerns do you have about the accuracy or reliability of AI-generated information?

Q7: What would make AI more useful for finding and processing information in your work?

Section 3: Reasoning

Q8: How do you typically work through complex problems or strategic decisions?

Q9: Have you used AI to help brainstorm ideas or explore different approaches to problems?

Q10: What's your experience with AI's ability to help you think through complex issues?

Q11: Are there reasoning tasks where you wouldn't want to involve AI? Why?

Q12: How could AI better support your thinking and problem-solving processes?

Section 4: Analysis

Q13: What types of data analysis or quantitative work do you do in your role?

Q14: Have you used AI to help with calculations, data interpretation, or analytical tasks?

Q:15 How do you evaluate the quality of AI-generated analysis or recommendations?

Q:16 What challenges have you encountered when using AI for analytical work?

Q:17 What analytical capabilities would make AI more valuable for your decision-making?

Section 5: Overall Adoption

Q18: What gets in the way of using AI more in your work overall?

Q:19 How do you see AI fitting into decision-making in your organization going forward?

Practice Case

Ämne: Projektförfrågan – Behöver 2 konsulter

Från: brysen.barnette@shipping.se

Till: rejlers.@rejlers.se

Hej,

Vi behöver ett gäng konsulter för vår hamnverksamhet. Vi ska implementera ett "smart harbour" system för att förbättra fartygsschemaläggning, lastlogistik och underhållsövervakning. Målet är att förbättra effektiviteten och i längden även kostnadsreducering. Vi kommer jobba med ett internt team för detta, och vi behöver 2 konsulter på heltid. Minst en konsult behöver ha erfarenhet från systemintegration (gärna marina sådana), och toppen om en av dem också är van att uppgradera äldre IT-system. Vi behöver schemalägga vårt interna team baserat på hamnaktivitetens nivåer. Kan du lite snabbt kolla upp allmänna trender för hur hamntrafiken fluktuerar mellan augusti och december i norra Europa?

Vi har en primär budget på ca 1,5 miljoner. En viktig arbetsuppgift för er är process-etablering, bland annat kopplat till våran seawater conditioning unit. Denna enhet måste sannolikt använda ett GAC-filter för att rensa bort giftiga kemikalier. Vi kommer förbruka många av dessa och behöver en process för avfallshantering. De ska kunna sorteras som vanligt avfall vilket då är en enkel process, detta blir ert ansvar och vi räknar med att ni grejar det.

En stor del av våra maritima kunder måste ha detta system på plats innan det blir minusgrader ute till havs, så detta är en kritisk deadline (säg 1a december). Om vi inte är färdiga innan detta inträffat vill vi kunna ta ut ett vite på 25% av projektets kostnad. Projektet kommer kunna öppna dörrar till specialistuppdrag inom sjöfartsteknik för ditt team.

- Projektstart 1 augusti.
- Arbetstid är 40 timmar per vecka per konsult.

Namn	Kompetensområde	Timpris (SEK/h)	Intern Kostnad (SEK/h)	Nyckelstyrkor
Emma (Senior Projektledare)	Systemintegration & Teknisk Implementering	1500	900	Erfarenhet av komplexa integrationsprojekt inom tekniska miljöer.
Johan (IT-specialist)	IT-struktur & Systemutveckling	1250	850	Specialiserad på att uppgradera & modernisera befintliga system.
Sara (Logistikrådgivare)	Logiskt & Processoptimering	1150	725	Starka analytiska färdigheter inom verksamhetsutveckling & effektivisering.
Markus (Miljö- och regelverksexpert)	Regelverk & Hållbarhetsarbetare	950	675	Expert på processer & regelefterlevnad inom hållbarhets- och miljöfrågor.
Anna (Junior Dataanalytiker)	Dataanalys & Digitalisering	900	600	Erfaren inom databearbetning & optimering av digitala arbetsflöden.