A Work Project, presented as part of the requirements for the Award of a Master's degree in Management from the Nova School of Business and Economics.

**Generative AI and Strategic Decision-Making:
Cognitive Shifts, Collaboration and Organizational Change - Managerial Skills and Human - Artificial Intelligence Collaboration**

SÜHEYLA UYAR (64455)

Work project carried out under the supervision of:

Professor João Castro

15/12/2025

Abstract

This thesis examines how Generative AI reshapes cognitive work, managerial expertise, organizational culture, and innovation logic in strategic decision-making environments. Using a mixed-methods approach, the study combines a quantitative survey on cognitive offloading with qualitative expert interviews across three subtopics. These were analyzed using Mayring's content analysis method. The results demonstrate that, although Generative AI increases efficiency, it also introduces risks such as overreliance, cultural resistance, and creative convergence. Across all levels, AI integration creates new tensions between automation and human contribution. Overall, the findings suggest that Generative AI redefines human agency and organizational distinctiveness, making responsible, human-centered collaboration essential.

Keywords: Artificial Intelligence, Generative AI, Knowledge Work, Decision-Making, Human-AI Collaboration, Skills, Expertise, Change Management, Cultural Values, Leadership, Cognitive Offloading, Overreliance, Psychological Ownership, Agency, Critical Thinking, Cognitive Engagement, Innovation Homogenization, Cognitive Convergence, Bias, Creative Variance

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Table of Contents

1. Introduction

1.1. Context & Background

The growing importance and widespread use of generative AI (GenAI) in businesses creates new opportunities such as enhanced efficiency and superior decision-making (DM) processes. However, it also introduces new risks and requirements. Public discussions, such as the case of an AI-supported Deloitte report for the Australian government that contained erroneous and fictious sources, illustrate how quickly challenges can arise (Paoli 2025). Moreover, studies have revealed that approximately one-third of responses derived from GenAI tools are AI-generated and subsequently presented as factual (Schieb 2025). It emphasizes that integrating AI requires sufficient awareness, expertise, and cultural preparation. While cases like Deloitte might be exceptions, they show that successful AI integration requires more than just technical expertise. In many companies, GenAI tools like ChatGPT, Gemini, and Claude have become integral to daily work routines and significantly impact DM processes and the way collaboration is structured (McKinsey 2025). Change is happening on several levels simultaneously. Individually, employees are developing new ways to interact with AI systems. At the organizational level, managers must maintain a balance between innovation and governance while adapting to employees' needs and the changes that AI introduces into everyday work (Zhu et al. 2021). In this context, the question is no longer whether organizations should use GenAI, but rather, how they can use it responsibly and effectively.

1.2. Relevance of the Topic

The significance of examining how GenAI affects strategic DM stems from the rapid and extensive spread of these technologies into economic and societal structures. Global analyses forecast that GenAI could contribute between USD 2.6 and 4.4 trillion annually, while productivity gains in advanced economies are expected to reach double-digit percentages once adoption matures (Goldman Sachs 2025; McKinsey 2025). Adoption rates have increased sharply, with nearly four out of five organizations now using AI in at least one business function, however, the majority continue to struggle with scaling and effective implementation (World Economic Forum 2025). These developments mark a shift not only in technology, but also in cognition and organization. While research shows that AI can improve the quality and speed of DM, it also raises concerns about overreliance, memory erosion, and blurred responsibility (Al Rousan 2025; Fabre et al. 2020; Kosmyna et al. 2025; Mundhe 2024). Overall, these developments point to a profound transformation in how decisions are made and, moreover, justified. As organizations, managers, and individuals increasingly collaborate with GenAI, the need to answer fundamental questions about agency and the distinctiveness of organizational DM processes becomes more urgent. Therefore, understanding these shifts is essential for identifying the strategic and cognitive implications of GenAI in contemporary DM environments.

1.3. Research Objectives and Central Research Question

This thesis explores the impact of GenAI on strategic DM from multiple levels of analysis, offering a multi-layered exploration of how GenAI is reshaping human work, cognition, and organizational identity. The research program progresses from individual cognitive changes, through transformations at the managerial level, to cultural dynamics, and finally to strategic and organizational consequences. Taken together, these perspectives examine whether the integration of GenAI extends far beyond technological efficiency, fundamentally altering the structure of human agency and the cultural logic of organizations, as well as the qualities that define them. The overarching research question guiding this thesis therefore is:

> *How does the integration of GenAI into strategic DM environments reshape individual and managerial DM as well as organizational distinctiveness?*

1.4. Structure of the Thesis

This thesis is divided into nine chapters, combining a common theoretical foundation with four in-depth subtopics and a joint discussion.

The subsequent chapter provides the theoretical and conceptual grounding, exploring how GenAI is transforming knowledge work (KW), cognition, managerial capabilities, organizational culture, and strategic logic. Chapter 3 outlines the methodological approach, combining both quantitative and qualitative methods to address the subtopics. Chapter 4 presents the first subtopic, focusing on how GenAI affects cognitive offloading, psychological ownership, and responsibility. Chapter 5 introduces the second subtopic, which focuses on the impact of GenAI on managerial skills, the role of human intuition, and effective human-AI collaboration. Chapter 6 examines the organizational aspects of AI transformation, with a focus on effective change management and leadership requirements. Chapter 7 explores the impact of GenAI on innovation practices, emphasizing the dynamics between efficiency and originality and the cognitive tendencies that influence human-AI collaboration. Chapter 8 synthesizes insights from all subtopics into a joint discussion, emphasizing cross-topic patterns. Chapter 9 concludes the thesis by summarizing key findings, outlining theoretical and managerial contributions, reflecting on limitations, and offering suggestions for future research. The sections combined provide a thorough and multi-perspective understanding of the impact of GenAI on KW.

2. Theoretical Foundation & Literature Review

2.1. Generative AI and the Foundations of Knowledge Work

2.1.1. Generative AI as a Catalyst for Change

GenAI refers to a class of AI systems designed to generate new content autonomously based on existing data (Feuerriegel et al. 2023). Unlike traditional rule-based or discriminative models, GenAI models rely on deep learning architectures, such as transformer-based large language models (LLMs), which are trained using substantial quantities of text, code or visual data. These systems can produce fluent text, generate realistic images, write executable code, and create music and video content. Their functionality spans summarization, translation, ideation, simulation, and synthesis, enabling a wide range of applications across domains (Feuerriegel et al. 2023). Technically, GenAI operates by predicting the next most likely output token based on context (Huang and Rust 2025). This means that such systems function purely through statistical pattern recognition and the recombination of existing data. Therefore, they possess no moral intent, consciousness, or capacity for reasoning (Reyes and Huet n.d.). It is important to recognize this distinction, as GenAI systems can easily appear intelligent to users despite not thinking or understanding in a human sense (Messeri and Crockett 2024). The development of GenAI is considered so important that it forms the basis of this work, especially as its low barrier to entry is making these tools an indispensable part of daily workflows (Bick et al. 2024). They are accessible to the public, easy to use, and increasingly embedded in popular software and professional ecosystems. Adoption has spread rapidly across sectors and skill levels, outpacing previous technological shifts (Bick et al. 2024; Hsu and Ching 2023). Unlike past innovations, which primarily changed the way humans work or communicate, GenAI has the potential to transform the way humans think, reflect, and interact with their own ideas (Wiederhold 2025).

2.1.2. Defining Knowledge Work and Cognitive Demands

Work can take many forms, ranging from manual labor and routine administrative tasks to creative, analytical, and strategic efforts. This thesis focuses on KW, which is centered on the application of expertise, judgment, and complex problem solving. KW is on the cusp of transformation through the integration of GenAI (Bolívar 2015). Peter Drucker (1999) coined the term “knowledge worker” to describe individuals whose primary capital is knowledge and whose tasks involve interpreting, generating and applying ideas rather than executing predefined procedures. Typical knowledge-intensive roles include consultants, executives, policymakers, researchers, analysts, designers, and scientists. These professionals are central to the modern economy's innovation capacity. They navigate ambiguity, frame complex problems, and often craft strategies or drive change in dynamic contexts (Drucker 1999).

To understand the implications of KW, it is essential to first define the cognitive demands that define effective KW. At its core is critical thinking, the ability to analyze, evaluate, and synthesize information to make sound judgments (Chance 1986; Scriven and Paul 1992). Gerlich (2025) emphasizes that critical thinking is essential not only for problem solving but also for resisting misinformation and sustaining intellectual independence. In high-stakes, knowledge-intensive roles, critical thinking enables professionals to link abstract ideas and navigate trade-offs, helping them to adapt to uncertainty. Drawing on Bloom's taxonomy, Lee et al. (2025) describe critical thinking as a layered process involving comprehension, application, evaluation, and synthesis. In professional contexts, this thinking must be contextual and anchored in ambiguity, organizational goals, and evolving constraints, making it strategic and reflective.

Metacognition, the ability to monitor, evaluate, and regulate one's own thinking, is closely related. It enables individuals to recognize cognitive biases, assess the reliability of their reasoning, and determine when to focus, or seek external input (Getenet et al. 2024; Guo et al. 2022). In AI-supported environments, metacognitive oversight is essential. Ghosh et al. (2025) argue that deciding whether to offload a task to a system, such as ChatGPT, is a form of metacognitive oversight. Users must judge the task's complexity and time constraints, as well as their own confidence and the risks of delegating too much cognitive responsibility.

Another essential aspect of KW is the ability to learn and reflect over an extended period. Expertise is not a static asset; rather, it develops over time through struggle, feedback and repetition (Ericsson et al. 1993). This view is supported by Wiederhold (2025), who emphasizes that deep understanding emerges through mentally demanding processes, such as revising and applying knowledge under pressure. These activities challenge the brain to consolidate abstract patterns, update assumptions, and internalize learning in a lasting way. Biologically, this is tied to neuroplasticity: The hippocampus, the brain region associated with memory and learning, continuously produces new neurons that only survive if stimulated through active learning (Shors et al. 2011).

Taken together, these insights highlight the fact that the cognitive demands of KW are complex and fragile. Skills such as critical thinking, metacognition, and reflective learning require constant reinforcement. While GenAI can support these skills, it can also erode them, particularly if used passively or without intent.

2.1.3. When Generative AI Meets Knowledge Work

The integration of GenAI into KW marks a fundamental shift in how cognitive labor is performed. While earlier digital tools, such as search engines, shaped how professionals accessed and processed information, GenAI now participates in the creation and refinement of knowledge itself (Cerchione et al. 2025; Fisher et al. 2021). The distinction between a tool and a co-agent is becoming increasingly blurred (Falconer 2025). Today, knowledge workers use GenAI to generate documents autonomously, design prototypes, simulate outcomes, and predict future trends by analyzing past and current data streams (Mao et al. 2016). Tools like ChatGPT accelerate ideation and iteration by providing context-specific responses and exploring alternatives (Ray 2023). These systems reduce repetitive cognitive load and enable faster output generation (DiGiacomo 2025). However, this shift is not only operational but also cognitive. According to Warner (2023), overreliance on GenAI tools can bypass the internal processes essential for developing complex ideas. Rather than engaging in mental exploration, users often rely on prompting. While this may increase short-term efficiency, it can result in the long-term erosion of abstraction and reflection, which are two key faculties for individuals in strategic roles (Jadhav 2025). Frequent interaction with GenAI tools carries the risk of uncritical automation, like accepting strategic suggestions without checking assumptions or data. Fisher et al. (2021) demonstrate that frequent use of search engines can inflate users' confidence in their knowledge without them learning anything. GenAI intensifies this effect by reducing memory retention and motivation to think reflectively (Gerlich 2025; Ghosh et al. 2025; Sparrow et al. 2011). In fact, Chen et al. (2025) found that moderate support, such as partial prompts or summaries, leads to better learning outcomes than fully automated support. Nevertheless, many users report feeling more productive when using AI, even if their performance does not improve. This discrepancy between subjective perception and actual output can be dangerous in high-stakes situations and the growing reliance on AI tools has structural consequences (Morey 2025). As control over DM shifts gradually from humans to AI systems, the risk of responsibility diffusion increases (Fabre et al. 2020). Users may defer to outputs not because they are more accurate but because they are more convenient, faster, or because they misplace their trust. This is particularly likely when systems present results with high confidence but little transparency (Fabre et al. 2020). GenAI is not just a productivity tool; it is becoming a cognitive partner that reshapes thought processes as well as outputs. While GenAI brings speed and fluency, it also introduces risks, exposing the fundamental trade-off between efficiency and autonomy in modern KW.

2.2. Cognitive Offloading and AI-Augmented Thinking

The presence of GenAI in KW offers clear benefits, including reducing decision fatigue, accelerating analysis, supporting novice learners, and enabling rapid ideation (DiGiacomo 2025; Yang 2025). In many cases, it enables professionals to focus on higher-order reasoning by automating repetitive or low-value tasks (Gerlich 2025). According to Gerlich (2025), AI systems can reduce cognitive load, creating mental space for strategic and creative thinking. However, this apparent efficiency conceals a deeper transformation in the structure of thought itself. Humans are “cognitive misers” by nature, preferring to reduce effort through external aids (Jadhav 2025; Risko and Gilbert 2016). Learners often prioritize convenience over cognitive challenge, even when it impairs reflection and memory (Chen et al. 2025). Therefore, this behavior is highly relevant and must be understood to anticipate its consequences and develop strategies to mitigate potential cognitive downsides.

2.2.1. Cognitive Offloading: Definition and Patterns

One of the most significant downsides of integrating AI into KW is the phenomenon of cognitive offloading, which is the tendency to delegate thinking processes to external systems rather than performing them internally (Gerlich 2025). Rather than relying on internal reflection or active problem-solving, users are increasingly leaning on AI systems to retrieve, generate, or evaluate information. Risko and Gilbert (2016) defined this process as including aids like notes or calculators. Today, however, it increasingly involves AI tools designed to reduce effort across nearly all cognitive tasks. While this can improve efficiency and allow users to focus on complex problems, it also carries risks. Gerlich (2025) notes that excessive offloading can erode memory, reflection, and analytical reasoning. This pattern first became visible with the rise of search engines when users began delegating memory retrieval to external sources. This behavior has been described as the "Google effect" and illustrates how easily accessible information can lead to weaker recall and inflated confidence (Fisher et al. 2021; Sparrow et al. 2011). In AI-supported environments, this tendency expands further. Users not only outsource memory but also increasingly externalize thinking itself (Ghosh et al. 2025). Knowledge workers tend to make offloading decisions based on situational judgments about task demands and perceived returns. They are especially likely to offload tasks when learning gains are perceived as low, even when doing so is unnecessary (Dunlosky and Thiede 1998; Jadhav 2025). This behavior is captured by what Jadhav (2025) terms the "Cognitive Cost Comparator": individuals subconsciously weigh factors such as task complexity, confidence in their abilities, time investment, and the reliability of available tools. The findings of Lee et al. (2025) further support this, as they examined the role of trust in the offloading process. They found that users who have high confidence in AI systems tend to be less critical. Regarding self-confidence, the study revealed that low self-confidence predicts stronger dependence on AI and diminished problem-solving capacity.

The deeper cognitive consequences of this shift are becoming increasingly evident in neurocognitive research. For example, Kosmyna et al. (2025) reported diminished neural activity and interconnectivity among ChatGPT users, particularly in brain regions associated with creativity and language processing. Functional magnetic resonance imaging studies have confirmed reduced activation in memory and reasoning areas when AI systems generate content compared to self-authored tasks (Ghosh et al. 2025). These findings imply that, when KW primarily involves prompting rather than generating, the mental scaffolding that supports higher-order thinking begins to weaken. As Wiederhold (2025) warns, GenAI may push cognitive offloading to new extremes, gradually eroding not only how we process information but also how we maintain the mental autonomy that defines effective KW. What begins as a convenience can evolve into habitual dependence if left unexamined.

2.2.2. From Offloading to Overreliance

When cognitive offloading becomes routine, it can evolve into overreliance, a problematic form of dependence. This occurs when users stop treating AI as a support system and start relying on its outputs without sufficient scrutiny, even when those outputs are flawed or superficial. Overreliance is commonly defined as uncritically accepting incorrect or minimally satisfactory AI-generated recommendations (Lee et al. 2025).

This condition can emerge through two main pathways. One pathway is behavioral: what begins as a way to manage cognitive load gradually displaces internal reasoning. Reduced mental effort leads to reduced abstraction and metacognitive engagement, which reinforces further offloading. Over time, this can result in representational atrophy, or the weakening of the internal mental structures necessary for deep, reflective thinking, as defined by Jadhav (2025).

Another driver is trust. Fluent and confident AI outputs can create a misleading sense of reliability, even when transparency and understanding are lacking (Lee et al. 2025). In such cases, users may disengage from critical analysis and rely on AI for quick answers. Gerlich (2025) warns that this cognitive laziness is not a failure of intelligence, but rather a byproduct of overconfidence in seamless tools. Similarly, Hlavinka (2025) argues that the danger lies less in AI's capabilities than in the excessive dependence it fosters, particularly when users become accustomed to instant, convincing results.

The assistance dilemma, first introduced by Koedinger and Aleven (2007) and expanded upon by Chen et al. (2025), captures the central tension: too much support can hinder learning and autonomy, while too little can lead to overwhelm under pressure. AI systems optimized for usability often err on the side of over-assistance, making passive consumption more likely.

These shifts are not only cognitive, but also strategic. For example, overreliance in leadership and managerial contexts can erode situational awareness, judgment, and long-term analytical resilience (DiGiacomo 2025). The ultimate risk is not access to information per se, but rather the erosion of the mental discipline required for critical thinking in the face of effortless, high-quality outputs.

2.2.3. Ownership, Agency, and Responsibility Shifts

Beyond altering how people think, the integration of AI into cognitive work is also transforming how responsibility for outcomes is perceived. As generative systems increasingly support ideation, writing, and DM processes, users often interact with content they did not independently create, which can result in a reduced sense of authorship and agency (Draxler et al. 2023). Research indicates that psychological ownership is not automatically preserved in AI-supported contexts. Rather, it depends on the user's perceived level of control, cognitive involvement, and alignment with the final outcome (Draxler et al. 2023; Xu et al. 2024). When AI-generated results are accepted with minimal reflection or revision, the cognitive connection between intention and result weakens. In such cases, users are less likely to perceive the output as something they created, even if they initiated the process.

Building on the previous perspective of individual cognition and responsibility, the following section offers a complementary view, also situated at the individual level. It focuses on how GenAI interacts with intuition, expertise, and analytical reasoning, thereby broadening the understanding of psychological dynamics in AI-supported professional environments.

2.3. Intuition and Expertise under AI

The rapid advancement of GenAI, including everyday tools like ChatGPT, is leading to a profound transformation in the way decisions are made and skills are applied within organizations (Giraud et al. 2022; Mundhe 2023; Nivetha and Prasanth 2024). As AI becomes an integral part of managerial practice, it challenges traditional ways of thinking and acting, leading to shifts in the required capabilities and in the balance between human and machine intelligence. This development raises key questions about the interaction between human intuition and judgement and data-driven reasoning, the effective structuring of collaboration between humans and AI, and the value of expertise in an increasingly automated world (Broeckx 2025; Harbath 2025; Jarrahi 2018; Vincent 2021).

2.3.1. The Concept of Intuition

Although GenAI is transforming how managerial decisions are made, intuition and human judgment remain essential uniquely human capabilities that technology cannot fully replicate. Therefore, understanding intuition is key to explaining how humans continue to create value in increasingly automated DM environments.

Contemporary DM research views intuition and rationality as two distinct yet complementary modes of thinking (Julmi 2019; Wang et al. 2017). Rationality, also known as analytical thinking, involves deliberate, effortful, rule-based reasoning (Evans 2008; Kahneman 2003). It operates through conscious control, sequential processing, and the logical decomposition of problems (Hogarth 2010). Decisions made through rational analysis rely on structured information and aim to minimize errors through conscious reflection (Betsch and Glöckner 2010; Kahneman 2011). In contrast, intuition is defined as a rapid, automatic, and emotional form of cognition (Evans 2008; Kahneman 2003; Stanovich and West 2000). It is characterized by the spontaneous emergence of unconscious associations and emotional cues that are often not subject to conscious deliberation (Krumay et al. 2018). Intuitive decisions are defined as the integration of dispersed information into a coherent pattern, allowing individuals to process large volumes of data in a short time without conscious effort (Betsch and Glöckner 2010). Intuition is often referred to as “knowing without knowing why” or a “gut feeling” (Claxton 1998). It is based on implicit knowledge acquired through experience, but its effectiveness depends on the context and the structure of the problem. It performs best in environments that are poorly structured, ambiguous, complex, or uncertain, where analytical decomposition is difficult and rational models may fail to capture contextual nuances (Betsch and Glöckner 2010; Daft and Lengel 1986; Dane and Pratt 2007; Dane et al. 2012; Julmi 2019). Conversely, in well-structured problems with clear parameters, analytical reasoning tends to be more reliable (Scherm et al. 2016). The quality of intuitive judgment also depends on the presence of sufficient implicit knowledge and domain-specific expertise, which allow individuals to interpret complex cues accurately (Dane et al. 2012; Hodkinson et al. 2008). Without such experience, intuitive decisions may become biased or unreliable. Furthermore, intuition is susceptible to systematic cognitive biases, such as confirmation bias, which can distort judgment even in experienced decision-makers (Mercier 2016). Individual preferences for intuitive or analytical thinking also influence the accuracy and utilization of these tools (Phillips et al. 2016). Therefore, while intuition is a powerful human capability that enables rapid, holistic DM, it is most effective when grounded in experience and applied in environments characterized by uncertainty and ambiguity.

In the context of AI-driven DM, intuition has gained renewed attention as one of the few human capabilities that AI cannot replicate. While AI demonstrates proficiency in processing structured data and identifying analytical patterns, it lacks the tacit knowledge, emotional awareness, and contextual sensitivity that underpin human intuitive judgment (Abby 2025; Jarrahi 2018; Vincent 2021). Therefore, intuition compensates for the inherent limitations of AI, which relies heavily on historical data (Cantonis 2025; Dane and Pratt 2007; Julmi 2019). This unique ability to act under uncertainty makes intuition a central focus when examining the evolving role of human judgment in an increasingly automated managerial environment.

2.3.2. The Dimensions of Professional Expertise

Intuition plays a critical role in professional expertise, yet the increasing use of AI in automating analytical and procedural aspects of work challenges this concept. Examining the evolution of expertise in these conditions provides insights that inform the future role of human contribution in intelligent systems.

Professional expertise can be defined as the integration of explicit and tacit knowledge, each with distinct characteristics and implications for AI integration (Ganuthula and Balaraman 2025). Explicit or codified knowledge, also referred to as public or propositional knowledge, is knowledge that is formally expressed and subject to validation. This validation can occur through academic publications, peer review, or professional debate (Eraut 2000). In contrast, tacit or implicit knowledge is experiential and intuitive, encompassing pattern recognition, contextual awareness, and the ability to "know more than we can tell" (Autor 2015; with reference to Polanyi 1966; Ganuthula and Balaraman 2025). It emerges through "socially embedded mechanisms" and often operates beneath conscious awareness, expressed through practical action or shared collective understanding (Baumard 1999; Ganuthula and Balaraman 2025, 4).

As AI becomes increasingly prevalent in professional settings, the distinction between explicit and tacit knowledge becomes paramount. AI systems are particularly adept at processing explicit knowledge, defined as codified rules, data, and procedures that can be formalized into algorithms or training datasets (Jarrahi 2018; Shrestha et al. 2019). Tasks that primarily rely on analytical reasoning or structured information, such as data classification or procedural DM, are therefore highly automatable (Autor 2015; Levy and Murnane 2004). However, tacit knowledge – the intuitive, context-dependent understanding developed through experience – remains challenging to replicate. This is because if people cannot articulate why they perform a task in a certain way, it is difficult to automate it (Autor 2015). It requires situational flexibility, empathy, and judgment, qualities that current AI systems lack (Autor 2015; Norman 2017). Consequently, while AI extends the reach of explicit expertise, it simultaneously heightens the value of human tacit knowledge. This makes collaboration between both forms of intelligence increasingly central to professional performance.

In the current era of AI, intuition and expertise are pivotal, as is the way humans collaborate with technology. As Badmus (2024) emphasizes, effective AI integration requires a nuanced interplay between human intuition and machine intelligence, as well as favorable organizational conditions, including leadership support, cultural readiness, and trust. These factors determine whether these new forms of collaboration can truly take root. They also provide the foundation for a sustainable AI transformation, which is examined in the following section.

2.4. Meditating Role of Organizational Culture

Analyzing organizational culture provides a link between individuals and the strategic dimensions of AI transformation. While previous sections focused on how GenAI reshapes cognition and human-AI collaboration, this section emphasizes the social and cultural infrastructure that enables these individual-level adaptations to be scaled up to achieve sustainable collective transformation.

2.4.1. Organizational Culture as the Invisible Layer of AI Transformations

Organizational culture is characterized by the values, beliefs, norms, and practices that jointly influence the behaviors and interactions of individuals within an organization (Murire 2024). It provides the underlying framework that guides DM, work practices, and social dynamics across various organizational levels (Murire 2024). Overall, organizational culture is a form of holding the entire organization together (Sherba et al. 2025). With the emerging integration of AI in the business landscape, this digital transformation is having a profound impact on established work practices (Thilagavathy and Venkatasamy 2023). Digital transformation extends far beyond technology as it fundamentally involves people, mindset and leadership (Goran et al. 2017). Within this context, organizational culture represents the often indivisible yet decisive layer of AI transformation processes that shapes how new technologies, such as AI, are adopted. Firican (2023) states that digital culture can act as both, an enabler and a barrier to transformation, depending on how flexible the organization is to change. Rigid and deeply embedded cultural values can impede transformation efforts. This observation is confirmed by Hartl and Hess (2017), who found that many transformation initiatives fail due to entrenched cultural norms. Supporting this view, Buvat et al. (2018) report that 62% of executives identify culture as the greatest obstacle to digital transformation. Taken together, these insights highlight the fact that a successful AI transformation requires creating an organizational environment shaped by shared cultural values and mindsets that enables organizations to adapt to and sustain technological change over time.

2.4.2. How AI triggers Cultural Change

Integrating AI into an organization has a significant impact on more than just efficiency. It reshapes how employees interact, make decisions, and define value (Aldoseri et al. 2023). AI offers organizations many advantages and opportunities. For example, implementing AI-driven automation of routine tasks enables employees to focus on more strategic, creative, or valueadding tasks. This, in turn, encourages a culture of innovation and sustainable improvement by reinforcing openness to experimentation and learning (Chaudhary et al. 2023). Consequently, such developments can strengthen trust in technology and increase engagement in transformation processes. However, implementing AI can also introduce cultural tensions. Aghion et al. (2019) note that AI automation can lead employees to fear job displacement and skills obsolescence, resulting in overall resistance to change. These reactions reflect underlying cultural concerns about control and trust in technology, which are overall central issues in AI transformation. The rapid integration of AI technologies has triggered significant changes in organizational cultures, compelling organizations to reconsider their values and leadership strategies (Murire 2024). Research shows that understanding and managing these shifts is complex, as they involve an interplay between technological adaptation and cultural evolution (Ademola 2024). Therefore, the capacity of an organization to sustain transformation is dependent upon its ability to cultivate a culture of flexibility, continuous learning, and psychological safety (Murire 2024). These dynamics reveal that transformation is an ongoing negotiation between technological advancement and cultural adaptation, not a linear process.

2.4.3. Resistance to Change in AI Transformations

Resistance to change is a common challenge in organizational digital transformation processes. According to Kotter (1996), many change initiatives fail because organizations underestimate the importance of a clear vision, effective communication, and employee involvement. These factors are part of Kotter's well-known eight-step model for transformation, and they are all crucial for overcoming resistance and enabling sustainable change. In the context of AI transformations, these factors are even more critical because the introduction of intelligent systems fundamentally alters established ways of working and DM. Haefner et al. (2023) emphasize that, although AI offers significant potential for innovation and growth, many organizations lack the structured frameworks necessary to successfully implement and scale these technologies. Structural uncertainty can foster hesitation and resistance as employees and managers struggle to navigate ambiguous expectations. Similarly, uncertainty regarding the return on investment and the timeline of AI initiatives were identified as key organizational risk factors that reinforce skepticism and resistance toward AI transformations (Bérubé et al. 2021). Beyond structural and strategic barriers, effective governance is essential for mitigating resistance to change. Zabala (2023) emphasizes that clear governance principles, such as ensuring that AI is used ethically and responsibly, help to foster trust and legitimacy. These are essential for employees to engage entirely. Additionally, it is argued that resistance often arises when employees cannot make sense of the purpose of the change (Zetterberg and Palestro 2024). Overall, these insights suggest that resistance to AI transformation is multidimensional and rooted in structural uncertainty and organizational culture.

2.4.4. Fostering Cultural Readiness

Resistance to change reflects the barriers and concerns organizations face during transformation. In contrast, cultural readiness represents an organization's proactive capacity to embrace, align with, and sustain technological innovation. Cultural readiness is more than the absence of resistance; it is the presence of shared values, norms, and beliefs that enable adaptation and learning (Weiner 2009). Cultural readiness encompasses the commitment to change and the collective efficacy necessary for its successful implementation (Shea et al. 2014). According to Weiner's (2009) foundational theory of organizational readiness, readiness emerges when members collectively believe that the organization is willing and capable of changing. When applied to AI transformation, this implies that cultural readiness reflects a state in which employees trust the purpose of AI adoption, perceive its alignment with organizational values, and feel empowered to use AI effectively. Furthermore, researchers argue that such readiness depends on cultivating a culture of innovation, learning, and flexibility, where experimentation and knowledge sharing are encouraged, and mistakes are viewed as opportunities for growth

(Hasan et al. 2025). Similarly, Jewapatarakul and Ueasangkomsa (2024) demonstrate that a robust digital organizational culture promotes readiness by facilitating knowledge acquisition and collaboration during technological transformation. Rather than viewing cultural readiness as a fixed state, it should be understood as a dynamic organizational capability that supports ongoing learning, adaptation, and the effective integration of new technologies into existing cultural structures (Alabi 2025). Culturally ready organizations move beyond defensive reactions to change, transforming uncertainty into resilience and enabling the effective and sustainable integration of AI. According to Murire (2024), cultural readiness provides the foundation for the sustainable adoption of AI and creates the conditions for broader organizational change, particularly in the evolution of innovation and strategic direction through technological integration.

2.5. The Changing Logic of Innovation under AI

Once AI has been successfully integrated into organizational practices, a new challenge emerges: understanding how this transformation reshapes the innovation process. Innovation has long been considered a key source of competitive advantage and economic progress. It involves generating and implementing novel ideas that create value and differentiation (Schumpeter 1934; Tidd and Bessant 2021). To foster creativity, organizations are increasingly adopting GenAI tools, particularly to support idea generation (IBM 2023, 2024). As GenAI becomes more embedded in business processes, it alters how organizations generate, evaluate, and implement creative ideas (Csaszar et al. 2024; Felin and Holweg 2024). Recent studies have linked AI adoption to growing cognitive and strategic alignment across firms (Anderson et al. 2024; Calvino et al. 2025; Csaszar et al. 2024; Felin and Holweg 2024). This alignment reflects the gradual synchronization of DM and innovation processes across organizations through reliance on AI systems, creating conditions for convergence rather than differentiation (Csaszar et al. 2024; Felin and Holweg 2024). The very thing that was once an engine of differentiation now risks becoming a standardized, data-driven process, paving the way for a new phenomenon: homogenization in innovation processes.

2.5.1. The Shift from Differentiation to Homogenization

The term "innovation homogenization" is here used to describe the systematic reduction in the variance of ideas and creative outputs across organizations. This reduction is driven by a shared reliance on similar datasets, models, and interaction patterns with GenAI (Bommasani et al. 2022). In other words, as firms become more dependent on the same algorithmic infrastructures, the diversity of creative and strategic outcomes decreases (Anderson et al. 2024; Csaszar et al. 2024). This concept is related to the idea of algorithmic monoculture. Algorithmic monoculture refers to the risks that arise when multiple actors rely on the same or highly correlated algorithms for DM. Even when a model is accurate on an individual level, collective dependence on it can reduce the overall quality and diversity of outcomes (Bommasani et al. 2022; Kleinberg and Raghavan 2021). Kleinberg and Raghavan (2021) demonstrate that this convergence can impede performance. Identical evaluations cause decision-makers to overlook unconventional yet valuable opportunities, thereby stifling innovation and reducing social welfare. A related concern is model collapse, which occurs when AI systems are repeatedly trained on their own outputs. This causes them to lose information about the true data distribution, gradually erasing rare elements and converging toward average patterns (Shumailov et al. 2024). Over time, this recursive training reduces variance and depth, thereby reinforcing homogenization both technically and conceptually.

2.5.2. Mechanisms and Empirical Evidence of Homogenization

At the practical level, GenAI systems tend to produce outputs based on the statistical mean of their training data. This privileges the reproduction of conventional patterns over truly original and divergent creative solutions (Desdevises 2025; Xie and Xie 2025). While these tools democratize creative capabilities, scholars emphasize that they can also diminish the diversity and originality of innovation outcomes (Csaszar et al. 2024; Felin and Holweg, 2024; Fréry 2024). Even when firms use different AI platforms, their reliance on data-driven, backward-looking models leads to convergent results and a collective narrowing of creativity (Mariani and Dwivedi 2024). Empirical research confirms this homogenizing effect. Findings suggest that, while GenAI can make outputs appear more original and higher in quality, it simultaneously reduces collective novelty (Doshi and Hauser 2024). When aggregated, AI-assisted outputs become increasingly similar, revealing a social dilemma in which individual gains in creativity come at the cost of collective diversity (Doshi and Hauser 2024). Other research demonstrates that LLMs produce semantically similar and less diverse outputs for creative ideation and writing tasks (Anderson et al. 2024; Wenger and Kenett 2025). These results suggest that algorithmic assistance amplifies uniformity rather than fostering divergent creativity (Anderson et al. 2024; Wenger and Kenett 2025). Together, these findings suggest that homogenization stems not from cultural inertia but from the shared cognitive and computational architectures underlying GenAI systems.

2.5.3. Strategic Implications for Competitive Advantage

From a strategic management perspective, these developments challenge the principles underlying the 'Resource-Based View". According to Barney (1991), sustainable competitive advantage relies on resources that are valuable, rare, inimitable, and non-substitutable. However, as Tang et al. (2024) and Abonamah et al. (2021) point out, GenAI transforms many of these rare capabilities – such as analytical reasoning, design expertise, and creative ideation – into standardized, widely accessible functions. In effect, AI democratizes what was once distinctive (Fréry 2024). When every organization can produce similar analyses or designs at a comparable speed, the traditional basis for differentiation weakens (Csaszar et al. 2024; Felin and Holweg 2024). The future of AI-enabled organizations ultimately depends on how these technologies are implemented and whether firms can preserve the cognitive and cultural conditions that sustain originality and innovation. These dynamics reveal how technological alignment and efficiency gains not only reshape organizational strategy, but also the logic of innovation itself. This sets the stage for an integrated understanding of how GenAI transforms KW.

2.6. Linking the Threads

This literature review is structured to build a layered understanding of how GenAI is transforming KW across individual and organizational levels. It begins with an exploration of GenAI's technological foundations, outlining how it operates and why its rapid adoption signals a deeper transformation in the production and application of knowledge. The review then turns to the specific nature of KW, focusing on cognitively demanding fields like strategy, communication, and research. In such environments, professionals rely heavily on abstract thinking and situational judgment – qualities that GenAI may enhance but also potentially undermine.

The analytical core of the review is organized along two interconnected dimensions: the "Individual Level" and the "Organizational Level", each consisting of two subtopics. On the individual side, Subtopic 1 focuses on the cognitive consequences of GenAI use, particularly automation-driven offloading, overreliance, and changes in users' sense of ownership and responsibility. Subtopic 2 expands this perspective by examining how GenAI affects professional capabilities, namely shifts in expertise, skill development, and the role of intuition in DM. The organizational dimension begins in Subtopic 3, which investigates how GenAI adoption challenges leadership approaches, structural design, and cultural readiness. Subtopic 4 then focuses on the dynamics of innovation and human-AI collaboration, especially the interplay between efficiency and originality.

These subtopics are not discrete. Figure 1 illustrates how individual behavior and cognition directly influence organizational change, while organizational structures and culture in turn shape individual attitudes toward AI. For example, convergent AI outputs can narrow users' cognitive search space (Subtopic 1 → 4), while innovation processes may redefine how individuals apply expertise (Subtopic 4 → 2). Leadership culture can either foster trust and engagement or reinforce overload and resistance (Subtopic 3 → 1), just as evolving individual skill sets may pressure organizations to adapt roles, workflows, and leadership styles (Subtopic 2 → 3). These interconnections are structurally grounded in the fact that individuals act within organizations, and that organizations rely on individual behavior to function and evolve. Consequently, the line between individual and organizational impact is fluid. Organizational transformation depends not only on formal change, but also on the informal cognitive and behavioral shifts already underway among users. The adoption barrier visualized in Figure 1 reflects this tension: GenAI is often introduced bottom-up, with individual users experimenting in informal ways before organizations formally adapt. Overcoming this barrier requires deliberate alignment between emerging usage patterns and strategic enablement.

Together, these interdependent subtopics form a coherent view of how GenAI does not simply automate tasks, but fundamentally reconfigures cognitive processes, ownership structures, and innovation pathways in knowledge-intensive work. The following chapters explore each subtopic in depth, building on this shared analytical foundation.

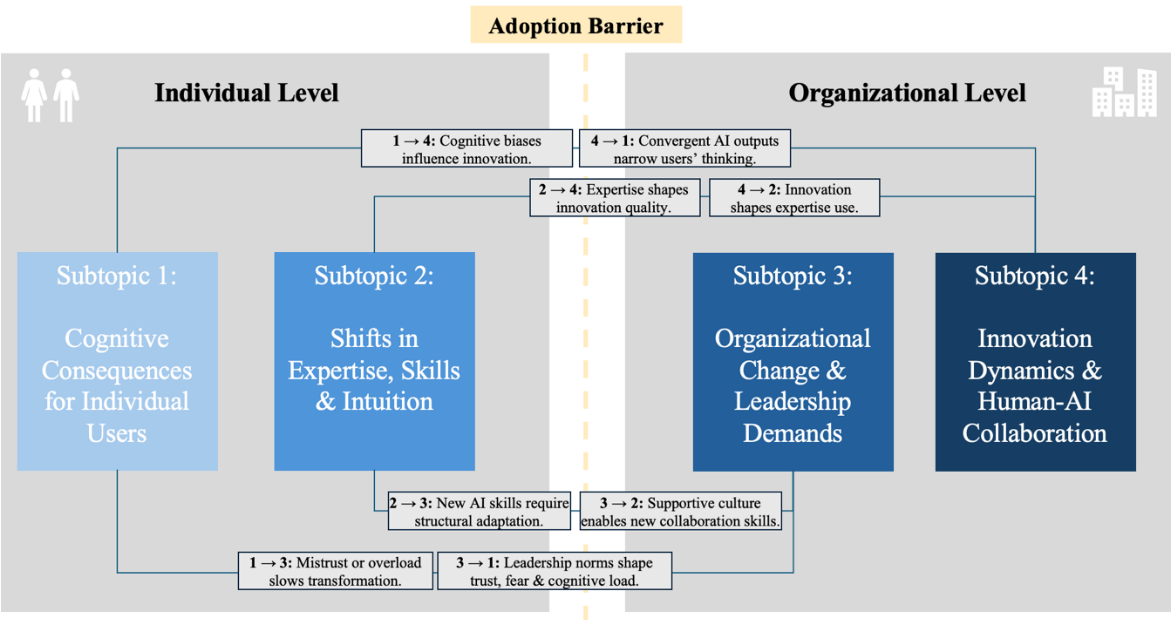

Figure 1: *From Individuals to Organizations: Mapping the Effects of GenAI | Source: Own.*

3. Methodology

3.1. Research Philosophy and Methodological Approach

This thesis adopts a pragmatic mixed-methods research philosophy. It integrates both quantitative and qualitative approaches to capture the multifaceted impact of GenAI on cognition, DM, organizational dynamics, and innovation processes. The overarching goal is to understand how the integration of GenAI shifts not just workflows, but the deeper cognitive and cultural foundations of knowledge-intensive work. A mixed-methods approach allows each subtopic to apply the most suitable methodological lens while ensuring that findings remain comparable under a shared research objective. Subtopic 1 utilizes a quantitative survey to measure patterns of cognitive offloading and perceptions of agency across a broader sample. Subtopics 2, 3, and 4 rely on qualitative semi-structured interviews to uncover how individuals navigate intuition, innovation, and cultural paradoxes in the context of AI adoption. This combination of scale and depth strengthens the validity of the overall thesis by enabling both generalizability and context-sensitive interpretation.

3.2. Research Design, Justification and Data Analysis Strategy

3.2.1. Quantitative Design

To examine patterns of cognitive offloading, authorship perception, and responsibility in AI-supported KW, Subtopic 1 applied a quantitative research design. This methodological approach is well-suited for identifying behavioral patterns and psychological perceptions related to GenAI use in professional contexts (Ghanad 2023). The primary research instrument was a self-administered, structured online survey developed using Google Forms (see Appendix 0). This format enabled scalable, low-friction distribution and standardized data collection across a diverse target group. Participants were recruited through a combination of purposive and snowball sampling. The survey specifically targeted professionals, early-career employees, and advanced students with relevant work experience in knowledge-intensive fields such as strategy, consulting, communications, research, or technology. Participation was both voluntary and anonymous. Ethical standards were upheld throughout: informed consent was obtained, and no personal or sensitive data was collected.

The survey combined several question types to capture a wide range of responses. Likert-scale items were used to measure levels of agreement or disagreement with AI-related statements. Multiple-choice and checkbox items allowed participants to indicate one or more predefined options, while optional open-text fields invited them to elaborate on their own experiences and views. This design enabled the capture of both structured metrics and more nuanced individual perspectives. The questionnaire was conceptually grounded in the theoretical constructs of trust in AI outputs, cognitive effort, psychological ownership, and responsibility attribution. The resulting data was analyzed using the statistical software Jamovi, which supported both descriptive exploration and inferential testing. These analyses form the empirical basis for the hypotheses explored in the subtopic.

3.2.2. Qualitative Design

Subtopics 2 through 4 follow a qualitative research design, relying on semi-structured interviews to explore how individuals experience and interpret the integration of GenAI in areas such as strategic intuition, cultural tension, and innovation logic. This design is well-suited to investigate context-sensitive and nuanced dynamics that cannot be meaningfully quantified. In addition, various case studies were examined in detail; these could not have been covered in a survey. Semi-structured interviews strike a balance between thematic consistency and conversational openness. They provide sufficient structure to ensure alignment with research objectives, while remaining flexible enough to uncover unexpected insights or associations (Gläser and Laudel 2010). As Gläser and Laudel (2010) emphasize, this format allows for an in-depth understanding of the underlying mechanisms, perspectives, and tensions that shape how individuals and organizations engage with AI. The interview guide plays a crucial role in expert interviews, defined as interviews with individuals who, due to their professional position, education, or practical experience, possess specialized knowledge that extends beyond general awareness (Genau 2021). This includes all the study's relevant questions as well as the necessary procedural steps for conducting an expert interview. This guideline is instrumental in ensuring the consistency and quality of the interviews, as well as facilitating meaningful comparisons between them (Gläser and Laudel 2010). The interactive guide is a translation of the research interests and theoretical assumptions, and as such, it must be created with great care (Gläser and Laudel 2010). In qualitative social research, the interview process is characterized by open-ended questions. These tools enable interviewees to present relevant contexts through their own formulations, facts, and illustrative examples (Züll and Menold 2014). The same interview guide was used for all interviews within each subtopic. This was necessary for the research interests of this thesis to ask the selected experts identical questions to meaningfully compare their responses. The objective of the questions was to document the experts' opinions and experiences on the research topic, test hypotheses based on these and answer the research question. The interviews followed a three-part structure: an opening section with introductory questions, a main part addressing the research topic, and a short closing statement. The complete interview guide for each subtopic can be found in Appendix 2 of the thesis.

All experts were identified and approached via the respective researcher's professional LinkedIn network. Each expert received a message outlining the study's purpose and relevance and was invited to participate. Prior to the interviews, participants were provided with an introductory document containing a brief presentation of the researcher, an overview of the research objectives, and a concise explanation of the key concepts. This document ensured a shared understanding of terminology during the conversation. The document also included the interview questions and an indication of the expected duration of approximately 30 to 45 minutes. Prior to conducting the expert interviews, a pilot test was conducted to evaluate the interview guide and ensure that the procedure was well-prepared and logically structured. This preliminary step was essential for identifying potential challenges and adjusting the phrasing or sequence of questions accordingly. The interviews were then conducted, all via online video calls. After obtaining verbal consent for the recording, the interview proceeded with the pre-tested interview framework. The qualitative data analysis followed a structured process rooted in Mayring's Qualitative Content Analysis (Mayring and Fenzl 2019). This approach enables a theory-guided, transparent, and replicable analysis of textual interview data. It is particularly well-suited for applied research that aims to identify underlying patterns in expert narratives while maintaining sensitivity to context. After the translation and transcription of all interviews was completed, the data analysis began with a deductive category framework based on relevant literature and the respective interview guides. During the initial review of the transcripts, these initial categories were refined and expanded inductively to reflect emerging themes and concepts expressed by participants. Each category was then clearly defined with coding rules and supported by anchor examples to ensure consistent application (Appendix 3). To ensure the integrity of the coding system, a test run was performed on a selection of transcripts. This step was designed to evaluate the clarity of category definitions and the effectiveness of coding rules. After careful consideration of the pilot round's results, the coding scheme has been revised and finalized. All interview materials were then fully coded according to the updated structure. The final categories provide the analytical foundation for interpreting the findings in the respective subtopics, linking empirical observations to theoretical constructs. This systematic, multi-stage coding process ensures that individual meaning-making, perceived tensions, and implicit assumptions around GenAI use are captured in sufficient depth. It also facilitates a systematic comparison across subtopics, revealing how GenAI affects cognition, culture, and strategic behavior at different levels of analysis.

4. Offloading Thought: How Generative AI Reshapes Ownership and Responsibility [not included in this version]

5. Managerial Skills and Human-AI Collaboration

5.1. Introduction

This subtopic focuses on the transformations occurring at the individual managerial level, particularly regarding the evolving skill landscape and the collaboration between humans and AI. In recent years, there has been a rapid acceleration in technological progress, particularly in the field of GenAI (World Economic Forum 2025). By leveraging natural language processing technologies, GenAI allows users to interact with systems as if they were communicating with another human being. Consequently, the increasing accessibility and versatility of AI have had a profound impact on the nature of managerial work, reducing the need for specialized technical knowledge (World Economic Forum 2025). According to Merten (2025), algorithms have the potential to automate up to 67% of managerial tasks, including resource planning, budgeting, and organizational coordination. Even at the executive level, the estimated automation potential remains high at 55%, suggesting that AI can assume a wide range of analytical and administrative functions (Merten et al. 2025). Consequently, the remaining share of human work becomes more crucial than ever. Recent reports further emphasize the economic implications of this shift. AI has been shown to enhance worker productivity and generate quantifiable value for organizations (PricewaterhouseCoopers 2025). Industries that demonstrate the greatest aptitude for integrating AI technologies have been observed to experience three times higher growth in revenue per employee compared to those with less adaptability to AI sectors (PricewaterhouseCoopers 2025). These developments indicate a fundamental shift in the composition of managerial skills. Following this introduction, the theoretical background will introduce the framework for the two research questions. This is followed by a description of the qualitative methodology and expert sample and the presentation of the coded findings. The chapter then provides an interpretation of the results considering the research questions, outlines managerial implications, and concludes with a summary of the main insights.

5.2. Theoretical Background

5.2.1. Managerial Skill Transformation and Human Expertise

AI is fundamentally transforming the skill landscape of modern organizations. Its growing analytical and predictive capabilities are changing how work is performed and which human abilities are essential (Mundhe 2023). There are three major developments that can be observed in this transformation. Some skills are augmented by AI, others are replaced, and a third group is substituted by automation (Giraud et al. 2022).

AI's substantial data-processing capacity enables it to execute repetitive tasks with exceptional efficiency. It automates standardized procedures, supports basic DM, and enables fast, inexpensive prediction across a wide range of contexts (Abby 2025; Agrawal et al. 2017; 2019; Giraud et al. 2022; Mundhe 2023; Norman 2017). Importantly, the system is capable of performing complex analytical functions that were previously exclusive to humans (Huang and Rust 2018). These advances are transforming the landscape of human work, with AI assuming responsibility for analytical precision while humans focus on the more interpersonal, creative, and interpretive aspects of problem-solving (Agrawal et al. 2017; 2019; Berente et al. 2021; Giraud et al. 2022; Huang and Rust 2018; Huang et al. 2019; Kolbjørnsrud et al. 2016; Mundhe 2023; Pistrui 2018; Sousa and Rocha 2019).

Consequently, there is a growing focus on competencies that are either too complex or too abstract for algorithms to replicate effectively. Emotional intelligence and critical thinking are two examples of such enduring competencies. Huang et al. (2019) describe this transformation as the emergence of a "Feeling Economy". As AI continues to develop and mimic human intelligence, the competitive edge of humans shifts towards "feeling tasks", which require empathy, intuition, and social sensitivity (Huang et al. 2019, 44). Managers must adopt an interpersonal approach to leadership, shifting their focus from data-driven strategies. The "soft" side of managerial work is now seen as the defining feature of effective human contribution in an AI-augmented environment (Huang and Rust 2018; Huang et al. 2019, 44). Another capability gaining relevance is adaptability. In the face of accelerating technological cycles, managers must commit to continuous learning and adaptation in response to the evolving landscape of AI applications (Mundhe 2023). Adaptability is therefore defined as both a cognitive and behavioral skill, combining curiosity, resilience, and a willingness to re-learn (Mundhe 2023). Many traditional management tasks, including parts of the DM process, can now be delegated to AI (Merten et al. 2025). However, this process paradoxically increases the need for distinctly human capabilities. As Huang et al. (2019, 44) state, "AI both replaces and augments". This paradox gives rise to a critical managerial question: how can leaders stay relevant in an era of automation? Broeckx (2025) illustrates this duality through the Iceberg Problem. AI can execute the 10% visible above the surface, standardized processes, and explicit knowledge flawlessly. However, most of this knowledge is tacit. This includes understanding the interplay of control systems, anticipating risks, interpreting cultural nuances, and recognizing when formal mechanisms fail. While AI has proven highly effective in recalling frameworks, it falls short in terms of the deep contextual understanding that characterizes professional mastery. The true challenge lies not in replacing expertise but in leveraging it alongside AI to unlock its full potential. In this new environment, professionals who succeed are not those who compete with algorithms, but rather those who combine their expertise with AI (Broeckx 2025; Harbath 2025). This approach necessitates the same level of expertise as the previous one, but also requires better questioning, recognizing flawed assumptions, and understanding AI outputs within their organizational context (Mishra 2025). As AI systems become more sophisticated, the dependence on human expertise for managing, interpreting, and troubleshooting these systems only increases (Mawson 2025). Accordingly, the first research question is:

RQ 1: *How does the increasing use of AI in managerial DM transform the composition of managerial skills, and how does human expertise remain valuable or risk being replaced?*

5.2.2. Human-AI Collaboration

As the previous section demonstrated, the integration of AI into managerial contexts has not rendered human skills obsolete. Instead, it has reshaped how human and machine capabilities complement one another. Because both humans and AI systems exhibit bias, their distinct limitations create opportunities for mutual reinforcement (Vincent 2021).

AI demonstrates exceptional capabilities in tasks involving data processing, logic, and pattern recognition, operating with high speed, accuracy, and consistency (Abby 2025; Jarrahi 2018; Norman 2017; Paschen et al. 2020; Shrestha et al. 2019). Its strength lies in its ability to analyze vast data volumes and identify complex relationships that exceed human cognitive capacity. However, the performance of AI systems deteriorates in situations that are ambiguous, novel, or poorly structured, and that require creativity, adaptability, and emotional understanding (Abby 2025; Jarrahi 2018). It operates strictly within the boundaries of its training data and predefined parameters, lacking contextual awareness and the ability to interpret meaning beyond encoded information (Abby 2025; Vincent 2021).

Humans, by contrast, demonstrate strengths in areas where AI exhibits limitations. They excel best in uncertain and complex environments, relying on tacit experience, intuition, and social awareness to interpret context and make sense of ambiguity (Jarrahi 2018; Norman 2017; Shrestha et al. 2019). Human decision-makers can envision alternative futures, apply judgment under uncertainty, and inspire others through emotion and meaning. These capabilities remain beyond the capacity of algorithms to replicate (Jarrahi 2018). In this sense, intuition “thrives in uncertainty”, while AI depends on data (Abby 2025, para. 2).

This complementary division of cognitive labor reflects the principle of "intelligence augmentation", which emphasizes that AI should enhance human intelligence (Jarrahi 2018, 577; Norman 2017; Shrestha et al. 2019). Instead of considering AI a replacement, forward-thinking leaders are increasingly using it as a decision-support tool, an assistant that accelerates analysis but still requires human interpretation (Abby 2025; Badmus 2024; Barro and Davenport 2019; Jarrahi 2018; Kuzmanko and Vrbová 2024). AI can thus be regarded as a colleague or team member in the DM process (Huang et al. 2019; Kolbjørnsrud et al. 2016; Shrestha et al. 2019). Combining the speed and precision of AI with the intuition and creativity of human judgment enhances both efficiency and strategic quality (Badmus 2024; Vincent 2021). As Norman (2017, 27) observes, "the human mind is far more powerful when coupled with a smart tool", emphasizing the efficacy of augmented DM (Abby 2025). By integrating computational analysis with human creativity, organizations can uncover insights that the human mind alone might overlook (Abby 2025). Based on this understanding, the following research question is hereby proposed:

RQ 2: *How can a combined approach, integrating human judgment and intuition with AI-driven analysis, enhance the effectiveness of managerial DM in comparison to relying on either system alone?*

5.3. Methodology

The selection of experts is a critical factor in ensuring the quality of the interviews conducted. For this subtopic, the selection of interview partners followed clear criteria to ensure informed and reflective insights rather than naive or superficial perspectives on AI usage. A key requirement was that all participants had at least five years of professional experience, ensuring they could draw on practical exposure to DM and technological adoption. This is particularly relevant in the context of the widespread accessibility of AI tools, which are often used without critical evaluation or a comprehensive understanding of their implications (Venkatesh 2022). In contrast, experienced professionals can provide a more nuanced and critical assessment of the impact of AI on managerial expertise, judgment, and DM processes (Inkpen et al. 2023). Therefore, the final sample consisted primarily of individuals in senior or executive positions, such as managing director, founder, or department head (see Table 1). Several participants also hold a PhD in AI-related fields or have founded companies specializing in AI-based solutions. These criteria ensured that all interviewees possessed not only deep domain knowledge, but also strategic DM experience relevant to this research topic.

ID	**Industry**	**Field of Expertise**	**Experience**	**Position**	**Interview Date**
E1	HRTech / AI Recruitment Automation	Digital Transformation & Sustainable Finance	18 years	COO & Co-Founder	20.10.25
E2	Consulting / Technology & AI	AI Strategy & Transformation	7 years	Director	21.10.25
E3	Consulting / Supply Chain & Operations	Business Transformation & Supply Chain Management	27 years	Managing Director	21.10.25
E4	Consulting / Technology & AI	AI Strategy & Data Transformation	6 years	Senior Consultant	23.10.25
E5	Technology / SaaS & AI	Investment Banking & Business Strategy	12 years	CEO & Founder	25.10.25

Table 1: *Overview of Interview Partners E1-E5*

5.4. Data Presentation

The following presentation is structured according to the categories and subcategories defined in the coding guide (see Appendix 3.1). The results offer insights into the individual perspectives and experiences of the interview participants, allowing for the identification of both shared patterns and individual nuances. In accordance with Mayring's (2019) qualitative content analysis methodology, a thorough examination of the expert interviews identified three primary categories: "DM Process" (C1), "Skills" (C2), and "Expertise" (C3) (see Figure 2). These categories reflect the core dimensions of the academic discourse on human and AI. Each category was further divided into specific subcategories that capture more detailed aspects of the topic. The subsequent section presents these categories and their respective subcategories in detail, illustrated with representative excerpts from the interview data.

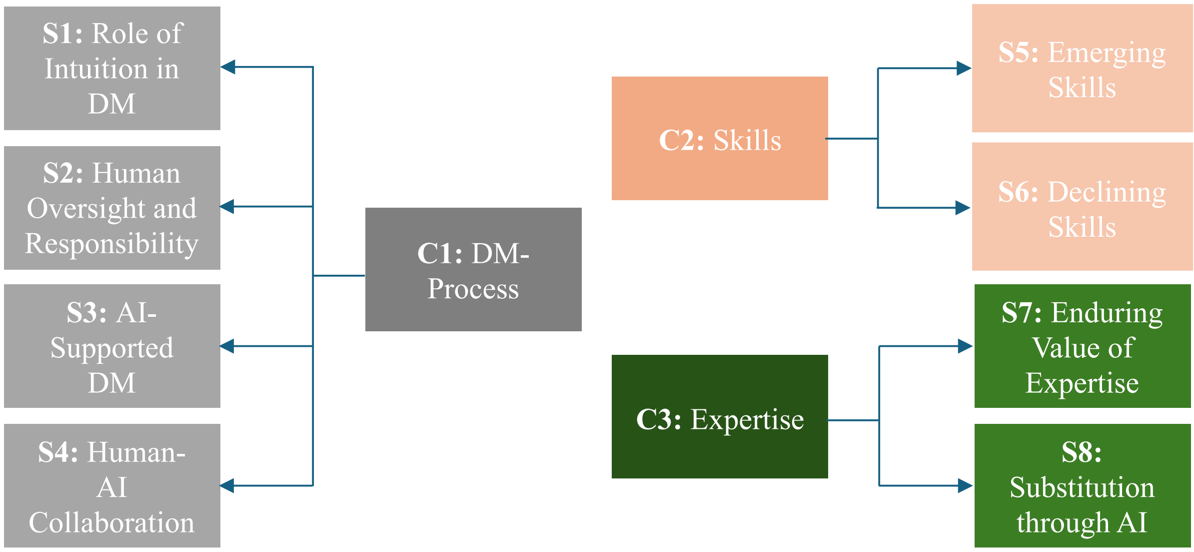

Figure 2: *Categorization of Expert Statements E1-E5 | Source: Own.*

C1 DM Process. The first category is the largest, with 109 assigned quotes and four subcategories: *"Role of Intuition in DM"* (22 citations), *"Human Oversight and Responsibility"* (17 citations), *"AI-Supported DM"* (27 citations), and *"Human-AI Collaboration"* (27 citations). The first subcategory consists of statements regarding intuitive DM. Intuition is described as a "guiding authority" and a "layer of quality assurance" that helps to determine whether a decision feels "right or wrong" (E4 2025, L. 25ff., L. 58ff.). Furthermore, it is applied in interpersonal situations, in operational DM, and in future-oriented or uncertain areas (E3 2025; E4 2025; E5 2025). In the context of AI, some experts argue that the role of intuition has remained constant but still significant (E2 2025; E3 2025; E5 2025). Others argue that intuition has become more important because it must now be used more consciously and because the amount of data that can be generated in a short time is enormous (E1 2025; E4 2025).

The second subcategory, *"Human Oversight and Responsibility"*, encompasses statements highlighting the importance of human involvement in DM. All experts concur that the ultimate decision rests with humans, who assess the outcome and determine its acceptability (E1 2025;

E2 2025; E3 2025; E4 2025; E5 2025). The reasons cited include humans' capacity to comprehend connections, exercise judgment, and determine the appropriate approach for various situations (E3 2025; E4 2025). E4 (2025, L. 91ff.) provides the following example to illustrate this point: "If, like me, you work internationally and deal with different cultures, you know that you cannot apply the same approach everywhere. […] The proud Spaniard, for example, does not respond well to the very direct German style". However, E5 (2025, L. 60ff.) takes a slightly different stance, emphasizing that he is "not a big fan of saying that certain things must necessarily be decided by humans", and arguing that "if AI demonstrably achieves better results, then it should also be allowed to make decisions".

The subcategory *"AI-Supported DM"* focuses on statements discussing the role of AI in DM, including when AI is used and its advantages and disadvantages. AI is primarily applied when "deeper understanding and broader perspectives" are required and is often used to prepare decisions and structure information (E1 2025, L. 18ff.; E5 2025). All experts agree that the primary advantages of AI are speed and efficiency, which is why it would make "little sense to work without AI" (E1 2025, L. 24ff.; E2 2025; E3 2025; E4 2025; E5 2025). E3 (2025) acknowledges that this also contributes to competitiveness, as faster and better-informed decisions can reduce costs – an assessment shared by E1 (2025). However, it is important to note that AI is not flawless, and therefore, it should not be regarded as a "miracle solution" (E1 2025, L. 179ff.; E5 2025). Additionally, concerns have been raised about the potential limitations of AI in terms of memory and continuous understanding. Without proper guidance, AI systems may not always produce the intended results (E5 2025).

The final subcategory, *"Human-AI Collaboration"*, includes statements addressing the interaction between humans and AI, focusing on their collaboration. Experts concur on the role of AI, which is described as a "tool", "partner", or "assistant", illustrating how tasks are divided between humans and AI (E2 2025; E4 2025; E5 2025). For instance, E1 (2025, L. 48ff.) states that “you have to work with it as you would with a junior employee”. This concept underscores the notion of ongoing collaboration. AI is primarily used for information provision, initial idea generation, brainstorming, and obtaining inspiration or a second opinion (E2 2025; E3 2025; E4 2025; E5 2025). In turn, humans provide input, integrate AI-generated results into a coherent whole, interpret the information, and refine the outcomes (E1 2025; E4 2025; E5 2025). The primary reason why humans continue to play a crucial role is that AI lacks contextual understanding and cannot account for key factors unless they are explicitly provided (E2 2025). For these reasons, “human-centric DM will continue for a long time” (E3 2025, L. 97ff.). As E2 (2025, L. 57ff.) underscores:

> […] AI is always a means to an end, a tool to solve problems that cannot be solved through exact mathematical models. […] This means that AI, by definition, always includes an element of error because it is never entirely accurate. For that reason, humans must always remain part of the DM process. This uncertainty is an inherent part of AI, sometimes stronger, sometimes weaker.

C2 Skills. The second category comprises 32 assigned quotes and is divided into two subtopics: “Emerging Skills” (27 citations) and “Declining Skills” (5 citations). The first subcategory focuses on newly important or increasingly valuable skills in AI-supported work environments. Relevant competencies include the ability to work effectively with AI. This involves proper prompting as well as understanding the different forms of AI and how to apply them appropriately (E3 2025; E4 2025; E5 2025). E3 (2025) even states that completing specific AI training sessions is mandatory in their company and directly linked to employees’ variable compensation. Another essential skill is critical thinking, which involves reflecting on and questioning AI-generated results, “instead of blindly trusting the AI”, which is particularly important given AI’s tendency to present results with high confidence (E1 2025; E4 2025, L. 52f.). E1 (2025, L. 144ff.) emphasizes in this context: “If people don’t use AI, they lose a competitive advantage in the long run, but if they use it without reflection, new risks emerge". Additional relevant skills include adaptability and forward-thinking when processes or models suddenly change, as well as interpersonal skills, such as presenting data effectively, engaging others, and adapting one's reasoning based on others' reactions (E1 2025; E4 2025). E5 (2025, L. 154ff.) also underscores the significance of creativity and strategic thinking over mere execution, using programming as an example: "[…] it's no longer about having someone who simply writes clean code, but about having someone who thinks strategically, who decides which language to use, what the infrastructure should look like, where to host, and how systems interact".

The second subcategory, *"Declining Skills"*, addresses skills that are becoming less relevant, which is a noticeably smaller group. The "element of learning" that occurs during work processes is diminishing, as the rapid upload of data and instant feedback are replacing the slower, more reflective learning experience, leading to a less engaged approach to topics (E1 2025, L. 54ff.). Consequently, individuals often exhibit signs of mental slowness and complacency in their thinking, as they receive results that are both expeditious and highly customized (E1 2025; E5 2025). One expert also points out that technical skills becoming less valuable, as many of these can now be performed by AI (E5 2025).

C3 Expertise. The third category stems from the question of how valuable expertise remains in a context where AI can increasingly take over human tasks. It comprises 21 assigned quotes and is divided into two subcategories: "Enduring Value of Expertise" (14 citations) and "Substitution through AI" (7 citations). The first subcategory includes statements emphasizing the continuing value of expertise in AI-driven environments. The value of expertise in such contexts depends largely on its degree of specialization (E1 2025). In highly specialized roles that require deep experiential knowledge and contextual understanding, the human element remains essential (E1 2025). Individuals who have demonstrated consistent success in a specific field for many years and possess extensive domain knowledge possess practical, experience-based expertise that cannot easily be replicated by AI (E5 2025). This knowledge is derived from real-life experiences rather than from books or theoretical frameworks (E4 2025; E5 2025). AI has its limitations in areas that are deeply contextual and highly complex, especially when solutions must be customized to meet the unique needs of individual clients (E2 2025). E3 (2025, L. 204ff.) further contends that the issue at hand transcends mere technical expertise, encompassing a dimension that extends beyond it:

> If you ask me what I'm actually paid for, I would argue that it's not for my knowledge. At my level, the most important skills are facilitation and communication, bringing people and diverse interests together. […] Technical expertise comes next, and that can be supported very well by AI. But the deliberation, the actual DM process, is what I'm really paid for.

The second subcategory, *"Substitution through AI"*, contains statements discussing situations in which humans could potentially be replaced. This is particularly evident in standardized roles, or in areas where decisions are highly data-driven and knowledge is widely accessible (E1 2025; E2 2025; E5 2025). Strategy consulting exemplifies this point. Recommendations that are overly general can be easily replicated by AI. However, the more context-specific and less standardized the advice, the harder it is for AI to replicate (E2 2025).

5.5. Interpretation & Discussion

The first research question explores how AI integration affects the composition of managerial skills and the value of professional expertise. As the literature review indicates, emotional and interpersonal skills are expected to become increasingly important, while expertise itself may gain value in AI-driven contexts. The empirical findings support this assumption and reveal two skill areas that have become particularly central: first, the ability to work effectively with AI, and second, interpersonal skills. Competence in dealing with AI involves not only the technical ability to formulate precise prompts and questions but also the cognitive ability to contextualize, verify, and critically reflect on the results. Interpersonal skills, on the other hand, refer to the ability to translate complex data into meaningful communication. This includes the ability to present results persuasively, integrate others' reactions, and apply empathy and emotional intelligence in doing so. In this sense, effective management in the age of AI requires less execution and more strategic and forward-oriented thinking. As AI becomes increasingly prevalent in analytical and repetitive tasks, technical and procedural skills are becoming less relevant.

When it comes to expertise, the distinction between its two core dimensions, explicit and tacit knowledge, is decisive. Explicit knowledge, being standardized, codified, and widely accessible, is easily replicated by AI systems and therefore at risk of losing value. Tacit knowledge, by contrast, remains uniquely human. It is experiential, contextual, and rooted in real-world understanding. This dimension enables professionals to navigate ambiguity, interpret nuance, and adapt judgment to complex situations, abilities that AI cannot replicate. Consequently, expertise continues to hold value as long as its tacit dimension predominates. As it becomes more standardized and explicit, it becomes more vulnerable to substitution.

In summary, the initial research question has been answered in the affirmative. AI undeniably transforms the composition of managerial skills, shifting the emphasis from technical proficiency toward more human-centered and meta-cognitive capabilities. At the same time, human expertise remains essential, particularly in situations that require experience, interpretation, and contextual understanding. The expertise of professionals is at risk of being replaced by technology only when it becomes overly standardized and data-driven.

The second research question explores whether combining human and AI expertise leads to more effective managerial DM than relying solely on human intuition or AI-generated analysis. As the results demonstrate, all experts agree that, in its current state, AI cannot make autonomous decisions. The final responsibility for judgment remains with humans, and therefore, the combination of human and AI capabilities constitutes the most effective form of DM. This shared perspective is based on two central insights: first, that AI systems trained on large qualitative and quantitative datasets can provide valuable analytical support and broaden the range of possible solutions; and second, that AI still lacks several key capacities that are essential for complex managerial decisions. While AI technology is advancing, it still has limited capacity to make decisions independently or provide the necessary context. Although AI can efficiently process vast amounts of information and identify relevant patterns, its outputs often lack clarity or situational nuance. Therefore, human intuition remains a vital component for integrating diverse insights into a cohesive whole. The application of AI does not inherently guarantee increased transparency or simplicity in DM processes, particularly in circumstances involving ambiguity, uncertainty, or value-based considerations. In such cases, intuition remains the most effective mechanism for making judgments in complex situations.

In addition to intuition, other distinctly human qualities are necessary to complement AI. Since AI lacks contextual understanding, it is essential for humans to contribute their domain knowledge and situational awareness. This involves understanding which approaches or solutions provided by AI are appropriate in specific contexts and how they affect different stakeholders and objectives. This interpretive and ethical dimension of DM remains beyond the reach of current AI systems. Concurrently, one of AI's most notable benefits is its capacity to expedite DM processes. By automating tasks such as information retrieval and the simulation of alternative scenarios, AI enables decision-makers to devote more time to evaluating strategic options and reflecting on implications. In this sense, AI serves as a robust analytical foundation upon which human intuition and judgment can be more effectively applied.

Overall, the combined use of AI and human cognition enhances both the efficiency and quality of decisions. By integrating AI's analytical precision with human intuition, contextual understanding, and empathy, organizations can achieve decision processes that are not only faster and more cost-effective but also more coherent, balanced, and strategically informed.

5.6. Managerial Implications

The study's findings offer several significant implications for managerial practice and organizational strategy. As technological advances continue to transform the nature of human work, it becomes imperative for organizations to identify effective methods for human and AI collaboration. This approach has been shown to enhance organizational efficiency, reduce feelings of threat among employees, and foster greater openness toward working with AI (Vincent 2021). The value of AI in supporting and advancing organizational processes is directly related to the degree of collaboration and complementarity that can be cultivated between human workers and AI systems (Vincent 2021). Therefore, it is essential to demonstrate to employees that AI enhances their capabilities, thereby fostering greater trust in the technology and encouraging its adoption within the organization (PricewaterhouseCoopers 2025).

A practical illustration of how organizations can leverage AI to enhance, not diminish, human contributions is seen in Southwest Airlines' collaboration with PwC to modernize its legacy systems through AI integration. Rather than replacing employees, the initiative freed up valuable time, allowing teams to focus on critical thinking, innovation, and complex problem-solving, while AI handled repetitive and data-intensive tasks (PricewaterhouseCoopers 2025).

Considering these developments, organizations are advised to engage early with the implementation of AI technologies in DM processes. During the planning phase, organizations should integrate structured ethical guidelines into AI-supported DM. This includes formulating principles for responsible AI adoption, embedding human-centered design throughout the development and implementation process, and aligning practices with existing regulatory standards

(Hossain et al. 2025). Such principles should ensure human oversight, safeguard fairness, and promote the explainability of AI systems (Hossain et al. 2025).

A critical practical step involves training and education. As the findings demonstrate, proficiency in handling AI has emerged as a central skill for the future of managerial work. To address this need, organizations should consider investing in comprehensive training programs that cover both the technical operation of AI systems and a deeper understanding of how these systems function (Badmus 2024). Such initiatives can take the form of formal academic programs as well as on-the-job learning opportunities (Badmus 2024). Maintaining a balanced human-AI symbiosis also requires continuous adaptation. As AI evolves, both managers and employees must continuously update their AI literacy while strengthening their uniquely human comparative advantages, such as intuition, holistic judgment, and emotional intelligence (Jarrahi 2018).

5.7. Subtopic Conclusion

This subtopic examined how the integration of AI reshapes the skill composition and expertise requirements of managers, emphasizing that automation does not diminish the human role but rather redefines it. The findings indicate a marked transition from technical and procedural competencies to meta-cognitive, interpersonal, and reflective capabilities, such as critical thinking, adaptability, and emotional intelligence. In this new paradigm, human expertise continues to be valuable due to its reliance on tacit, context-dependent knowledge. Furthermore, the study emphasizes that optimal DM efficacy is achieved by integrating human intuition and contextual awareness with AI's analytical capabilities.

In the broader context of this thesis, these insights contribute to understanding how GenAI transforms human agency by redefining what constitutes valuable managerial contribution in strategic DM. As AI becomes increasingly sophisticated, it is estimated that human roles will evolve to encompass more interpretive, sense-making, and ethically grounded responsibilities within organizations. Future research and practice should therefore focus on developing frameworks for human-AI complementarity, ensuring that technological advancement enhances rather than erodes the distinctly human dimensions of expertise, judgment, and leadership.

6. The Meditating Role of Organizational Culture [not included in this version]

7. Cognitive Convergence in AI-Supported Innovation [not included in this version]

8. Joint Discussion

This thesis examined how the integration of GenAI reshapes strategic DM processes at four analytical levels: individual cognition, managerial work, organizational culture, and innovation practices. Each section provides a distinct perspective on these transformations, and their collective insights reveal a consistent pattern. GenAI does more than automate tasks or accelerate workflows. It also redistributes cognitive effort, alters the role and expression of human expertise, and transforms the cultural conditions under which creative and responsible DM can occur. The findings across these levels converge on the central research question guiding this thesis: *How does integrating GenAI into strategic DM environments reshape individual and managerial judgment, as well as organizational distinctiveness?* Taken together, the results suggest that GenAI is not only a technological development, but also a cognitive, cultural, and creative shift. The following discussion synthesizes these insights to provide an integrated understanding of how GenAI reshapes DM in contemporary organizations.

8.1. Efficiency Gains and the Tension between Speed and Depth

A dominant theme that cuts across all chapters is the growing tension between efficiency and cognitive depth. The findings show that GenAI significantly accelerates drafting, structuring, and information processing. While this enhances productivity, it also creates strong incentives for cognitive offloading. Users skip reflective steps, adopt AI-generated material prematurely, and rely on plausibility rather than verification. At the managerial level, the same efficiency logic alters the composition of work: routine analytical tasks are delegated to AI, thereby increasing the importance of interpretive, relational, and judgment-oriented skills. Thus, efficiency reduces operational burdens but simultaneously raises the stakes for human judgment because the remaining tasks are more ambiguous and context-sensitive.

Organizational culture can amplify or dampen this dynamic. Cultures characterized by limited transparency or low psychological safety encourage employees to use AI superficially or defensively. When employees feel underinformed or excluded from sense-making, they either avoid AI entirely or use it in a shallow, compliance-driven manner. Both patterns intensify the offloading tendencies identified at the individual level. The consequences are most visible in innovation work. When many people start from the same AI-generated baseline, innovation can become homogenized: ideas converge toward statistically probable, familiar, and low-variance outputs. Rather than expanding the idea space, efficiency-driven AI use risks shrinking it.

Together, these findings demonstrate that efficiency is not a neutral benefit. Without countermeasures, efficiency reduces cognitive depth, weakens managerial judgment, and narrows creative variance. Therefore, the core challenge is not to increase efficiency further but to balance it with deliberate reflection and human-led exploration.

8.2. Redefining Human Contribution: From Execution to Sense-Making

Across all analytical layers, the findings reveal a redefinition of what constitutes a meaningful human contribution. At the individual level, small acts of reinterpretation, questioning, or contextual correction reestablish psychological ownership and accountability. This demonstrates that, in AI-mediated work, contributions lie less in producing every element of content and more in directing, evaluating, and making sense of what AI provides.

This shift is even more pronounced in managerial work. As AI takes over routine analytical tasks, humans' comparative advantage increasingly rests in metacognitive and interpersonal capabilities, such as critical judgment, intuitive reasoning, tacit knowledge, contextual awareness, and the ability to synthesize ambiguous information. These abilities, once considered supplementary, are becoming the foundation of competence in AI-augmented environments.

However, these roles do not emerge automatically. Organizational culture determines whether individuals engage reflectively or resort to avoidance and overreliance. Cultures that tolerate mistakes, normalize uncertainty, and encourage experimentation allow employees to view AI as a cognitive partner rather than a shortcut. Where such norms are absent, people respond defensively, either ceding too much autonomy to AI or retreating into passive compliance.

Innovation practices further underscore this redefinition of contribution. While AI can accelerate idea generation, it rarely produces deep, unconventional, or nonlinear insights on its own. Genuine divergence, moving beyond the “most likely answer”, remains largely human-driven. Breaking out of AI’s statistical tendencies and introducing novelty into the innovation process requires imagination, intuition, and critical detachment.

Taken together, these findings suggest that GenAI shifts the focus of human value creation from execution to sense-making. In this new paradigm, humans become curators, interpreters, and creative navigators rather than mere producers. This transition requires deliberate skill development and supportive cultural conditions, not simply technological availability.

8.3. Cognitive Shortcuts and the Need for Deliberate Counterweights

A unifying pattern across all chapters is the amplification of cognitive shortcuts. The fluency and confidence of GenAI outputs foster automation bias, or the tendency to accept suggestions without sufficient scrutiny. In DM contexts, this weakens accountability and reduces cognitive engagement. In innovation contexts, it fuels fixation bias, whereby early AI suggestions limit thinking and prematurely narrow the search space. Managerial capabilities provide the necessary counterweights. Emerging skills such as AI literacy, prompt design, critical evaluation, bias awareness, and structured oversight enable individuals to interrupt automated defaults and preserve cognitive agency. These skills serve as practical safeguards for depth, responsibility, and originality. Whether these counterweights can develop depends strongly on organizational culture. Environments marked by fear, ambiguity, or weak communication make bias-prone behavior more likely as employees either rely on AI defensively or avoid reflective engagement.

In contrast, cultures that provide psychological safety, shared meaning, and time for experimentation strengthen employees' ability to question, refine, and reframe AI outputs.

The risks across these perspectives share a common root: cognitive displacement, human thinking being replaced by automated patterns. The countermeasures also share a common foundation: deliberate human engagement supported by skills, norms, and leadership.

8.4. Culture and Leadership as the Decisive Switch

One of the strongest integrative insights is that organizational culture and leadership determine whether GenAI becomes a source of augmentation or erosion. While individual and managerial dynamics explain how people interact with AI, culture explains why the same technology produces different outcomes across organizations.

Learning-oriented cultures, characterized by openness, psychological safety, shared meaning, and tolerance for mistakes, enable individuals to maintain cognitive engagement. In such environments, employees view AI as a supportive tool, experiment with prompting strategies, and apply their judgment to outputs. Leadership plays a central role in cultivating these conditions by modeling reflective AI use, offering time and resources for exploration, and clearly communicating purpose and expectations. In contrast, hierarchical or fear-driven cultures amplify overreliance, resistance, ambiguity, and convergence. When leaders promote AI without adequate explanation, employees feel displaced rather than empowered. Under such conditions, the cognitive risks described in earlier sections – offloading, bias, and homogenization – accelerate. Thus, culture and leadership influence not only adoption but also the trajectory of cognitive, managerial, and creative outcomes. GenAI does not determine these outcomes, organizations do.

8.5. From Cognitive and Cultural Dynamics to Organizational Distinctiveness

The integrated findings directly address the overarching research question. GenAI reshapes individual and managerial DM as well as the foundations of organizational distinctiveness.

At the individual level, DM becomes increasingly dependent on intentional reflection, ownership, and critical oversight. From a managerial perspective, distinctiveness stems from human-centered competencies that GenAI cannot replicate, such as intuition, contextual understanding, relational skills, and sense-making. At the cultural level, distinctiveness depends on collective capabilities, such as shared meaning, psychological safety, and a willingness to experiment. From an innovation perspective, distinctiveness is challenged by GenAI's tendency toward convergence, yet it is strengthened when humans use AI to broaden rather than narrow exploration.

9. Conclusion

9.1. Summary of Key Findings

The joint findings of this thesis reveal a coherent pattern. Rather than diminishing the role of human judgment, GenAI elevates and reconfigures it. The results show that, from cognitive, managerial, cultural, and innovation-related perspectives, GenAI reshapes DM by shifting how cognitive work is performed, redefining how expertise is applied, and influencing the ways organizations create meaning and sustain distinctiveness. While GenAI reliably enhances the efficiency of knowledge-intensive work, this acceleration introduces new vulnerabilities. Unreflective engagement with GenAI has the potential to erode deliberative depth and attenuate individuals' sense of authorship within the decision process, thereby rendering rushed consent more probable. This underscores the notion that gains in efficiency do not inherently guarantee the robustness or quality of DM processes. At the same time, the findings underscore that GenAI's positive potential emerges when humans remain actively and critically engaged. Human expertise, particularly intuition, contextual understanding, sense-making, and ethical judgment, become more central as GenAI takes over procedural or analytical tasks. Consequently, the human contribution shifts from execution to evaluative and interpretive work. This expanded sense-making role is essential for maintaining depth, accountability, and organizational uniqueness in DM processes.

The results also highlight the decisive influence of organizational culture and leadership. Psychological safety, shared meaning, transparency, and time for exploration determine whether employees engage with GenAI constructively or defensively. Learning-oriented cultures mitigate cognitive risks and enable broader exploration. In contrast, environments oriented solely toward speed and output amplify overreliance and uniformity, ultimately weakening organizational differentiation.

Taken together, the findings answer the overarching research question, showing that GenAI's impact on strategic DM stems not from the technology itself, but from how it reshapes the architecture of human judgment and organizational meaning-making. GenAI is reshaping the way decisions are formed and interpreted, altering how expertise is exercised and how organizations generate value. Its influence unfolds through shifts in cognitive effort, evolving managerial roles, and cultural norms that determine whether employees engage reflectively or default to algorithmic convenience. Thus, GenAI becomes a strategic force only when embedded in human-centered structures that sustain critical thinking, encourage exploration, and anchor technological capabilities in shared purpose. Without these conditions, GenAI risks narrowing thought patterns and undermining the uniqueness it promises to enhance.

9.2. Theoretical Contributions

This work's theoretical contribution lies in its integration of fragmented perspectives on individual cognition, professional capabilities, organizational transformation, and strategic innovation. While prior literature often examines these dimensions in isolation, this study develops an interconnected, layered view that demonstrates how GenAI alters KW at multiple levels, from the internal cognitive processes of individual users to the structural and cultural shifts within organizations. This integrated perspective advances the theoretical understanding of GenAI by positioning it not merely as a technological input, but as a socio-cognitive force that reshapes the conditions under which organizations produce judgment and value.

A core theoretical contribution is the explicit link between individual-level dynamics and organizational-level change processes. By integrating insights on cognitive offloading, psychological ownership, and human-AI collaboration with findings on organizational readiness, leadership, and innovation strategy, the thesis shows how microlevel cognitive shifts can influence and be shaped by macrolevel structures, with organizational structure serving as the mediating role that links these levels. This bidirectional perspective addresses a critical gap in the current discourse, which often treats user behavior and organizational transformation as separate issues. Thus, the study clarifies how cognitive mechanisms mediate the relationship between GenAI and organizational outcomes, offering a more relational theoretical model.

9.3. Managerial Implications and Recommendations

The findings across the four subtopics make clear that the integration of GenAI is a strategic, cultural, and human transformation rather than a strictly technical one. As Badmus (2024) emphasizes, AI will be crucial for long-term competitiveness, but its value hinges on aligning technological investments with ethical safeguards and strategic clarity. Therefore, organizations must articulate explicit principles for responsible AI use and ensure that their implementation strategies are tailored to their specific environmental and organizational conditions rather than following uniform adoption patterns (Badmus 2024).

A central implication is organizational readiness. Employees often view AI as a significant change, so transparent communication and reassurance about job security are essential for maintaining trust and engagement (Hengstler et al. 2016). Without psychological safety and meaningful employee involvement, resistance and disengagement are likely to occur, which limits the impact of well-designed AI initiatives.

The findings also underscore the growing importance of human capabilities. To avoid overreliance and cognitive offloading as well as the resulting erosion of ownership, organizations must treat metacognitive skills, such as critical reflection or self-monitoring, as strategic competencies (Jadhav 2025; Wiederhold 2025). This complements insights which show that managerial effectiveness increasingly relies on contextual judgment and AI literacy. Rather than focusing on projected job displacement, leaders should prepare their workforce for the substantial number of new roles and skills associated with AI-driven growth (Alupo et al. 2022; McKinsey 2025). Framing AI as a growth enabler rather than a cost-reduction tool allows firms to unlock new markets and value-creation opportunities. This reinforces the idea that AI often expands rather than reduces employment in exposed roles (PricewaterhouseCoopers 2025). Responsible human-AI collaboration requires careful design and governance. Interfaces that encourage explanation, comparison, and iterative reflection help preserve agency and accountability (Lee et al. 2025; Reyes and Huet n.d.). Transparent decision paths and clear authorship norms also strengthen psychological ownership (Fabre et al. 2020; Xu et al. 2024). Review protocols and shared prompting standards are governance structures that are essential for ensuring the strategic alignment and high quality of AI use, particularly in innovation contexts where the risk of homogenization is pronounced (Consumer Goods Technology 2025).

Lastly, AI transformation must be understood as an ongoing learning process. Successful transformation requires a supportive social context that includes a clear vision for the role of AI, robust technical foundations, and cultural conditions that encourage learning and experimentation (Haefner et al. 2023). As employee behavior evolves with the increased use of GenAI, organizations require continuous development mechanisms rather than one-off training sessions (Calvino et al. 2025). Ultimately, managers must orchestrate cognitive, cultural, and structural shifts that enable humans and AI systems to effectively complement one another; a task that remains fundamentally human, even as technology advances (Badmus 2024; McAfee and Brynjolfsson 2017).

9.4. Limitations and Future Research

Despite the implications of this work, there remain some limitations to which attention is drawn here, and which offer opportunities for future research.

When interpreting the findings of this subtopic, it is important to acknowledge several empirical limitations. First, Subtopics 2-4 employed a qualitative approach exclusively. Combining information from the interviews with quantitative data ensures a more holistic understanding of the studied phenomenon (Baxter and Jack 2008; Eisenhardt and Bourgeois 1988; Giraud et al. 2022). Analogously, Subtopic 1 employed a quantitative approach exclusively. Employing a combination of these two approaches assists in determining the generalizability of the results (Giraud et al. 2022). Secondly, there is a lack of diversity with respect to country of residence, as well as industries. Notably, almost all interviewees reside in Germany and are employed there, which also reduces the transferability and dependability of the results (Guba and Lincoln 1994). Thirdly the interviews were not conducted until saturation point, where additional data collection would not provide further explanatory insights (Charmaz 2006). It is possible that conducting additional interviews would have led to more generalizable results (Sousa and Rocha 2019). This limitation also applies to the survey. Fourthly, the survey did not collect gender data, making it impossible to analyze potential differences in AI adoption, reflection behavior, or agency perception across gender groups. This omission limits the ability to explore intersectional patterns in cognitive offloading or accountability attribution. Furthermore, given the variability in the capabilities of AI tools (e.g., writing assistants versus decision-support systems), it is possible that participants had different interpretations of what it means to “use AI”. While the survey provided examples, respondents may have applied the questions to varying contexts, potentially affecting the consistency of responses. Fifthly, it is important to note that participants may have adjusted their responses due to social desirability or organizational constraints, especially when discussing AI-related strategic decisions (Bispo Júnior 2022). Research indicates that people often overestimate their critical engagement or underreport cognitive shortcuts, especially in professional settings (Fisher 1993; Podsakoff et al. 2003). This, for example, may help to explain why fixation bias appeared less frequently in the interviews. As cognitive biases often operate unconsciously, individuals may find it difficult to recognize them accurately (Kahneman 2011). Finally, the insights reflect a moment in time within a rapidly evolving technological landscape. AI capabilities, organizational expectations, and leadership practices are in a constant state of flux, meaning that some findings may require re-evaluation as GenAI becomes more widely institutionalized (McKinsey 2025). Future studies should therefore include longitudinal and multi-stakeholder designs to capture how cultural and leadership dynamics develop across different organizational settings and over time.

Beyond methodological concerns, there are also conceptual limitations. Regarding Subtopic 2, while the study identifies key managerial skills and forms of expertise relevant in AI-augmented environments, the analysis does not account for the full breadth of factors that shape effective human-AI collaboration. Trust in AI systems plays a critical role in determining whether humans rely on or override algorithmic recommendations. This is a fundamental aspect of human-AI interactions, given the inherent risks associated with the complexity, opacity, and nondeterministic behavior of these systems (Glikson and Woolley 2020). Trust significantly impacts behavior in DM. Initially, individuals may place trust in an algorithm, but if it makes mistakes, even when it still outperforms human judgment overall, they often abandon it in favor of human decision-makers (Dietvorst et al. 2015). This subtopic only touched upon these dynamics indirectly, leaving an important conceptual dimension underexplored. A more explicit examination of trust and related psychological variables would likely have provided deeper insights into how and when managers choose to collaborate with, rely on, or reject AI systems. The analysis of Subtopic 3 was shaped by a conceptual focus on cultural readiness, resistance, and leadershipmediated change mechanisms. While this approach allowed for a structured examination of the influence of culture and leadership on AI transformation, it also limited the observable range of organizational dynamics. A key limitation stems from the composition of the interview sample; all participants were external consultants. While their insights offer valuable cross-organizational perspectives, they remain indirect and filtered through client interactions rather than being grounded in internal, lived experience. Consequently, the findings reflect interpretations of organizational culture from an outside-in viewpoint and may overlook informal practices, micro-level interactions, and internal power dynamics (Nesheim and Hunskaar 2015). Additionally, the interviews capture perceived patterns rather than longitudinal cultural evolution, which limits the observation of deeper cultural shifts or internal resistance processes (Kashima 2014). These constraints suggest that to develop a more granular account of cultural mechanisms in AI transformation, complementary data from internal stakeholders or ethnographic perspectives would be necessary. Regarding Subtopic 4, the analysis was guided by a specific theoretical lens that focused on homogenization, the efficiency-originality paradox, and two cognitive biases. While this approach allowed for an in-depth analysis of cognitive convergence in GenAI-supported innovation, it limited the range of observable dynamics (Eisenhardt 1989). Other mechanisms relevant to AI-assisted creativity, such as trust formation, emotional responses, and collaborative team processes, were beyond the scope of the study.

10. References

Abby. 2025. "The AI-Intuition Dilemma: Can Machines Replicate Human Instinct?" *Medium*, February 14. https://sen-abby.medium.com/the-ai-intuition-dilemma-can-machines-replicate-human-instinct-4d522ca19a2b.

Abonamah, Abdullah A., Muhammad Usman Tariq, and Samar Shilbayeh. 2021. 'On the Commoditization of Artificial Intelligence'. Frontiers in Psychology 12 (September): 696346. https://doi.org/10.3389/fpsyg.2021.696346.

Ademola, OE. 2024. "Change Management Trends in the AI Modern World: Adapting to the Future of Work." *Journal of Behavioral Informatics* 10 (1): 41–50.

Aghion, Philippe, Céline Antonin, and Simon Bunel. 2020. "Artificial Intelligence, Growth and Employment: The Role of Policy." *Economie et Statistique / Economics and Statistics*, nos. 510-511–512 (January): 149–64. https://doi.org/10.24187/ecostat.2019.510t.1994.

Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2017. "What to Expect From Artificial Intelligence." *MIT Sloan Management Review* 58 (3): 23–26.

Agrawal, Ajay, Joshua S. Gans, and Avi Goldfarb. 2019. "Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction." *Journal of Economic Perspectives* 33 (2): 31–50. https://doi.org/10.1257/jep.33.2.31.

Alabi, Moses. 2025. *Organizational Culture and Its Impact on Technology Adoption and Business Agility*.

Aldoseri, Abdulaziz, Khalifa Al-Khalifa, and Abdelmagid Hamouda. 2023. "A Roadmap for Integrating Automation with Process Optimization for AI-Powered Digital Transformation." Preprint, Engineering, October 17. https://doi.org/10.20944/preprints202310.1055.v1.

Al Rousan, Waseem. 2025. "Data Analytics in 2025: How AI Will Revolutionize Decision-Making." *DataHub*. https://datahubanalytics.com/data-analytics-in-2025-how-ai-will-revolutionize-decision-making/.

Anderson, Barrett R., Jash Hemant Shah, and Max Kreminski. 2024. Homogenization Effects of Large Language Models on Human Creative Ideation. 2024. https://doi.org/10.48550/ARXIV.2402.01536.

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29 (3): 3–30. https://doi.org/10.1257/jep.29.3.3.

Badmus, Oluwatobi. 2024. "From Gut Feeling to Algorithmic Thinking: AI-Driven Decision-Making in Strategic Management." *Algora* 1 (02): 1–15.

Barney, Jay. 1991. 'Firm Resources and Sustained Competitive Advantage'. Journal of Management 17 (1): 99–120. https://doi.org/10.1177/014920639101700108.

Barro, Senén, and Thomas H. Davenport. 2019. "People and Machines: Partners in Innovation." *MIT Sloan Management Review* 60 (4): 22–28.

Baumard, Philippe. 1999. *Tacit Knowledge in Organizations*. SAGE Publications Ltd. https://doi.org/10.4135/9781446217375.

Berente, Nicholas, Bin Gu, Jan Recker, and Radhika Santhanam. 2021. "Managing Artificial Intelligence." *MIS Quarterly* 45 (3): 1433–50. https://doi.org/10.25300/MISQ/2021/16274.

Bérubé, Mathieu, Tanya Giannelia, and Gregory Vial. 2021. *Barriers to the Implementation of AI in Organizations: Findings from a Delphi Study*.

Betsch, Tilmann, and Andreas Glöckner. 2010. "Intuition in Judgment and Decision Making: Extensive Thinking Without Effort." *Psychological Inquiry* 21 (4): 279–94. https://doi.org/10.1080/1047840X.2010.517737.

Bick, Alexander, Adam Blandin, and David Deming. 2024. "The Rapid Adoption of Generative AI." https://doi.org/10.3386/w32966.

Bispo Júnior, José Patrício. 2022. "Social desirability bias in qualitative health research." *Revista de saude publica* (Brazil) 56: 101. https://doi.org/10.11606/s1518-8787.2022056004164.

Bolívar, José Miguel. 2015. "The Value of Work and Knowledge Workers - Glocalthinking." Glocalthinking. April 24, 2015. https://glocalthinking.com/en/the-value-of-work-and-knowledge-workers/.

Bommasani, Rishi, Kathleen A. Creel, Ananya Kumar, Dan Jurafsky, and Percy Liang. 2022. 'Picking on the Same Person: Does Algorithmic Monoculture Lead to Outcome Homogenization?' Preprint, arXiv. https://doi.org/10.48550/ARXIV.2211.13972.

Broeckx, Ben. 2025. "The AI Paradox: Why Tomorrow's Professionals Need to Know More, Not Less." LinkedIn. https://www.linkedin.com/pulse/ai-paradox-why-tomorrows-professionals-need-know-more-ben-broeckx-cvc8e/.

Buvat, Jerome, Brian Solis, and Claudia Crummenerl. 2018. "The Digital Culture Challenge: Closing the Employee-Leadership Gap." *Capgemini*.

Calvino, Flavio, Jelmer Reijerink, and Lea Samek. 2025. The Effects of Generative AI on Productivity, Innovation and Entrepreneurship. OECD Artificial Intelligence Papers. https://doi.org/10.1787/b21df222-en.

Cantonis, Steve. 2025. "Why Human Intuition Still Matters in the Age of AI & Analytics." Pariveda, August 26. https://parivedasolutions.com/resources/why-human-intuition-still-matters-in-the-age-of-ai-and-predictive-analytics/.

Cerchione, Roberto, Giuseppe Liccardo, and Renato Passaro. 2025. "Artificial Knowledge Generation: Investigating the Revolutionary Role of Generative AI in Knowledge Management." Journal of Innovation & Knowledge 11 (November): 100866. https://doi.org/10.1016/j.jik.2025.100866.

Chance, Paul. 1986. “Thinking in the Classroom : A Survey of Programs.” Teachers College Press.

Charmaz, Kathy. 2006. *Constructing Grounded Theory: A Practical Guide through Qualitative Analysis*. Sage.

Chaudhary, Shreya, Shravan Kumar, Komil Kumar, Samta Kathuria, Prafful Negi, and Gunjan Chhabra. 2023. “Role of Artificial Intelligence in Organizational Culture and Workplace.” *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, March 23, 528–32. https://doi.org/10.1109/ICSCDS56580.2023.10104697.

Chen, Xiaoyan, and Limin Xiao. „Serendipitous sparks: AI information encounter, cognitive flexibility, AI literacy, and university student creativity“. *Frontiers in Psychology* 16 (November 2025): 1623730. https://doi.org/10.3389/fpsyg.2025.1623730.

Chen, Xinyue, Kunlin Ruan, Kexin Phyllis Ju, Nathan Yap, and Xu Wang. 2025. “More AI Assistance Reduces Cognitive Engagement: Examining the AI Assistance Dilemma in AI-Supported Note-Taking.” Proceedings of the ACM on Human-Computer Interaction 9 (7): 1–29. https://doi.org/10.1145/3757632.

Claxton, GL. 1998. “Investigating Human Intuition: Knowing without Knowing Why.” *Psychologist* 11 (5): 217–20.

Consumer Goods Technology. 2025. ‘P&G, Harvard Study Says Gen AI Gets CPG Teams Working 12% Faster’. April 4. https://consumergoods.com/pg-harvard-study-says-gen-ai-gets-cpg-teams-working-12-faster.

Csaszar, Felipe A., Harsh Ketkar, and Hyunjin Kim. 2024. ‘Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors’. arXiv:2408.08811. Preprint, arXiv. https://doi.org/10.48550/arXiv.2408.08811.

Daft, Richard L., and Robert H. Lengel. 1986. “Organizational Information Requirements, Media Richness and Structural Design.” *Management Science* 32 (5): 554–71. https://doi.org/10.1287/mnsc.32.5.554.

Dane, Erik, and Michael G. Pratt. 2007. “Exploring Intuition and Its Role in Managerial Decision Making.” *Academy of Management Review* 32 (1): 33–54. https://doi.org/10.5465/amr.2007.23463682.

Dane, Erik, Kevin W. Rockmann, and Michael G. Pratt. 2012. “When Should I Trust My Gut? Linking Domain Expertise to Intuitive Decision-Making Effectiveness.” *Organizational Behavior and Human Decision Processes* 119 (2): 187–94. https://doi.org/10.1016/j.obhdp.2012.07.009.

Desdevises, Joy. 2025. ‘The Paradox of Creativity in Generative AI: High Performance, Human-like Bias, and Limited Differential Evaluation’. Frontiers in Psychology 16 (August): 1628486. https://doi.org/10.3389/fpsyg.2025.1628486.

Dietvorst, Berkeley J., Joseph P. Simmons, and Cade Massey. 2015. “Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err.” *Journal of Experimental Psychology: General* 144 (1): 114.

DiGiacomo, Cristina. 2025. "Decision Fatigue in the Age of AI: How Critical Thinking Keeps Leaders Ahead." C-Suitenetwork. September 5, 2025. https://c-suitenetwork.com/decision-fatigue-in-the-age-of-ai-how-critical-thinking-keeps-leaders-ahead/.

Doshi, Anil R., and Oliver P. Hauser. 2024. 'Generative AI Enhances Individual Creativity but Reduces the Collective Diversity of Novel Content'. Science Advances 10 (28): eadn5290. https://doi.org/10.1126/sciadv.adn5290.

Draxler, Fiona, Anna Werner, Florian Lehmann, Matthias Hoppe, Albrecht Schmidt, Daniel Buschek, and Robin Welsch. 2023. "The AI Ghostwriter Effect: When Users Do Not Perceive Ownership of AI-Generated Text but Self-Declare as Authors." ACM Transactions on Computer-Human Interaction 31 (2): 1–40. https://doi.org/10.1145/3637875.

Drucker, Peter F. 1999. "Knowledge-Worker Productivity: The Biggest Challenge." California Management Review 41 (2): 79–94. https://doi.org/10.2307/41165987.

Dunlosky, John, and Keith W Thiede. 1998. "What Makes People Study More? An Evaluation of Factors That Affect Self-paced Study." Acta Psychologica 98 (1): 37–56. https://doi.org/10.1016/s0001-6918(97)00051-6.

Eisenhardt, K. M., and L. J. Bourgeois. 1988. "Politics of Strategic Decision Making in High-Velocity Environments: Toward a Midrange Theory." *Academy of Management Journal* 31 (4): 737–70. https://doi.org/10.2307/256337.

Eisenhardt, Kathleen M. „Building Theories from Case Study Research". *The Academy of Management Review*, Bd. 14, Nr. 4, Oktober 1989, S. 532. *DOI.org (Crossref)*, https://doi.org/10.2307/258557.

Eraut, Michael. 2000. "Non-formal Learning and Tacit Knowledge in Professional Work." *British Journal of Educational Psychology* 70 (1): 113–36. https://doi.org/10.1348/000709900158001.

Ericsson, K. Anders, Ralf T. Krampe, and Clemens Tesch-Römer. 1993. "The Role of Deliberate Practice in the Acquisition of Expert Performance." Psychological Review 100 (3): 363–406. https://doi.org/10.1037/0033-295x.100.3.363.

Evans, Jonathan St. B. T. 2008. "Dual-Processing Accounts of Reasoning, Judgment, and Social Cognition." *Annual Review of Psychology* 59 (1): 255–78. https://doi.org/10.1146/annurev.psych.59.103006.093629.

Fabre, Raul Gonzalez, Javier Camacho Ibáñez, and Pedro Tejedor Escobar. 2020. "Moral Control and Ownership in AI Systems." AI & Society 36 (1): 289–303. https://doi.org/10.1007/s00146-020-01020-z.

Falconer, Sean. 2025. "We keep talking about AI agents, but do we ever know what they are?" Venturebeat.Com, October 12, 2025. https://venturebeat.com/ai/we-keep-talking-about-ai-agents-but-do-we-ever-know-what-they-are.

Felin, Teppo, and Matthias Holweg. 2024. 'Theory Is All You Need: AI, Human Cognition, and Causal Reasoning'. Strategy Science 9 (4): 346–71. https://doi.org/10.1287/stsc.2024.0189.

Feuerriegel, Stefan, Jochen Hartmann, Christian Janiesch, and Patrick Zschech. 2023. “Generative AI.” Business & Information Systems Engineering 66 (1): 111–26. https://doi.org/10.1007/s12599-023-00834-7.

Firican, Diana Andreea. 2023. “Digital Transformation and Digital Culture: A Literature Review of the Digital Cultural Attributes to Enable Digital Transformation.” *Proceedings of the International Conference on Business Excellence* 17 (1): 791–99. https://doi.org/10.2478/picbe-2023-0073.

Fisher, Matthew, Adam H. Smiley, and Tito L. H. Grillo. 2021. “Information Without Knowledge: The Effects of Internet Search on Learning.” Memory 30 (4): 375–87. https://doi.org/10.1080/09658211.2021.1882501.

Fisher, Robert J. „Social Desirability Bias and the Validity of Indirect Questioning“. *Journal of Consumer Research*, Bd. 20, Nr. 2, September 1993, S. 303. *DOI.org (Crossref)*, https://doi.org/10.1086/209351.

Fréry, Frédéric . 2024. ‘When Artificial Intelligence Turns Strategic Resources into Ordinary Resources’. ESCP Impact Paper No.2024-48-EN. https://academ.escpeurope.eu/pub/IP2024-48%20Fréry.pdf.

Ganuthula, Venkat Ram Reddy, and Krishna Kumar Balaraman. 2025. “The Paradox of Professional Input: How Expert Collaboration with AI Systems Shapes Their Future Value.” Version 1. Preprint, arXiv. https://doi.org/10.48550/ARXIV.2504.12654.

Genau, Lea. 2021. “Experte - Definition Und Wie Du Einen Experten Findest.” Scribbr. https://www.scribbr.de/methodik/definition-experte/.

Gerlich, Michael. 2025. “AI Tools in Society: Impacts on Cognitive Offloading and the Future of Critical Thinking.” Societies 15 (1): 6. https://doi.org/10.3390/soc15010006.

Getenet, Seyum, Robert Cantle, Petrea Redmond, and Peter Albion. 2024. “Students’ Digital Technology Attitude, Literacy and Self-efficacy and Their Effect on Online Learning Engagement.” International Journal of Educational Technology in Higher Education 21 (1). https://doi.org/10.1186/s41239-023-00437-y.

Ghanad, Anahita. 2023. “An Overview of Quantitative Research Methods.” INTERNATIONAL *JOURNAL OF MULTIDISCIPLINARY RESEARCH AND ANALYSIS* 06 (08). https://doi.org/10.47191/ijmra/v6-i8-52.

Ghosh, Dyuti, Dibya Ghosh, and Debi Prasad Ghosh. 2025. “Cognitive Off-Loading in the Age of AI: A Hierarchical Risk Model for Human-RAG Systems.” https://doi.org/10.13140/rg.2.2.26569.86888.

Giraud, Laurent, Ali Zaher, Selena Hernandez, and Al Ariss Akram. 2022. “The Impacts of Artificial Intelligence on Managerial Skills.” *Journal of Decision Systems* 32 (3): 566–99. https://doi.org/10.1080/12460125.2022.2069537.

Gläser, Jochen, and Grit Laudel. 2010. *Experteninterviews Und Qualitative Inhaltsanalyse*. Springer-Verlag.

Glikson, Ella, and Anita Williams Woolley. 2020. “Human Trust in Artificial Intelligence: Review of Empirical Research.” *Academy of Management Annals* 14 (2): 627–60. https://doi.org/10.5465/annals.2018.0057.

Goldman Sachs. 2025. “How Will AI Affect the Global Workforce?” https://www.goldmansachs.com/insights/articles/how-will-ai-affect-the-global-workforce.

Goran, Julie, Laura LaBerge, and Ramesh Srinivasan. 2017. “Culture for a Digital Age.” *McKinsey*.

Guba, Egon G., and Yvonna S. Lincoln. 1994. “Competing Paradigms in Qualitative Research.” *Handbook of Qualitative Research* 2 (163–194): 105.

Guo, Kai, Yuchun Zhong, Danling Li, and Samuel Kai Wah Chu. 2023. “Effects of Chatbot-assisted In-class Debates on Students’ Argumentation Skills and Task Motivation.” Computers & Education 203 (June): 104862. https://doi.org/10.1016/j.compedu.2023.104862.

Haefner, Naomi, Vinit Parida, Oliver Gassmann, and Joakim Wincent. 2023. “Implementing and Scaling Artificial Intelligence: A Review, Framework, and Research Agenda.” *Technological Forecasting and Social Change* 197 (December): 122878. https://doi.org/10.1016/j.techfore.2023.122878.

Harbath, Katie. 2025. “The Expertise Paradox.” Substack newsletter. *Anchor Change with Katie Harbath*, June 4. https://anchorchange.substack.com/p/the-expertise-paradox.

Hartl, Eva, and Thomas Hess. 2017. *The Role of Cultural Values for Digital Transformation: Insights from a Delphi Study*.

Hasan, Elina F., Mohammad Abdalkarim Alzuod, Khalid Hasan Al Jasimee, Sajead Mowafaq Alshdaifat, Areej Faeik Hijazin, and Laith T. Khrais. 2025. “The Role of Organizational Culture in Digital Transformation and Modern Accounting Practices Among Jordanian SMEs.” *Journal of Risk and Financial Management* 18 (3): 147. https://doi.org/10.3390/jrfm18030147.

Hlavinka, Elizabeth. 2025. “Is AI Making Us Stupid? The Answer Is Complicated.” Salon.Com, June 10, 2025. https://www.salon.com/2025/06/08/were-offloading-mental-tasks-to-ai-it-could-be-making-us-stupid/.

Hodkinson, Phil, Gert Biesta, and David James. 2008. “Understanding Learning Culturally: Overcoming the Dualism Between Social and Individual Views of Learning.” *Vocations and Learning* 1 (1): 27–47. https://doi.org/10.1007/s12186-007-9001-y.

Hogarth, Robin M. 2010. “Intuition: A Challenge for Psychological Research on Decision Making.” *Psychological Inquiry* 21 (4): 338–53. https://doi.org/10.1080/1047840X.2010.520260.

Hossain, Sahadat, Mario Fernando, and Shahriar Akter. 2025. “The Influence of Artificial Intelligence-Driven Capabilities on Responsible Leadership: A Future Research Agenda.” *Journal of Management & Organization* 31 (5): 2360–84. https://doi.org/10.1017/jmo.2025.10010.

Hsu, Yu-Chang, and Yu-Hui Ching. 2023. “Generative Artificial Intelligence in Education, Part One: The Dynamic Frontier.” TechTrends 67 (4): 603–7. https://doi.org/10.1007/s11528-023-00863-9.

Huang, Ming-Hui, and Roland T Rust. 2025. “The GenAI Future of Consumer Research.”

Journal of Consumer Research 52 (1): 4–17. https://doi.org/10.1093/jcr/ucaf013.

Huang, Ming-Hui, and Roland T. Rust. 2018. “Artificial Intelligence in Service.” *Journal of Service Research* 21 (2): 155–72. https://doi.org/10.1177/1094670517752459.

Huang, Ming-Hui, Roland Rust, and Vojislav Maksimovic. 2019. “The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI).” *California Management Review* 61 (4): 43–65. https://doi.org/10.1177/0008125619863436.

Huet, Romain, and Adonis Reyes. n.d. “How Do We Balance Innovation With Legal and Ethical Accountability.” TMC. https://www.themembercompany.com/story/how-do-we-balance-innovation-with-legal-and-ethical-accountability.

IBM. 2023. ‘The Ingenuity of Generative AI at Scale’. https://www.ibm.com/thought-leadership/institute-business-value/en-us/report/scale-generative-ai.

IBM. 2024. ‘Generative Use Cases, Examples, & Applications’. February 13. https://www.ibm.com/think/topics/generative-ai-use-cases.

Jadhav, Arya. 2025. “Distributed Atrophy 2.0: Cognitive Offloading and the Reshaping of Thought.” https://doi.org/10.31234/osf.io/8yr92_v2.

Jarrahi, Mohammad Hossein. 2018. “Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making.” *Business Horizons* 61 (4): 577–86. https://doi.org/10.1016/j.bushor.2018.03.007.

Jewapatarakul, Darun, and Pittawat Ueasangkomsate. 2024. “Digital Organizational Culture, Organizational Readiness, and Knowledge Acquisition Affecting Digital Transformation in SMEs from Food Manufacturing Sector.” *Sage Open* 14 (4): 21582440241297405. https://doi.org/10.1177/21582440241297405.

Julmi, Christian. 2019. “When Rational Decision-Making Becomes Irrational: A Critical Assessment and Re-Conceptualization of Intuition Effectiveness.” *Business Research* 12 (1): 291–314. https://doi.org/10.1007/s40685-019-0096-4.

Kahneman, Daniel. 2003. “A Perspective on Judgment and Choice: Mapping Bounded Rationality.” *American Psychologist* 58 (9): 697–720. https://doi.org/10.1037/0003-066X.58.9.697.

Kahneman, Daniel. 2011. *Thinking, Fast and Slow*. Farrar, Straus and Giroux.

Kashima, Yoshihisa. 2014. “How Can You Capture Cultural Dynamics?” *Frontiers in Psychology* 5 (September). https://doi.org/10.3389/fpsyg.2014.00995.

Kleinberg, Jon, and Manish Raghavan. 2021. 'Algorithmic Monoculture and Social Welfare'. Proceedings of the National Academy of Sciences 118 (22): e2018340118. https://doi.org/10.1073/pnas.2018340118.

Koedinger, Kenneth R., and Vincent Aleven. 2007. "Exploring the Assistance Dilemma in Experiments With Cognitive Tutors." Educational Psychology Review 19 (3): 239–64. https://doi.org/10.1007/s10648-007-9049-0.

Kolbjørnsrud, Vegard, Richard Amico, and Robert J Thomas. 2016. "How Artificial Intelligence Will Redefine Management." *Harvard Business Review* 2 (1): 3–10.

Kosmyna, Nataliya, Eugene Hauptmann, Ye Tong Yuan, Jessica Situ, Xian-Hao Liao, Ashly Vivian Beresnitzky, Iris Braunstein, and Pattie Maes. 2025. "Your Brain on ChatGPT: Accumulation of Cognitive Debt When Using an AI Assistant for Essay Writing Task." arXiv.Org. June 10, 2025. https://arxiv.org/abs/2506.08872.

Kotter, John P. 1996. *Leading Change*. Harvard Business School Press.

Krumay, Barbara, David Rückel, Philipp Wicke, and Stefan Koch. 2018. "Verbreitung und Akzeptanz von Bauchentscheidungen im Management." *HMD Praxis der Wirtschaftsinformatik* 55 (4): 701–13. https://doi.org/10.1365/s40702-018-0435-5.

Kuzmanko, Jonathan, and Lucie Vrbová. 2024. "AI vs Humans in Strategic Decision-Making: A Systematic Review." Preprint, SSRN. https://doi.org/10.2139/ssrn.5144866.

Lee, Hao-Ping, Advait Sarkar, Lev Tankelevitch, Ian Drosos, Sean Rintel, Richard Banks, and Nicholas Wilson. 2025. "The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers." CHI '25: Proceedings of the 2025 CHI Conference on Human Factors in Computing System, April, 1–22. https://doi.org/10.1145/3706598.3713778.

Levy, Frank, and Richard J. Murnane. 2004. *The New Division of Labor*. Princeton University Press. JSTOR. http://www.jstor.org/stable/j.ctt1r2frw.

Mao, Hongyi, Shan Liu, Jinlong Zhang, and Zhaohua Deng. 2016. "Information Technology Resource, Knowledge Management Capability, and Competitive Advantage: The Moderating Role of Resource Commitment." International Journal of Information Management 36 (6): 1062–74. https://doi.org/10.1016/j.ijinfomgt.2016.07.001.

Mariani, Marcello, and Yogesh K. Dwivedi. 2024. 'Generative Artificial Intelligence in Innovation Management: A Preview of Future Research Developments'. Journal of Business Research 175 (March): 114542. https://doi.org/10.1016/j.jbusres.2024.114542.

Mawson, Andrew. 2025. "The AI Paradox: AI Makes Organizations More Dependent On Key Experts." Forbes, June 25. https://www.forbes.com/sites/amawson/2025/06/25/the-ai-paradox-ai-makes-organizations-more-dependent-on-key-experts/.

Mayring, Philipp, and Thomas Fenzl. 2019. "Qualitative Inhaltsanalyse." In *Handbuch Methoden Der Empirischen Sozialforschung*. Springer.

McKinsey. 2025. "The State of AI in 2025: Agents, Innovation, and Transformation.". https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai.

Mercier, Hugo. 2016. “Confirmation Bias – Myside Bias.” In *Cognitive Illusions*, 0 ed., edited by Rüdiger Pohl. Psychology Press. https://doi.org/10.4324/9781315696935-11.

Messeri, Lisa, and M J Crockett. 2024. “Artificial Intelligence and Illusions of Understanding in Scientific Research.” Nature 627 (8002): 49–58. https://doi.org/10.1038/s41586-024-07146-0.

Merten, Milena, Franziska Telser, Claudia Obmann, and Christof Kerkmann. 2025. “Und plötzlich werden auch Führungskräfte ersetzbar.” Handelsblatt, October 27. https://www.handelsblatt.com/unternehmen/management/ki-und-ploetzlich-werden-auch-fuehrungskraefte-ersetzbar/100137766.html.

Mishra, Punya. 2025. *The GenAI and Expertise Paradox: Why It Makes Expert Work More Important But Harder*. https://punyamishra.com/2025/02/13/the-genai-and-expertise-paradox-why-it-makes-expert-work-more-important-but-harder/.

Morey, Dane A. 2025. “How AI Can Degrade Human Performance in High-Stakes Settings.” AI Frontiers. November 10, 2025. https://ai-frontiers.org/articles/how-ai-can-degrade-human-performance-in-high-stakes-settings.

Mundhe, Eknath. 2023. *The Future of Management in the Age of AI*. 18 (1): 3–8.

Murire, Obrain Tinashe. 2024. “Artificial Intelligence and Its Role in Shaping Organizational Work Practices and Culture.” *Administrative Sciences* 14 (12): 316. https://doi.org/10.3390/admsci14120316.

Nesheim, Torstein, and Håavard Mørch Hunskaar. 2015. “When Employees and External Consultants Work Together on Projects: Challenges of Knowledge Sharing.” *International Journal of Project Management* 33 (7): 1417–24.

Nivetha, P., and S. Prasanth. 2024. “Transforming Management Decision - Making: Role of ChatGPT.” *Shanlax International Journal of Management* 11 (4): 29–33. https://doi.org/10.34293/management.v11i4.7486.

Norman, Don. 2017. “Design, Business Models, and Human-Technology Teamwork.” *Research-Technology Management* 60 (1): 26–30. https://doi.org/10.1080/08956308.2017.1255051.

Paoli, Nino. 2025. “Deloitte Was Caught Using AI in $290,000 Report to Help the Australian Government Crack down on Welfare after a Researcher Flagged Hallucinations.” *Fortune*. https://fortune.com/2025/10/07/deloitte-ai-australia-government-report-hallucinations-technology-290000-refund/.

Paschen, Jeannette, Matthew Wilson, and João J. Ferreira. 2020. “Collaborative Intelligence: How Human and Artificial Intelligence Create Value along the B2B Sales Funnel.” *Business Horizons* 63 (3): 403–14. https://doi.org/10.1016/j.bushor.2020.01.003.

Phillips, Wendy J., Jennifer M. Fletcher, Anthony D. G. Marks, and Donald W. Hine. 2016. “Thinking Styles and Decision Making: A Meta-Analysis.” *Psychological Bulletin* 142 (3): 260–90. https://doi.org/10.1037/bul0000027.

Pistrui, Joseph. 2018. *The Future of Human Work Is Imagination, Creativity, and Strategy*. January 18.

Podsakoff, Philip M., u. a. „Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies.“ *Journal of Applied Psychology*, Bd. 88, Nr. 5, 2003, S. 879–903. *DOI.org (Crossref)*, https://doi.org/10.1037/0021-9010.88.5.879.

Polanyi, Michael. 1966. *The Tacit Dimension.* Doubleday.

PricewaterhouseCoopers. 2025. “AI Jobs Barometer.” PwC, June 3. https://www.pwc.com/gx/en/issues/artificial-intelligence/ai-jobs-barometer.html.

Ray, Partha Pratim. 2023. “ChatGPT: A Comprehensive Review on Background, Applications, Key Challenges, Bias, Ethics, Limitations and Future Scope.” *Internet of Things and Cyber-Physical Systems* 3 (January): 121–54. https://doi.org/10.1016/j.iotcps.2023.04.003.

Risko, Evan F., and Sam J. Gilbert. 2016. “Cognitive Offloading.” Trends in Cognitive Sciences 20 (9): 676–88. https://doi.org/10.1016/j.tics.2016.07.002.

Scherm, Ewald, Christian Julmi, and Florian Lindner. 2016. “Intuitive versus analytische Entscheidungen – Überlegungen zur situativen Stimmigkeit.” In *Nachhaltiges Entscheiden*, edited by Heinz Ahn, Marcel Clermont, and Rainer Souren. Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-12506-6_16.

Schieb, Jörg. 2025. “KI Erfindet Jede Dritte Antwort.” *Tagesschau*. https://www.tagesschau.de/wissen/technologie/kuenstliche-intelligenz-fakten-100.html.

Schumpeter, Joseph A. 1934. The Theory of Economic Development; an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle,. Translated by Redvers Opie. Harvard Economic Studies., vol. XLVI. Cambridge.

Scriven, Michael, and Richard Paul. 1992. “Critical Thinking Defined.” Atlanta, Georgia, United States of America, November.

Shea, Christopher M, Sara R Jacobs, Denise A Esserman, Kerry Bruce, and Bryan J Weiner. 2014. “Organizational Readiness for Implementing Change: A Psychometric Assessment of a New Measure.” *Implementation Science* 9 (1): 7. https://doi.org/10.1186/1748-5908-9-7.

Sherba, Hassan A Mohammed, Ali Abed Hannoof, and Hussein A Mohammed Sherba. 2025. *The Mediating Role of Organizational Culture between Artificial Intelligence and Digital Transformation*.

Shors, T.J., M.L. Anderson, D.M. Curlik, and Nokia. 2011. “Use It or Lose It: How Neurogenesis Keeps the Brain Fit for Learning.” Behavioural Brain Research 227 (2): 450–58. https://doi.org/10.1016/j.bbr.2011.04.023.

Shrestha, Yash Raj, Shiko M. Ben-Menahem, and Georg Von Krogh. 2019. “Organizational Decision-Making Structures in the Age of Artificial Intelligence.” *California Management Review* 61 (4): 66–83. https://doi.org/10.1177/0008125619862257.

Shumailov, Ilia, Zakhar Shumaylov, Yiren Zhao, Nicolas Papernot, Ross Anderson, and Yarin Gal. 2024. ‘AI Models Collapse When Trained on Recursively Generated Data’. Nature 631 (8022): 755–59. https://doi.org/10.1038/s41586-024-07566-y.

Sousa, Maria José, and Álvaro Rocha. 2019. “Skills for Disruptive Digital Business.” *Journal of Business Research* 94: 257–63. https://doi.org/10.1016/j.jbusres.2017.12.051.

Sparrow, Betsy, Jenny Liu, and Daniel M. Wegner. 2011. “Google Effects on Memory: Cognitive Consequences of Having Information at Our Fingertips.” Science 333 (6043): 776–78. https://doi.org/10.1126/science.1207745.

Stanovich, Keith E., and Richard F. West. 2000. “Individual Differences in Reasoning: Implications for the Rationality Debate?” *Behavioral and Brain Sciences* 23 (5): 645–65. https://doi.org/10.1017/S0140525X00003435.

Tang, Yuying, Ningning Zhang, Mariana Ciancia, and Zhigang Wang. 2024. ‘Exploring the Impact of AI-Generated Image Tools on Professional and Non-Professional Users in the Art and Design Fields’. Companion Publication of the 2024 Conference on Computer-Supported Cooperative Work and Social Computing, 11 November 2024, 451–58. https://doi.org/10.1145/3678884.3681890.

Thilagavathy, Nirmala, and Ramasamy Venkatasamy. 2023. “Artificial Intelligence (AI) Technologies Adaptation in Business Management.” *Artificial Intelligence (AI)* 18: 2485–95.

Tidd, Joe, and John R. Bessant. 2021. Managing Innovation: Integrating Technological, Market and Organizational Change. Seventh edition. Hoboken, NJ: Wiley.

Vincent, Vinod U. 2021. “Integrating Intuition and Artificial Intelligence in Organizational Decision-Making.” *Business Horizons* 64 (4): 425–38. https://doi.org/10.1016/j.bushor.2021.02.008.

Wang, Yi, Scott Highhouse, Christopher J. Lake, Nicole L. Petersen, and Thaddeus B. Rada. 2017. “Meta-analytic Investigations of the Relation Between Intuition and Analysis.” *Journal of Behavioral Decision Making* 30 (1): 15–25. https://doi.org/10.1002/bdm.1903.

Warner, John. 2023. “ChatGPT Both Is and Is Not Like a Calculator.” Inside Higher Ed | Higher Education News, Events and Jobs. January 16, 2023. https://www.insidehighered.com/opinion/columns/just-visiting/2023/01/16/chatgpt-both-and-not-calculator.

Weiner, Bryan J. 2009. “A Theory of Organizational Readiness for Change.” *Implementation Science* 4 (1): 67. https://doi.org/10.1186/1748-5908-4-67.

Wenger, Emily, and Yoed Kenett. 2025. ‘We’re Different, We’re the Same: Creative Homogeneity Across LLMs’. Preprint, arXiv. https://doi.org/10.48550/ARXIV.2501.19361.

Wiederhold, Brenda K. 2025. “The Cost of Convenience: Does AI Undermine Critical Thinking?” Cyberpsychology Behavior and Social Networking 28 (8): 549–50. https://doi.org/10.1089/cyber.2025.0189.

World Economic Forum. 2025. “The Future of Jobs Report 2025.” World Economic Forum. https://www.weforum.org/publications/the-future-of-jobs-report-2025/.

Xie, Yu, and Yueqi Xie. 2025. ‘Variance Reduction in Output from Generative AI’. arXiv:2503.01033. Preprint, arXiv, March 4. https://doi.org/10.48550/arXiv.2503.01033.

Xu, Yuxin, Mengqiu Cheng, and Anastasia Kuzminykh. 2024. “What Makes It Mine? Exploring Psychological Ownership Over Human-AI Co-Creations.” Graphics Interface, June, 1–8. https://doi.org/10.1145/3670947.3670974.

Yang, Huili. 2025. “Harnessing Generative AI: Exploring Its Impact on Cognitive Engagement, Emotional Engagement, Learning Retention, Reward Sensitivity, and Motivation Through Reinforcement Theory.” Learning and Motivation 90 (May): 102136. https://doi.org/10.1016/j.lmot.2025.102136.

Ying, Ying, and Shanyue Jin. 2024. “Artificial Intelligence and Green Product Innovation: Moderating Effect of Organizational Capital.” *Heliyon* 10 (7).

Zabala, Francisco Javier Campos. 2023. *Grow Your Business with AI: A First Principles Approach for Scaling Artificial Intelligence in the Enterprise*. Springer.

Zetterberg, Arvid, and Simon Palestro. 2024. *The Way Forward, Humans and AI Together?: Investigating the Use of AI as an Enabler in Digital Transformation Initiatives*.

Zhu, Yu-Qian, Jacq Ueline Corbett, and Yi-Te Chiu. 2021. “Understanding Employees’ Responses to Artificial Intelligence.” *Organizational Dynamics* 50 (2): 100786. https://doi.org/10.1016/j.orgdyn.2020.100786.

Züll, Cornelia, and Natalja Menold. 2014. “Offene Fragen.” In *Handbuch Methoden Der Empirischen Sozialforschung*. Springer.

11. Appendix

Appendix 1: Interview Guide

A. Introduction of the Interviewer

- Brief introduction of the interviewer and outline of the study's purpose
- Confirmation of consent to mention names and company affiliations (declaration of consent)
- Commencement of the audio recording

B. Background of the Interviewee

- Introduction of the interviewee, including their current position and key responsibilities related to strategic DM and AI/advanced analytics

C. Thematic Questions

1) In the past 12 months, in which kinds of situations did you rely primarily on your own intuition rather than analysis or AI, and how common is that in your work?
2) Which strategic decisions do you prefer to make based on your own judgment rather than AI-supported analysis, and why? (For example: market entry, M&A, pricing, senior hiring, crisis response.)
3) Since adopting AI, how has the role, timing, or weight of your intuition changed within your decision process?
4) Which parts of your decision process must include a human because AI cannot substitute, and which distinctly human capabilities make the difference?
5) When a significant decision starts, how is the Human-AI collaboration architecture set in practice (full automation, human-in-the-loop, or combined outputs)?
6) In your own practice, where has AI clearly improved a real decision process? Please name one or two concrete decisions and explain what improved (e.g., speed, quality, consistency, risk) and how you know (e.g., KPIs, error rate, rework, stakeholder feedback).
7) Please indicate which of your day-to-day tasks are now being performed by AI. Has this been a net positive or a net negative?
8) Which new core leadership skills have become critical because of AI, and how are you building them across your team?
9) How irreplaceable are your own expertise, professional background, organizational knowledge, or accumulated intuition when it comes to making strategic decisions?
10) In your organization, to what extent is expertise still viewed as a critical asset in DM, especially as AI tools become more common?

Appendix 2: Coding Guide

Code	Category/ Sub-category	Coding Rules	Anchor Examples
C1	DM Process	All statements that relate to how decisions are made in human-AI contexts, including the roles of intuition, human responsibility, AI support, and human-AI interaction.	
S1	Role of Intuition in DM	Code statements that describe the use, value, or limitations of intuition or gut feeling in decision processes. It includes reflections on when and why intuitive judgments are applied.	"My intuition helps me especially in situations that are strongly interpersonal." (E4)
S2	Human Oversight and Responsibility	Code statements that emphasize which aspects of DM must remain under human control, such as accountability, ethical judgment, contextual understanding, and final validation of AI outputs.	"But the final decision should always be made by humans, they should ultimately use their intuition to make a judgment." (E1)
S3	AI-Supported DM	Code statements that discuss how AI informs or enhances decision processes. They include mentions of speed, efficiency, accuracy, data integration, and the use of AI as an analytical or decision support tool.	"[...] AI is extremely helpful because it speeds up the process enormously. It saves a tremendous amount of time and is therefore a clear advantage." (E2)
S4	Human–AI Collaboration	Code statements that emphasize collaborative or complementary interactions between humans and AI. They include the balance between automation and human input, and reflections on AI as a supportive or co-creative "partner" rather than a replacement.	"The AI simply accesses data sets and reproduces what it finds, but it cannot interpret the information the way a human can." (E4)
C2	Skills	All statements that relate to changing skill requirements in AI-supported work environments.	
S5	Emerging Skills	Code statements that highlight newly important or increasingly valuable skills in AI-supported work environments. They include	"But I believe critical thinking is just as important, the

		reflections on how professionals need to learn to collaborate with AI tools.	ability to question things, even when they seem convincing at first glance.” (E1)
S6	Declining Skills	Code statements that describe skills, tasks, or competencies that are becoming irrelevant due to automation, data processing, or AI assistance.	“In the past, technical skills or mastering certain standard processes were often crucial, but today those skills have lost some of their value.” (E5)
C3	Expertise	All statements that relate to the role or relevance of human expertise in AI-supported work.	
S7	Enduring Value of Expertise	Code statements that emphasize the continued or growing importance of human experience, contextual understanding, and tacit knowledge in complex or strategic contexts.	“In highly specialized roles that require contextual understanding, the human element remains essential.” (E1)
S8	Substitution through AI	Code statements that discuss areas in which AI can replicate or replace human expertise, particularly for standardized, data-driven, or repetitive tasks.	“However, where things become more standardized, such as in the handling of typical sales contracts, replacement becomes easier.” (E1)