STOCKHOLM SCHOOL OF ECONOMICS
1351 Master's thesis in Business Management
Academic year 2023–2025

May (A)I Replace You?

A Qualitative Case Study on Management Consultants' Perceptions of GenAI's Impact on Consulting Work — and Factors Shaping These Perceptions

Clara Gille (42564) and Lina Johansson (42561)

Abstract: The rapid emergence of Generative Artificial Intelligence (GenAI) has become an important topic in strategy talk and has attracted significant attention in business literature. While existing studies have primarily emphasized the technical capabilities and potential of GenAI, relatively little research has examined how professionals perceive and make sense of this technological shift. This gap is especially critical in knowledge-intensive contexts like management consulting, where work relies heavily on human expertise, an area now increasingly challenged by GenAI's capabilities. To address this, we sought to investigate how management consultants perceive the impact of GenAI on their work, and the factors shaping these perceptions, through an exploratory, qualitative case study at a global consulting firm. We interviewed 23 consultants across varying hierarchical positions and functions, using sensemaking theory (Weick, 1979) and the technological frames of reference framework (Orlikowski and Gash, 1994), as our guiding theoretical lenses in the analysis. Our findings reveal that GenAI is widely perceived as a productivity-enhancing tool that complements rather than replaces human expertise. However, perceptions diverge around GenAI's implications on professional learning and development, trust in their outputs, and strategic importance. These perceptions are found to be shaped by several factors including individual influences, organizational context, and anticipations of the future. Importantly, consultants emphasized the need for concrete, task-relevant examples to meaningfully integrate GenAI. These findings contribute to literature by offering a nuanced perspective of how GenAI adoption unfolds in practice, and by providing important insights for firms aiming to support sustainable and succesful GenAI integration.

Keywords: generative artificial intelligence (GenAI), knowledge work, management consulting, perceptions, sensemaking, technological frames of reference (TFR)

Supervisor: Katja Einola
Date examined: 26-05-2025
Discussant: Sahil Sharma
Examiners: Constanze Eib and Roberto Verganti

Acknowledgement

Katja Einola from Stockholm School of Economics, we would like to sincerely thank you, our supervisor, for your continued guidance, sharp reflections, and support throughout this process. Your ability to challenge our thinking while always encouraging us has meant a great deal.

We are also deeply grateful to our case company, Consultica, for welcoming us into your organization and allowing us to explore our topic from the inside. To all the consultants who generously shared your time and reflections this study would not have been possible without you. A special thank you goes to our internal mentor for your continued support, time, and enthusiasm along the way.

Lina & Clara

Table of Contents

List of Figures

1. Introduction

1.1 Background

> *"Artificial intelligence has arrived in the workplace and has the potential to be as transformative as the steam engine was to the 19th-century Industrial Revolution."* (Mayer *et al.*, 2025, p. 2)

For more than two centuries, technological advancements have fueled economic development and reshaped industries (Brynjolfsson and McAfee, 2017), yet few innovations have generated as much rapid debate as the launch of ChatGPT in late 2022, marking an important moment in the discourse on Artificial Intelligence (AI) and the future of work (Mayer *et al.*, 2025). The emergence of AI is rapidly transforming the business landscape, introducing both unprecedented opportunities and complex challenges. Unlike earlier tools, AI can adjust, learn, and make decisions, bringing humans and machines together in ways that can boost growth, and reshape how we interact with technology, and each other (Mayer *et al.*, 2025). Reflecting this, the share of companies implementing AI in at least one core business function doubled to 65% in just ten months (Singla *et* al., 2024), signaling the speed and scale of this transformation.

Amongst these technologies, Generative AI (GenAI) has emerged as a particularly disruptive force, described as the next generation of AI (Marr, 2023). As Mayer et al. (2025) describe, *"Imagine a world where machines not only perform physical labor but also think, learn, and make autonomous decisions."* (p.6) - that world is quickly becoming reality. Unlike earlier forms of AI, GenAI has the ability to create; generating original text, images, and other forms of content based on training data (Marr, 2023). In essence, GenAI enables automation in areas previously dependent on human creativity and cognitive judgment (Feuerriegel *et al.*, 2024). This makes GenAI especially transformative in knowledge-intensive sectors, where its capacity to perform cognitive tasks is reshaping traditional work structures and roles (Dăniloaia and Turturean, 2024).

A key concern in this transformation is how GenAI will affect specific tasks and ultimately the future of work in knowledge-based professions. While some researchers emphasize AI's potential to enhance productivity and support humans (Pettersen, 2019; Von Richthofen *et* al., 2022), others raise concern of job displacement as AI takes over tasks previously performed predominately by humans (Frey and Osborne, 2017). A Goldman Sachs (2023) report estimates that up to 300 million jobs in knowledge-intensive sectors could be affected by GenAI, underscoring the scale and urgency of this technological shift.

One sector that sits at the center of this transformation is management consulting. Traditionally rooted in human expertise and strategic judgment, consulting is not only adapting to GenAI, it is also guiding others through that very transformation. This dual role makes consultants both the architects and the subjects of the GenAI revolution. As consulting firms increasingly integrate GenAI into their operations, the nature of work is evolving. GenAI tools are now used to automate data-heavy tasks, support decision-making, and even generate client-facing deliverables (Dell'Acqua *et al.*, 2023; Nesemeier, 2024), fundamentally reshaping how consultants spend their time and add value. This shift raises important questions about the future role of the consultant, and how professionals within the industry perceive and respond to the integration of GenAI (Engström *et* al., 2024).

Despite this growing adoption of GenAI, and the enthusiasm around its technical benefits, there remains limited empirical research on how consultants themselves perceive this technological shift (Engström et al., 2024). Yet, understanding these perceptions is critical, as it shapes how the technology is adopted and how employees adapt to new work environments. If GenAI is viewed as a threat, it may lead to resistance and slow adoption (Gînguță *et al.*, 2023; Bai *et al.*, 2024), whereas if it is seen as a tool for enhancement, it can drive innovation and efficiency (Alavi *et al.*, 2024). Thus, understanding how consultants perceive GenAI is crucial for companies in supporting a successful and sustainable AI integration. This underscores the urgent need for further research into the cognitive process behind GenAI adoption, insights that can inform both organizational strategy and broader discussions on the future of knowledge work.

1.2 Purpose and Expected Contribution

This study is guided by a twofold purpose. Firstly, it aims to explore how management consultants perceive GenAI in the context of their daily work. Secondly, the study seeks to identify the factors that shape these perceptions. In doing so, this study offers a unique contribution by shifting focus from technological capabilities to the human experience of technological change, addressing a gap in current research (Coombs *et* al., 2020). By centering on human perceptions, we aim to provide a more nuanced understanding of GenAI adoption, recognizing that perceptions play a critical role in developing an effective GenAI strategy (Nesemeier, 2024). To fulfill this purpose, we combine sensemaking theory (Weick, 1979) with the technological frames of reference framework (TFR) (Orlikowski and Gash, 1994), allowing us to contribute to theory by showing how sensemaking processes give rise to different TFR, which in turn shape different perceptions of GenAI. This theoretical perspective allows us to move beyond traditional adoption models, examining not just whether GenAI is accepted, but how different perceptions are formed. Practically, the study aims to provide insights for consulting firms navigating the integration of GenAI. Understanding different perceptions and how they are formed can help organizations design more effective and successful GenAI adoption strategies.

1.3 Research Questions

To fulfill this purpose, the study aims to answer the following research questions:

RQ 1: How do management consultant's perceive GenAI's impact on their work?

RQ 2: How are management consultant's perceptions of GenAI shaped?

1.4 Delimitations

To fulfill the purpose of this study, several delimitations have been applied. Firstly, this study adopts a single-case study design, focusing on one multinational management consulting firm, referred to pseudonymously as 'Consultica'. This enables in-depth exploration but may limit the generalizability of the findings to other contexts. Management consulting was selected due to its heavy reliance on cognitive work, making it a highly relevant setting for studying how GenAI is perceived and integrated in knowledge-intensive environments. Secondly, the study focuses exclusively on GenAI tools, excluding other forms of AI and digital technologies, as GenAI presents unique opportunities and challenges through its ability to generate original content. Lastly, the study is delimited to the perceptions of consultants, rather than examining organizational strategies or measurable adoption outcomes.

2. Literature Review and Theory

2.1 AI in Professional Work

The rapid advancement of digital technologies and its transformative impact on professions have been widely debated in recent literature. More than 20 years back, Autor et al., (2003) explored how advances in computer technology influenced professional occupations, highlighting a significant shift in the labor market and on how work is performed. They introduced the concepts of augmentation and automation, explaining how computers might replace workers performing routine tasks that are easily codified by rules, but complement workers in nonroutine tasks that require flexibility, creativity, problem-solving, and complex communication. This dual role of technology, both as a tool for supporting and replacing tasks, has spurred ongoing discussions in more recent literature about how the rise of AI will continue to transform professional occupations (Brynjolfsson and McAfee, 2017; Frey and Osborne, 2017; Susskind and Susskind, 2017; Anthony et al., 2023).

While earlier research on computerization, such as that by Autor et al. (2003), suggested that automation would primarily impact routine tasks, more recent studies on AI and Big Data have shown that even non-cognitive tasks are at risk of automation (Brynjolfsson and McAfee, 2017; Frey and Osborne, 2017). Frey and Osborne's study (2017), which assessed the risk of automation across 702 occupations in the United States, has gained significant attention. Their findings suggested that nearly 47% of U.S. jobs are at high risk of automation, identifying not only routine jobs as *"jobs we expect could be automated relatively soon."* (Frey and Osborne, 2017, p. 268). This challenges the historical assumption that only routine tasks are vulnerable to automation.

Critics of Frey and Osborne's study (2017) argue that their conclusions treat occupations as fixed categories, overlooking the potential for AI to create new areas of work or transform existing occupations rather than simply eliminating them (Lester, 2020). Lester (2020) contends that distinguishing between AI as complementary or substitutive can often be difficult, as both roles may coexist within the same occupation, making the impact of AI more complex. Similarly, a more recent study by Raisch and Krakowski (2021) delves into the emerging use of AI in organizations, focusing on the roles of automation and augmentation in managerial tasks. The authors argue that automation and augmentation are not simply separate or opposing forces, as often portrayed, but are in fact interdependent and mutually reinforcing over time. They advocate for a more integrated approach that acknowledges that humans and machines both influence each other's behavior in an iterative process.

The current consensus in the literature on AI's impact on work suggests that it is expected to cause significant disruption to jobs (Brynjolfsson and McAfee, 2017; Frey and Osborne, 2017; Susskind and Susskind, 2017), although its overall effect will likely result in a combination of job losses and gains. Lester (2020) argues that it seems inevitable that "*this disruption will extend to professional occupations much more than has previously been the case, affecting the day-to-day work and skills of practitioners, but also extending to the way that professions are conceptualized and organized*" (p. 5). This signals not only a transformation in the tasks professionals perform, but also a fundamental change in how professions are structured and understood.

2.2 AI in Knowledge Work

As AI continues to transform industries, its impact is particularly pronounced in knowledge work, a domain historically defined by human knowledge and analytical reasoning. Knowledge-intensive organizations, which historically have depended heavily on the cognitive capabilities of their employees to generate value (Blackler, 1995; Alvesson, 2004), has become a focal point of contemporary research. As GenAI is becoming increasingly capable of augmenting, or even automating human tasks, its integration into knowledge work has sparked widespread discussions regarding the conditions for its adoption and broader implications for knowledge workers (Pettersen, 2019; Coombs *et al.*, 2020; Von Richthofen *et* al., 2022; Dăniloaia and Turturean, 2024; Ritala *et* al., 2024; Woodruff *et al.*, 2024).

While there is broad consensus that GenAI will significantly impact the industry, scholars remain divided on the extent of this transformation. While some argue that AI is far from replacing humans in creative tasks and rather enhances productivity by allowing them to focus on high-value activities (Pettersen, 2019), others caution that AI's increasing ability to perform complex, cognitive tasks may erode traditional knowledge work structures, potentially displacing professionals in key areas (Frey and Osborne, 2017). Dăniloaia and Turturean (2024) capture this duality, suggesting that while GenAI frees up time for high-level decision-making, it also challenges established divisions of labor by taking over tasks once considered uniquely human, raising concerns about deskilling. Ritala et al. (2024) partially support this view, noting that while tools like ChatGPT can handle repetitive tasks such as summarization and drafting, they still fall short in areas requiring deep contextual judgment and creativity. This reinforces the idea that GenAI functions best as a complement to, rather than a replacement of human expertise (Alavi *et* al., 2024).

Alongside debates on GenAI's impact on work, scholars have raised important concerns regarding the use of AI. A key issue is the problem of "black-boxing," where users rely on AI outputs without fully understanding the underlying algorithms or their limitations (Anthony, 2021). According to Anthony (2021), such opacity can lead to flawed decisions, particularly when human oversight is limited or absent. Despite these challenges, scholars continue to emphasize the potential for GenAI to support more meaningful work. Von Richthofen et al. (2022), for example, argue that automating repetitive tasks can empower knowledge workers to engage more deeply in complex problem-solving and innovation. However, as Shrestha et al. (2019) point out, this potential comes with the need to manage the accompanying risks of redundancy and skill erosion, once again highlighting a dual trajectory, enhancing efficiency while simultaneously raising fears of obsolescence.

2.3 AI in Management consulting

The evolving discourse on the impact of AI on knowledge work is particularly relevant to management consulting. The increasing adoption of AI-powered tools, capable of automating tasks traditionally performed by consultants, have raised important questions in literature about how AI is reshaping the industry (Tavoletti et al., 2022; Dell'Acqua *et al.*, 2023). A significant body of research highlights AI's role in enhancing efficiency, particularly through automation of core consulting tasks (Dell'Acqua *et* al., 2023; Oarue-Itseuwa, 2024, Samokhvalov, 2024). AI is no longer viewed as a supplementary tool; rather, it is becoming embedded in consulting workflows, automating phases such as problem diagnosis and strategy formulation (Mohan, 2024). Oarue-Itseuwa (2024) argues that AI is shifting consultants' roles from data handlers to strategic interpreters, fundamentally altering the knowledge-intensive nature of consulting work. Safiulina and Rabii (2025) contribute to this discussion by showing that AI's role in consulting extends beyond efficiency to reshaping careers and firm structures, further underscoring the importance of understanding how consultants experience and adapt to its growing influence. However, Dell'Acqua et al., (2023) emphasize that while AI can improve task completion, this is contingent upon appropriate use and sufficient human oversight.

Another stream of research focuses on the conditions shaping AI adoption in consulting, pointing to organizational alignment, workforce readiness, and leadership as key factors (Yang et al., 2024). Research on AI's integration into consulting firms suggests that perceptions of AI, both at an individual and organizational level, play a critical role in determining its adoption and long-term impact. Nesemeier (2024) finds that while many consultants recognize GenAI's strategic potential, concerns persist regarding its impact on work quality, career development, and job responsibilities. Crucially, Nesemeier (2024) highlights the need for further research into the evolving role of GenAI in management consulting, particularly concerning job roles, skill development, and long-term technology adoption. While the study provides an initial understanding of the factors influencing consultants' acceptance of GenAI, it acknowledges that as the technology matures, the determinants of adoption may shift. A key contribution of Nesemeiers research is the recognition that GenAI adoption is a dynamic interplay between corporate strategies and consultants' own agency. Rather than passively adopting AI, consultants actively interpret its role before integrating it into workflows (Malatji *et* al., 2020; Nesemeier, 2024).

2.4 Research Gap

While existing literature extensively explores AI's integration into professional work, emphasizing its potential to automate and augment tasks (e.g. Autor *et* al., 2003; Frey and Osborne, 2017), less attention has been paid to how professionals perceive this impact and how such perceptions impact the integration process (Nesemeier, 2024). As Coombs et al., (2020) highlight, most technically oriented studies on intelligent technologies largely overlook the human dimension, creating a significant gap in literature concerning how these technologies affect workers. This critique resonates with much of the current research, which emphasizes technical capabilities and organizational outcomes (Dell'Acqua *et* al., 2023; Oarue-Itseuwa, 2024), while often neglecting the individual and the processes through which individuals construct meaning around GenAI.

In the context of management consulting, discussions about GenAI have largely focused on efficiency gains and process automation. Yet, how consultants perceive GenAI's impact on their work, and how these perceptions are shaped, remains underexplored (Nesemeier, 2024). Understanding this is critical, as these interpretations influence whether, how, and to what extent consultants integrate GenAI into their daily work (Engström *et* al., 2024). Thus, this study not only overcomes the limitations of previous studies (Coombs *et* al., 2020), but also offers valuable understanding into how to support more effective and meaningful use of AI in knowledge-intensive professions.

2.5 Theory

Traditional technology adoption models, such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et* al., 2003), have primarily focused on perceived usefulness and ease of use as key determinants of technology acceptance. However, these models often overlook the cognitive process that shapes these key determinants. Building on this, recent research highlights the need to move beyond these models, emphasizing that adoption is shaped by individual interpretations. As Engström et al. (2024) argue, *"understanding how employees make sense of new technologies could help predict adoption challenges and guide more effective implementation strategies"* (p. 2457). This perspective underscores that technology adoption is not just a rational evaluation of utility and ease of use, but is also shaped by individuals' perceptions.

Given this, our study takes a step back and adopts sensemaking theory and TFR as the theoretical lens and framework for this study. By doing so, we provide a more nuanced understanding of how consultants perceive GenAI's impact on work and what shapes these perceptions.

2.5.1 Sensemaking in the Digital Era

Originally conceptualized by Weick (1979), sensemaking refers to the cognitive process through which individuals attempt to interpret and navigate ambiguous or novel situations. Maitlis and Christianson (2014), define it as *"... a process, prompted by violated expectations, that involves attending to and bracketing cues in the environment, creating intersubjective meaning through cycles of interpretation and action, and thereby enacting a more ordered environment from which further cues can be drawn."* (p. 67) Highlighting that sensemaking is an ongoing process, where individuals interpret disruptions in their environment and thus construct new meanings to restore a sense of order and coherence. Crucially, for this process to occur, researchers have argued that individuals need to notice information that disrupts their understanding of normal (Weick *et* al., 2005). In other words, sensemaking is triggered when people extract cues that conflict with their prior knowledge, prompting a reinterpretation to reconcile these disruptions. Once this process is triggered, sensemaking unfolds through three core stages; enactment (noticing cues and acting on them), selection (interpreting cues through the lens of past experiences), and retention (embedding new interpretations into one's identity) (Weick, *et* al., 2005). More recent scholars have further expanded this view by integrating Weick's (1979), seven core properties of sensemaking; grounded in identity construction, retrospective, enactive of sensible environments, social, ongoing, cue-based, and driven by plausibility rather than accuracy. In an integrative framework, Kudesia (2017) links each of these properties to specific stages within the sensemaking process. However, as this study focuses on the overall process of sensemaking rather than its individual stages, we refrain from mapping each property to a distinct phase to avoid unnecessary complexity. Thus, the overall process of sensemaking, as conceptualized by Kudesia (2017), is illustrated in Figure 1.

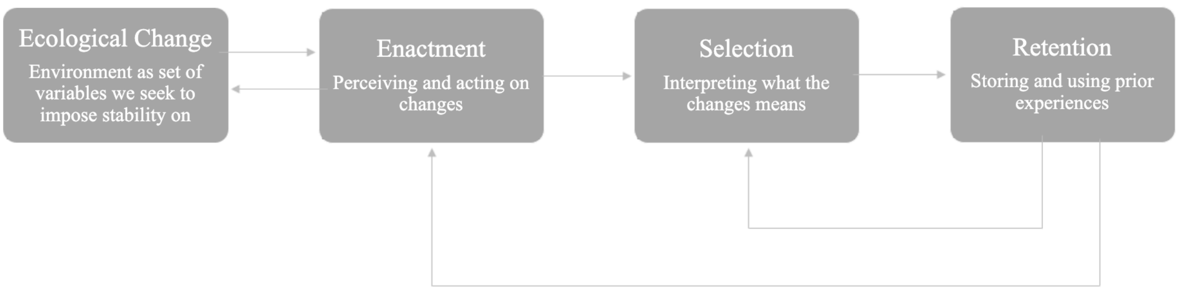


Figure 1. Kudesia's (2017) Enactment-Selection-Retention Framework

Building on the understanding that sensemaking is not an isolated but a socially constructed process, actors also shape others' sensemaking through a process known as sensegiving (Gioia and Chittipeddi, 1991). According to Gioia and Chittipeddi (1991) sensegiving can be defined as "*the process of attempting to influence the sensemaking and meaning construction of others toward a preferred redefinition of organizational reality"* (p. 442). Importantly, Maitlis and Christianson (2014), argue that organizational members do not passively accept meanings imposed by leaders through sensegiving, instead they engage in their own sensemaking process to interpret, reshape or even resist the meaning presented to them.

Recent studies, such as that by Engström et *al.* (2024), have contributed to the literature of sensemaking by investigating how it relates to AI technologies. The authors of this study demonstrate that the way AI technologies are perceived, either as abstract or concrete, shapes different sensemaking processes, which in turn influence workplace learning pathways. According to Engström et *al.* (2024), when AI is perceived as abstract, employees tend to adopt a feedback-driven learning approach, relying on directives from the organization. On the other hand, when it is seen as concrete, employees engage in an exploratory learning mode, experimenting with AI and envisioning its role in their future work (Ibid). This latter approach aligns with prospective sensemaking, wherein individuals make sense of AI by anticipating its future impact. While traditional sensemaking theory has primarily considered the process as retrospective, wherein individuals interpret past events to construct meaning (Weick, 1995), recent research has increasingly acknowledged that sensemaking can also be prospective (Kaplan and Orlikowski, 2013).

Goto (2022) expands on the literature of prospective sensemaking by developing a framework showing how professionals engage in a cycle of monitoring environmental changes, experimenting with AI applications, and developing blueprints for future integration. Importantly, the author finds that institutional norms strongly influence individuals' sensemaking process by imposing cognitive constraints that limit what professionals perceive as applicable to them. Thus, professionals may overlook or ignore technologies if it conflicts with the established norms and expectations of their industry.

2.5.2 Technological Frames of Reference

To explore the interplay of technology and perceptions even further, we draw on the TFR framework, developed by Orlikowski and Gash (1994). Grounded in sensemaking theory, TFR offers a valuable lens for examining how individuals interpret and make sense of technologies, in this case, GenAI. Goffman (1974) originally introduced the concept of frames as a tool for understanding and attributing meaning to a phenomenon. He argues that frames structure individuals' perceptions which in turn shapes how they interpret and act towards their environment. However, given the focus of this study, we do not delve deeper into the concept of frames, instead, we concentrate on TFR, which offers a more relevant perspective for understanding perceptions of GenAI.

TFR was first introduced by Orlikowski and Gash (1994), as an analytical perspective to understand the cognitive and social processes that influence technological adoption and change in organizations. TFR refers to the assumptions, expectations, and knowledge, or in other words cognitive structures, that individuals and groups within an organization develop around a particular technology (Ibid). According to Cornelissen and Werner (2014) these frames play a crucial role in shaping adoption of new technologies as they influence how members of organizations perceive a new technology, which in turn influences how they choose to interact with it. Orlikowski and Gash (1994) propose that TFR can be examined using three different “frame domains”, which help explain how individuals think and act around a technology. The first domain, Nature of Technology, refers to how individuals understand the technology and its functionality and capabilities. The second domain, Technology Strategy, focuses on people’s assumptions of the organization’s motivation for adopting the technology in the organization and their understanding of its value. Finally, the third domain, Technology in Use, emphasizes people’s views of how the technology should be used in daily activities and the consequences and conditions of this (Ibid). In this study, which examines perceptions of GenAI’s impact on work, all three frames are considered relevant to the analysis, as each captures a different dimension of how work is impacted.

Examining these frame domains, one may find that organizational members have divergent TFR, also known as frame incongruence. Incongruent frames arise when individuals hold differing assumptions, knowledge, or expectations about a technology (Orlikowski & Gash, 1994). According to Davidson (2006), these differences often stem from varied experiences and interactions with the technology, leading to conflicting understandings of its purpose and use. As a result, such misalignments can trigger resistance, skepticism, and hinder effective adoption of technologies (Orlikowski & Gash, 1994; Cornelissen and Werner, 2014). While research has largely studied frame incongruence between social groups (such as managers, suppliers etc.), differences in frames within the same group (intra-group inconsistencies), can also influence the integration of technology (Lundberg *et* al., 2022). Cornelissen and Werner (2014) emphasize that a certain degree of alignment across groups is essential to align behavior and ensure a smooth implementation process.

Azad and Faraj (2008) have extended the literature on frame incongruence by illustrating that achieving alignment in TFR between groups is often a dynamic and negotiated process, hopefully resulting in a so-called "truce frame". This study aligns with Kaplan and Tripsas (2008) perspective of how collective TFR emerges. They highlight that frames exist at multiple levels, including individuals, producers, and institutions, each with their own perspectives on how a technology should be used and integrated. Through ongoing interactions among actors, including discussions and negotiations, certain interpretations may gain traction, leading to the emergence of a collective TFR. Similar to Azad and Faraj's (2008) "truce frame", a collective TFR implies that members of an organization develop a somewhat shared understanding of the technology. This alignment helps reduce ambiguity, enhance cooperation, and facilitate smoother technology adoption (Kaplan and Tripsas, 2008).

2.6 Theoretical Framework

To better understand how individuals perceive GenAI's impact on work, this study adopts a theoretical framework grounded in sensemaking theory and the concept of TFR. By combining these, we aim to gain a better understanding of how the three concepts are interrelated and thus shape different perceptions of GenAI among consultants. The framework conceptualizes this process as dynamic and iterative, consisting of three interrelated components: Perceptions of GenAI, Sensemaking theory, and TFR, as visualized in Figure 2. Moreover, TFR provides a valuable lens for examining how consultants perceive GenAI's impact on their work, seeing that it focuses on individuals' assumptions, knowledge, and expectations of a technology. Sensemaking theory, in turn, helps us understand how these frames emerge and evolve through individuals' efforts to make sense of GenAI. Together, these offer a richer understanding of how consultants perceive GenAI, and what shapes those views in practice.

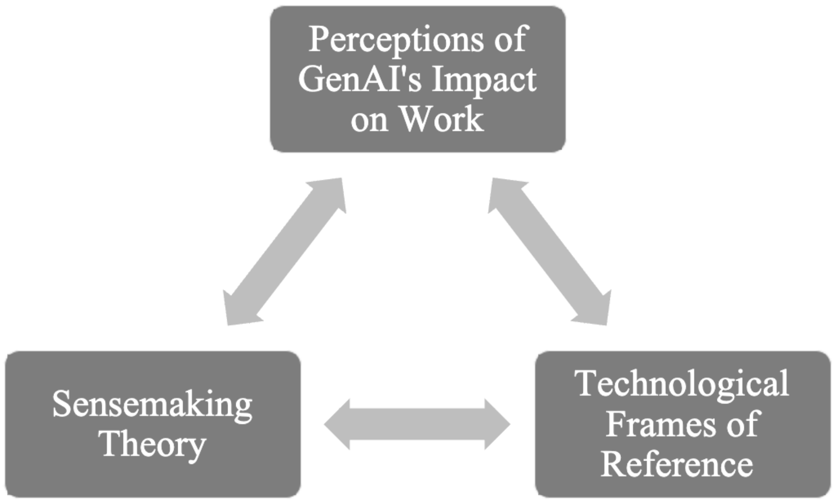


Figure 2. Theoretical Framework

3. Methodology

3.1 Methodological Fit

The introduction of GenAI in management consulting remains an underexplored area, particularly concerning the human dimension and how individuals perceive its impact on their work (Coombs *et* al., 2020). In response, this study adopts an exploratory approach aimed at producing new insights to inform and guide future research in the field (Edmondson and McManus, 2007; Makri and Neely, 2021). Following Edmondson and McManus (2007), who emphasize the value of open-ended inquiry in emerging research areas, we employ a qualitative design to capture the depth and complexity of consultants' cognitive processes. Aligned with our qualitative approach, the study is grounded in a constructivist ontology, which assumes that reality is socially constructed through human interpretation and interaction (Bell *et* al., 2022). Consistent with this ontological stance, we adopt an interpretivist epistemology, focused on understanding human behaviour and the processes through which meaning is created (Bell *et* al., 2022). From this perspective, the integration of GenAI is not viewed as an objective or fixed reality, but a socially constructed phenomenon, shaped by individuals' interpretations, experiences, and meanings they assign to it (Orlikowski and Baroudi, 1991). This aligns with our aim of understanding how individuals perceive GenAI's impact on their work and the factors shaping these perceptions.

In its early stages, this study followed an inductive research approach, viewing theory as the outcome of research rather than its starting point (Bell *et* al., 2022). In line with Gioia et al. (2013), we chose not to apply existing theoretical frameworks too early, instead letting concepts emerge from participants' lived experiences. As the study progressed, we shifted from inductive reasoning toward abductive reasoning, aligning with Alvesson and Kärreman's (2007) concept of "mystery construction". This shift enabled an iterative movement between empirical data and theory, where unexpected findings became triggers for theoretical exploration. Specifically, the diverse and sometimes contradictory perceptions of GenAI's impact on work among consultants emerged as the central puzzle, prompting us to engage more deeply with literature to find a suitable explanation of what shapes these perceptions. Through this abductive process (Bell *et* al., 2022), we identified sensemaking theory and TFR as valuable lenses to explain how these perceptions are formed, ultimately helping us make sense of the puzzle at the heart of this study.

3.2 Research Context

This study was conducted as a single-case study at a global management consulting firm, selected for its ongoing engagement with GenAI. Since our aim is to understand how consultants perceive GenAI in their daily work, studying one organization in detail enables us to capture rich insights (Yin, 2013), without being affected by inter-organizational variability, such as different levels of GenAI integration. While this may limit the generalizability of our findings, it strengthens the depth and relevance of our analysis within the selected context.

The chosen firm, referred to as *Consultica* to preserve anonymity, is a leading global management consulting firm known for its work across industries including finance, healthcare, and technology. With thousands of employees worldwide, Consultica delivers not only strategic advisory services, but also holds a strong position in areas such as audit and tax. Following Stake's (1995) typology, this study adopts an instrumental case study approach, not to generalize about Consultica per se, but to use the firm as a lens through which broader insights into GenAI adoption in knowledge work can be explored. While single-case studies are often criticized for limited generalizability, Flyvbjerg (2006) argues that such studies can indeed offer valuable general insights, particularly when the case is strategically chosen.

In our study, Consultica was deliberately selected due to its early engagement with GenAI and its position within a cognitively demanding sector. At the time of the study, Consultica was actively integrating GenAI applications in both client-facing and internal projects, offering a suitable setting to examine how consultants perceive its impact on their work. Specifically, it had rolled out two GenAI applications: Copilot, a GenAI assistant embedded in Microsoft tools (Outlook, Teams, Excel), and an internally developed chatbot tailored to the company and designed to maintain privacy (referred to as ConsultAI). These tools have been positioned as productivity enhancers, intended to streamline some aspects of consultants' tasks and free up time for more value-adding activities. To support adoption, Consultica also introduced several training initiatives, including onboarding materials, digital learning modules, and optional workshops. As such, Consultica offers a timely and relevant research context for this study. As an early mover in GenAI integration and a representative of high-skilled knowledge work, the firm serves as a prototype of what GenAI integration may increasingly look like across the professional services sector. Thus, its case offers valuable insights for other organizations in the sector seeking to navigate their own GenAI integration.

Ultimately, Flyvbjerg (2006) emphasizes that the purpose of case study research is not necessarily to generate universally applicable theories, but to engage deeply with lived experience and provide rich, contextualized understanding. This perspective aligns closely with the aim of this study, which explores individual perceptions that are often inaccessible without close, immersive engagement. Importantly, our position as employees at the case organization during the time of the study, allowed us to build trust, interact as peers with our interviewees, and gain a nuanced, insider perspective. This enabled us to uncover insights that may otherwise have remained hidden.

3.3 Data Collection

3.3.1 Preparatory Work

After having been employed by the case company, thus gaining access to potential participants, we began with an exploratory phase aimed at deepening our understanding of the organization and identifying a suitable focus area grounded in employees' lived experiences. Following a brief literature review to avoid reinventing the wheel, we identified differences in perceptions of GenAI across hierarchical roles as a promising focus for our preparatory interviews. Our preparatory work included five semi-structured interviews with consultants at different hierarchical levels (See Appendix A), as well as informal conversations with team members within the team we had been employed at. These early interactions helped us anchor the study in the lived experiences of consultants and ensure that our focus was informed by practice rather than preconceived notions. Interestingly, the preparatory study showed no clear divide in attitudes across juniors and seniors, but revealed a range of perceptions about GenAI's impact on work, both confirming and challenging previous literature. This prompted us to move beyond simply investigating differences between juniors and seniors, and instead explore how consultants across hierarchical levels perceive GenAI's impact on work more broadly. Thus, the interview guide and research questions were altered for the main study.

3.3.2 Main Study

Building on the insights from the preparatory phase, the main study explored how management consultants perceive GenAI's impact on their work, while also broadening to examine the factors shaping these perceptions. In particular, we sought to understand why consultants developed certain views and the processes behind them.

3.3.2.1 Data Sampling

Given the exploratory nature of this study, purposive sampling was used as the guiding approach to select participants based on their relevance to the research question (Bell *et* al., 2022). With the selected firm serving as the broader case context, we employed a generic purposive sampling strategy, to identify consultants whose roles positioned them to provide meaningful insights. Thus, participants were selected based on two key criteria: their position in the organizational hierarchy and their team function, see Appendix A for an overview. As visualized in the table, the five hierarchical levels have been grouped into two broader categories: junior consultants and senior consultants. This segmentation was made to enable clearer comparisons across levels of experience and responsibility. The junior category includes roles primarily involved in operational and analytical tasks covering level 1 and 2, while the senior category captures roles with more strategic, managerial, and client-facing responsibilities, covering levels 3 to 5. Additionally, participants were drawn from different functional teams within the consulting division to increase generalizability. Due to differences in team size, some functions - such as Team A - are more heavily represented. This reflects a priori purposive sampling approach (Bell *et* al., 2022), where inclusion criteria were defined in advance. Unlike theoretical sampling (Glaser and Strauss, 1967), our aim was not to reach saturation or build grounded theory. Instead, the focus was to select participants that could help our study be more generalizable and provide rich insights. As such, the sampling can be best described as generic purposive rather than theoretical.

3.3.2.2 Semi-structured Interviews

To explore how consultants perceive GenAI, we chose a qualitative approach centered on semi-structured interviews, well-suited for capturing the complexity of individual meaning-making (Bell *et* al., 2022). Positioned between fully structured and unstructured formats, semi-structured interviews allowed us to explore participants' interpretations in a flexible yet focused manner (Qu and Dumay, 2011). As the most widely used method in qualitative research (Alvesson & Deetz, 2021), they are particularly effective for exploring how individuals construct meaning within organizational life, how they interpret change, justify decisions, and navigate ambiguity (Qu and Dumay, 2011), thus aligning with the purpose of our study. While a general interview guide ensured coverage of key themes, the sequence and use of questions could be adapted based on the flow of the conversation. This enabled the interviewers to probe deeper into significant or unexpected responses, thereby enriching the data and guiding the direction of the study. Additionally, by treating the interview as a collaborative dialogue rather than a rigid question-and-answer exchange, we created space for interviewees to articulate their perspectives in their own words, revealing both what they think, and how they think (Rubin and Rubin, 2005). Central to this approach was treating interviewees as partners rather than subjects, as this fosters more meaningful, in-depth responses (Rubin and Rubin, 2005).

3.3.2.3 Conducting and Documenting Interviews

Before launching the full data collection, we conducted a pilot interview with our internal contact at Consultica to test the clarity, flow, and relevance of the interview guide. This allowed for minor adjustments to wording and structure, ensuring that questions were both understandable and aligned with the research objectives.

We conducted 23 interviews in English via online video conferencing, scheduled at participants convenience. This format offered logistical flexibility and broad accessibility, and is increasingly recognized as a valid method for qualitative research, despite offering less control over the interview setting (Curasi, 2001; Lobe *et* al., 2022). To mitigate potential limitations of rapport-building and the interpretation of non-verbal cues, each session began with informal conversation to build rapport and clarify the study's purpose and the importance of participants' perspectives. This approach, establishing a relaxed atmosphere and encouraging participant comfort and openness, has been shown to enhance data richness in online settings (Lobe *et* al., 2022). Furthermore, Lobe et al. (2022) note that online interviews are particularly well-suited for discussions about high engagement topics, making them an appropriate method for exploring consultants' experiences with GenAI. Moreover, all interviews were recorded with participants' consent and transcribed verbatim using a secure, company-internal AI transcription tool. This enabled full capture of the conversations and facilitated revisiting of the material during the analysis phase. The duration of interviews ranged from 36 to 65 minutes, averaging 46 minutes. Both researchers attended all sessions, alternating roles as lead interviewer and observer, enabling real-time reflection and minimizing individual bias.

3.4 Data Analysis

The data analysis and data collection were done simultaneously, meaning that after having conducted an interview, the authors immediately analyzed the data and adjusted the interview guide accordingly. This iterative process allowed us to refine the interview guide in real time, ensuring that subsequent interviews remained focused on the most relevant and emerging insights (Glaser and Strauss, 1967; Edmondson and McManus, 2007). As a result, our interview guide was significantly revised throughout the process (See Appendix B and C).

To guide our analysis, we applied the Gioia methodology (Gioia *et* al., 2013), which provides a systematic approach to concept development grounded in participants' lived experiences. Following this approach, we began with a first-order analysis, identifying informant-centric terms that captured how consultants themselves perceive GenAI. This allowed us to stay close to the language and meanings used by participants, avoiding theoretical imposition. To facilitate the analysis, we employed NVivo software, which allowed us to manage, organize, and code the interview transcripts efficiently. After each interview, transcripts were produced and immediately coded using NVivo. Through this process, we initially identified 48 first-order concepts. These were then individually reviewed and clustered into emerging themes to ensure we captured the full breadth of perspectives. After independent analysis, we came together to compare and reconcile our findings, reducing and refining the concepts into

23 first-order codes. These were subsequently organized into broader second-order themes, reflecting more abstract, researcher-centric interpretations of the data (Ibid). These second-order themes were further synthesized into aggregate dimensions, representing higher-level constructs. In line with Bell *et* al's., (2022) interpretation of the Gioia methodology, this stage of analysis encouraged us to *"think about [our] data theoretically"* (p. 1440), moving from raw empirical data to theoretical insights. Thus, after having identified themes related to TFR and sensemaking, we developed a visual data structure to map the analytical process (See Figure 3). This not only clarifies the logical flow of our coding process but also helps show the rigor of our approach to the reader, as suggested by Gioia et al. (2013). A complete overview of our methodological approach can be found in Appendix D.

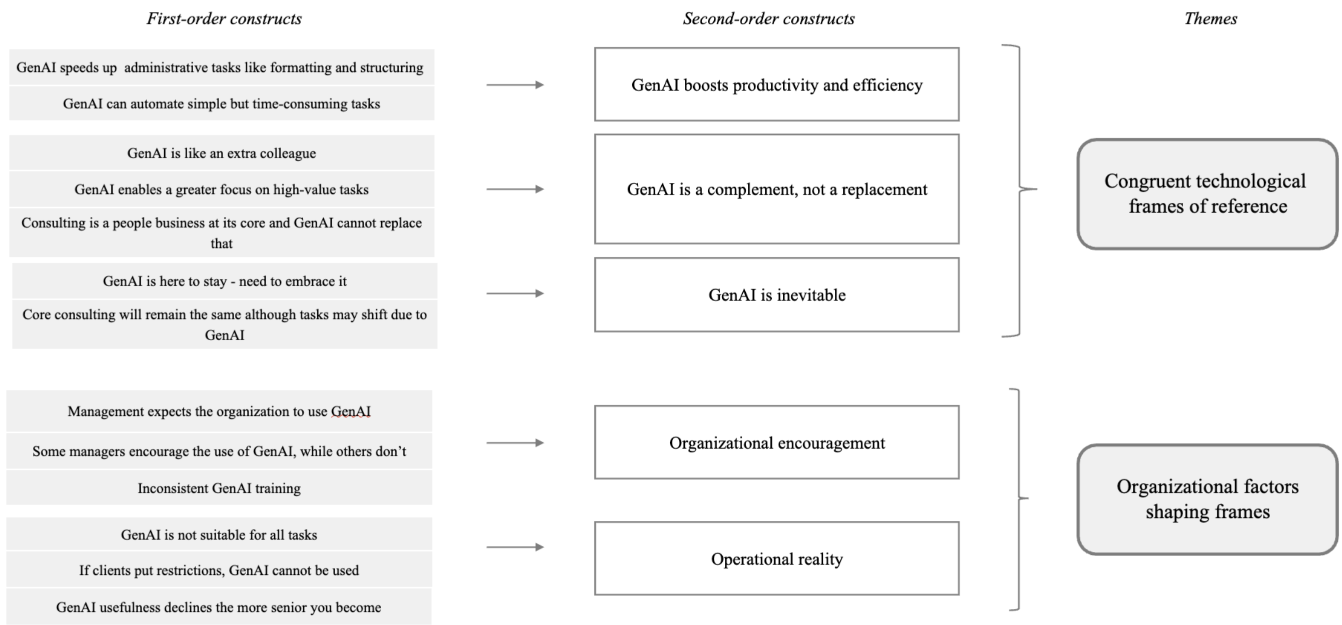


Figure 3. Extract of Methodological Approach

3.5 Quality of the Study

The assessment of qualitative research remains debated, as traditional criteria like reliability and validity often fail to capture the interpretive, context-dependent nature of this method (Bell et al., 2022). In response, frameworks such as Lincoln and Guba's (1985) concept of trustworthiness, used in this study, offer a better fit for interpretivist research.

3.5.1 Trustworthiness

Following Lincoln and Guba's (1985) framework, we address trustworthiness through four dimensions.

Credibility

According to Lincoln and Guba (1985), credibility is achieved when there is a strong alignment between how participants experience a phenomenon and how the researcher represents that experience. To strengthen credibility, we employed several strategies: First, semi-structured interviews enabled participants to articulate their views in their own words, offering space for nuance, complexity, and unexpected insights. Second, we conducted respondent validation, where participants were invited to review selected quotations in the draft findings to confirm accuracy and interpretation. This not only enhanced representational accuracy but also helped mitigate power imbalances (Bell *et* al., 2022). We also strengthened credibility through data and researcher triangulation, comparing perspectives from consultants across functions and seniority levels, and engaging both researchers in the interview and analysis process. This helped ensure that our findings were not overly shaped by a single researcher's perspective.

Transferability

Transferability concerns the extent to which the findings can be meaningfully applied in other contexts. While qualitative research does not aim for broad generalization, Lincoln and Guba (1985) argue that it is the responsibility of the researcher to provide rich contextual detail to support resonance across similar environments. Thus, we enhanced transferability by detailing the empirical context, including the company, the role of GenAI, and hierarchical role and team function of the interviewees. Rather than seeking statistical generalization, our study aims for analytic generalization, developing insights that may be transferable to similar organizational contexts (Yin, 2013).

Dependability

Dependability underscores the necessity of a transparent and systematically documented methodology that enables external observers to trace the logic of the study's design (Lincoln & Guba, 1985). In this study, dependability was addressed by documenting each stage of the research process, from the development of the interview guide to participant selection, transcription, coding, and theme generation, creating a clear methodological audit trail. Additionally, regular discussions with our academic supervisor and company contact served as an informal auditing mechanism, helping to identify inconsistencies and ensure our interpretations were grounded in data.

Confirmability

Confirmability relates to the objectivity of the research and the extent to which findings are shaped by the participants' responses rather than researcher bias. In qualitative research, where complete objectivity is neither possible nor the goal, confirmability instead emphasizes transparency, reflexivity, and evidence-based interpretation (Lincoln and Guba, 1985; Bell *et* al., 2022). To enhance this, both researchers independently analyzed the interviews before comparing, ensuring that insights were grounded in the data rather than shaped by individual assumptions.

3.5.2 Ethical Considerations

A fundamental ethical priority of this study was to ensure that the case organization 'Consultica' and all individuals involved in the interviews remained anonymous. To protect confidentiality we replaced all names with pseudonyms and used neutral labels for organizational team and hierarchical level. For example, rather than referring to specific job titles such as "Manager," we used generic hierarchical identifiers like "Level 3." These labels were carefully decided upon to ensure that the case organization could not be identified.

Prior to engaging in the research process and before any interviews were recorded, participants were fully briefed on the study's purpose and scope. They received an email inviting them to participate in an interview, outlining the research objectives and topic, along with a request of consent to participate (See Appendix E). This ensured they were well-informed about their involvement and the purpose of data collection (Bell *et* al., 2022).

4. Empirical Results

4.1 Congruent Technological Frames of Reference

4.1.1 GenAI Boosts Productivity and Efficiency

One of the most consistently expressed themes across interviews was the view of GenAI as a tool for enhancing productivity and efficiency within consulting workflows. This suggests a high degree of frame congruence, as several consultants shared similar assumptions and expectations regarding GenAI's functions. Rather than seeing the tools as a disruptive force, they commonly described it as a means to streamline routine tasks and free up time for more strategic and important work.

> *"Our work revolves a lot around hours and efficiency. For example, summarizing notes takes time - but if AI can handle that, we can focus on other things. So when you talk about AI, I guess it's mostly talk about reducing mundane tasks - and that's really what we're after." - I*

Among the 23 participants, 22 explicitly cited time saving and improved efficiency as the most salient benefits of integrating GenAI into their daily routines. Common use cases included summarizing lengthy documents, transcribing and organizing meeting notes, and synthesizing interview data, tasks frequently described as necessary but low-value.

> *"It used to take me so much time just to transcribe what was said during interviews. But now, you can just ask the AI to summarize the interview in ten key bullet points, and it actually works. It saves so much time and lets you focus on the results and what to do with them. I used to spend ages writing everything down and then summarizing it." - T*

Crucially, this frame extended beyond the individual level. Several consultants noted that Consultica's internal messaging around GenAI mirrored these sentiments, emphasizing improved efficiency and time saving. This suggests a shared understanding within the firm, where individual perceptions and organizational messaging align around the idea of GenAI as a tool for enhancing productivity and efficiency.

> *"I think the main reason Consultica has adopted these tools is to give us the possibility to work more efficiently and effectively." - M*

4.1.2 GenAI is a Complement, Not a Replacement

Across all levels of seniority, consultants consistently framed GenAI as a powerful support tool, enhancing, rather than replacing, human expertise. By allocating time-consuming activities to the GenAI tools, consultants expressed a growing ability to concentrate on core aspects of their role, namely, analysis, problem-solving, and client interaction. This reorientation was commonly interpreted as a form of professional enrichment.

> *"Instead of sitting and thinking about which words to use, or spending time on the layout of a PowerPoint, I can focus more on the recommendations and the thought process behind them. So yeah, it's a more productive use of my time, and hopefully that leads to better deliverables and more value for the client." - B*

Rather than competing with human capabilities, GenAI was often described as a "colleague" or "assistant" that lightens the cognitive load and sharpens focus. This perspective of AI as a collaborator reflected a broader belief - one where humans and machines work together.

> *"AI is like an extra colleague. It helps me take notes during meetings, summarize key points, and even clarify concepts in real-time. That's extremely useful, especially when dealing with complex topics or clients speaking with different accents" - K*

Importantly, consultants expressed confidence that GenAI would not replace their roles. They were nearly unanimous in their understanding that consulting remains fundamentally a people-driven profession, relying on interpersonal skills, human judgment, and emotional intelligence, qualities they believe GenAI cannot replace.

"I don't think it will, you know, steal our jobs. There will still be management consultants, I really believe that. It's such a people business at its core, and there are so many soft skills and qualities you need to have. AI can support, but it can't replace that human element." - C

Several consultants emphasized that the question of whether GenAI will replace humans is far more nuanced than it is often portrayed. Rather than a single outcome, some framed the issue as complex, involving both replacement and support. A recurring theme was the misconception that GenAI would outright replace human roles, when in fact its impact is likely to be more transformative than substitutive.

"Of course, AI will have a huge impact, and it already has. But I don't think it will simply replace humans. It will also create jobs for those who know how to use it. You can't just have an AI tool doing my job, you need a combination. I think it's a big misconception that AI will replace humans or certain roles. It really isn't that simple." - K

4.1.3 GenAI is Inevitable

While agreeing that GenAI will not replace human consultants, there was a widespread consensus that GenAI is not a temporary trend, it is here to stay. Rather than resisting it, most consultants viewed the technology as an inevitable part of the profession's future, even if its exact trajectory still remains unclear.

"I think AI will be a part of our future. It's difficult to speculate how much it will take over, but I guess the future will tell. Even if you have no choice, you have to adapt to it, and I'm looking forward to that." - M

This sense of inevitability was often paired with a sense of urgency. Interviewees acknowledged that those who fail to engage with the tools risk falling behind. This mindset reflects a competitive framing of GenAI, not as a threat to the profession, but as a differentiator between those who choose to integrate it and those who don't.

"If three people get the same task and one person uses AI while the others don't, the one using AI will complete it much faster. AI is a competitive advantage. [...] The key is to stay on track with AI development. The firms and consultants that adapt will thrive, while those who don't will struggle." - W

Building on the transformative potential of GenAI, consultants did not express fear of being replaced, but they did anticipate a reshaping of consulting work. Rather than eliminating positions, GenAI was expected to shift the nature of tasks and roles. Many consultants discussed a visible "pyramid shift" - a flattening of the traditional consulting hierarchy, as GenAI begins to automate tasks typically handled by junior staff. According to some, this shift could lead to faster upskilling, requiring junior consultants to adopt more senior-level tasks earlier in their careers.

"It's possible that we won't need as much junior support in a few years as we did in the past. That could mean a shift in the structure. We often talk about the consulting pyramid, with lots of juniors at the bottom and fewer people as you move up. Maybe that pyramid will change shape. Maybe the overall tasks will change and the tasks that the senior associate performs today will be performed by an associate in a few years." - B

Yet, consultants also acknowledged that such changes, while exciting, can also be unsettling. Embracing GenAI may require significant personal and professional adaptation, something not everyone is comfortable with.

"Of course, it's always a bit scary, because it means we have to develop and adapt. People don't like change, especially if you've been working in a certain area for a long time and suddenly AI can replace part of that. But it just means we have to evolve." - T

4.2 Incongruent Technological Frames of Reference

4.2.1 Reliability and Trustworthiness

A key point of divergence that emerged during our interviews was around the reliability and trustworthiness of GenAI outputs. Although GenAI was widely used for drafting and summarization, interviewees expressed different views on how much the content can be trusted.

This skepticism was particularly evident among more experienced consultants, who emphasized the need for critical oversight and human validation. For these consultants, GenAI was a useful assistant but its outputs were often described as preliminary, requiring human review before being shared with clients or relied upon in decision-making processes.

> *"My strong belief is that you'll never truly trust the AI's output unless a human has verified it, someone who can say it's grounded in experience, based on what other clients have done, or on what has actually proven to be successful." - I (Senior)*

Additionally, several consultants expressed concerns about overreliance on GenAI particularly when colleagues used it unquestioningly. Some spoke about situations where colleagues treated GenAI output as final, which raised concerns about accuracy and professional standards.

> *"I think it's important to review it very closely. And that's something I think some people are doing incorrectly. They just let it generate something and then send it away, and that's when it can go bad." - H (Senior)*

Notably, concerns about overreliance were most often directed toward more junior colleagues. Several senior consultants described instances where they received content from junior consultants that felt distinctly "AI-generated".

> *"On one hand, I really appreciate that juniors are trying to be efficient and produce things faster, that makes sense. But at the same time, there are moments when you*

receive something and you wonder, 'Did they even read this through themselves?' It can feel very AI or machine-produced, and you start questioning whether any real thought or analysis went into it. So yeah, it's a bit of a double-edged sword." - E (Senior)

Interestingly, this critique wasn't one-sided. Junior consultants, in turn, noted that some senior colleagues tended to overestimate what GenAI could do, treating it as a "magic tool" rather than understanding its actual capabilities and limitations.

"The more senior employees, who might not be as tech-savvy, think AI is a magic tool that can do anything for you, whereas juniors have a more pragmatic approach and see limitations that the seniors don't always recognize." - G (Junior)

4.2.2 Uncertain Impact on Learning

A second area of divergence concerned consultants' understanding of GenAI's impact on learning and skill development. When asked whether AI supports or inhibits learning, interviewees offered contrasting views, split along two broad but contrasting narratives.

The first narrative frames GenAI as a learning enabler, particularly among junior consultants and those navigating unfamiliar areas. In this view, GenAI accelerates knowledge acquisition by providing quick access to information that helps consultants get up to speed faster.

"I think AI leads to a faster learning journey. [...] With AI, it's much quicker to learn all the different terms and concepts, because as soon as you come across something new, you can just type it in and get a pretty good summary. Before AI, you had to put in a lot more effort to understand the broader context and the general topic." - J

This optimistic view was countered by concerns that GenAI may act as a barrier to skill development, especially for junior consultants. The core worry was that by outsourcing tasks to GenAI, consultants might miss the opportunity to develop foundational consulting skills, such as structuring sharp client deliverables, by bypassing the tasks traditionally seen as essential for building expertise and preparing for more senior roles.

> *“A big part of learning as a consultant is processing huge amounts of information, identifying key insights, and drawing conclusions. If AI does that for you, how will junior consultants develop the skills they need later in their careers? [...] In 20 years, today’s junior consultants will be in senior positions. If they’ve relied on AI for everything, will they have the business acumen and critical thinking needed for leadership roles?” - I*

Some consultants offered a more nuanced view, arguing that while GenAI may reduce the development of certain skills, it also reflects a broader shift in what skills are actually required. Rather than viewing this as a loss, they saw it as a shift, suggesting that the traditional path of learning might not be as relevant in a context where GenAI is available.

> *“In some ways, if you start using AI right away, then you're not going to be able to learn how to do, for example, the analysis by yourself in the same way as consultants did before. But at the same time, maybe you won’t need to do it by yourself anymore.” - U*

Many consultants also framed the future as one of collaboration between people and technology. They envisioned a hybrid model where human consultants and GenAI tools operate in tandem, each complementing the other.

> *"You need to work together. It’s about finding the right people and figuring out how they can work with the system. I’d say it’s really about setting up a process where you combine both the people and the technology." - P*

4.2.3 GenAI’s Strategic Significance

The third area of divergence concerns how strategically important consultants believe GenAI is, or should be, within the consulting profession. One group of consultants viewed GenAI as essential to maintaining a competitive edge, framing GenAI tools not as optional but as professional necessities. These consultants cited rising expectations from clients and Consultica to deliver insights faster and more efficiently. For them, mastering GenAI tools is becoming critical to be able to keep up.

> "*Consultica emphasizes AI adoption as essential to staying competitive. With industry leaders like BCG and McKinsey already leveraging AI, integrating these tools is no longer optional but necessary to keep up.*" - *K*

In contrast, other participants questioned the actual depth of AI's integration into consulting, and whether its significance is being overstated. They viewed GenAI as a tool useful for internal productivity but far from transformative. Some were openly skeptical about whether GenAI was delivering on its promises, describing it more as a buzzword used in firm strategy than a strategic necessity.

> *"There's a lot of talk about AI revolutionizing consulting, but what are we actually doing?" - L*

Some even pointed to previous waves of technological hype, such as blockchain or Industry 4.0, that generated significant attention but ultimately fell short of reshaping practices. While acknowledging AI's utility in certain areas, they were wary of overstating its role or any assumptions that it has fundamentally redefined what consultants do.

> *"Every few years, there's a new buzzword - Internet of Things, Industry 4.0, now AI. It's important, but we need to separate hype from real value. The biggest question is whether AI will actually boost productivity or if it's just another tech trend." - N*

4.3 Organizational Factors Shaping Frames

4.3.1 Organizational Encouragement

Many consultants noted that Consultica actively promotes GenAI use, framing GenAI adoption as essential to staying competitive. As a result, consultants described a sense of both encouragement and implicit pressure to integrate GenAI tools. Interviewees note that the organizational tone suggests that GenAI use is not just encouraged, it's expected, especially among junior consultants.

> *"Management wants the organization to utilize AI. So in that way, there's this sense that everyone is expected to use it. [...] I'd also say it's more likely that senior people expect juniors to use it than the opposite." - K*

Interviewees also pointed to variation in managerial attitudes toward GenAI. While some senior consultants actively promote and normalize its use, others remain more skeptical or disengaged.

> *"Some seniors have recommended it, but I'd say the majority don't really mention it or actively encourage us to use it." - E*

Building on encouragement, Consultica also provides structured training sessions and onboarding materials to facilitate GenAI adoption across the firm. However, interviewees report significant variation in both participation and awareness of these training initiatives.

> *"I don't think we had any special AI focus, not that I can remember of. So not really a clear introduction to the tools I would say." - M*

> *"I think there's been a lot of support. Microsoft has even visited us to talk specifically about Copilot and how we can use it in our work. So I'd say there's absolutely been a big push for everyone to get on board, and to help onboard others as well." - G*

Even among those who acknowledge that Consultica offers AI training programs, opinions on their effectiveness are divided. Many consultants describe the training as too general, lacking practical applications tailored to specific tasks. In particular they tend to focus on the functionalities of the GenAI tools rather than their application in daily work.

> *“We have access to AI tools, but no one is really telling us exactly how to use them in our daily work. We need to see clear examples of how we can work with AI, not just general talk about its potential.” - L*

That being said, consultants expressed that they need to see more clear use-cases on how to integrate the tools into their workflows.

> *“Instead of just watching a course, we should be required to try AI tools in real tasks. If we had weekly AI challenges, people would actually test it.” - D*

4.3.2 Operational Reality

At Consultica, perceptions of GenAI’s value and usability appeared to vary significantly depending on consultants’ day-to-day responsibilities and the nature of the projects they were involved in. These operational realities seemed to play a central role in shaping consultants' perceptions of GenAI’s usefulness. For instance, junior consultants whose work is constrained to more repetitive, structured tasks, tended to express more enthusiasm for GenAI.

> *“Every time I want to check my grammar or improve an email, or even ask for a shortcut in Excel, I use AI. So in my daily work, I really use it frequently. The ability to transcribe meetings and then ask Copilot what was said about topic A or B - it’s just common sense now, at least for me. I think it’s very helpful, and I’m very positive about it.” - W (Junior)*

In contrast, senior consultants described GenAI as less relevant to their daily work. Their responsibilities tend to focus more on strategic oversight, client interactions, and decision-making, areas where GenAI is perceived to have limited utility. Tasks such as conducting meetings or managing teams were commonly seen as less compatible with GenAI’s current capabilities.

“Junior consultants are more engaged with AI because they create more material. As you move up, it’s more about planning, delegating, and reviewing. So I would say AI use declines the further up the hierarchy you go. Some seniors only attend meetings all day, and AI can’t replace that.” - O (Senior)

This role-based differentiation also plays out in the nature of tasks. While GenAI performs well in straightforward or routine tasks, consultants noted that it struggles in high-context scenarios that require creativity or communication.

“I’ve tried using it more on the creative side to help with phrasing or structuring presentations. I’ve used it as a base to set up PowerPoints before, but I don’t really think Copilot is mature enough to actually save me time. Sure, it can generate a quick outline of how a presentation might look, but it doesn’t really add the kind of information I want to include in the final output.” - G

4.4 Individual Influences Shaping Frames

4.4.1 Prior Experience and Interest

Consultants’ perceptions of GenAI seem to be shaped not only by the organization but also by individual levels of experience and interest. Across interviews, it became evident that those with previous exposure to AI, whether through university, personal interest, or previous work, were quicker to adopt and experiment with GenAI. For these individuals, GenAI was not perceived as disruptive or unfamiliar, but rather as a natural extension of their existing toolkit.

"My first experience with it was in school when ChatGPT came out. At first, we were just playing around with it and didn’t use it much. But then, during my master’s thesis last spring, I started using it a lot more, for things like rewriting texts and summarizing articles. That’s when I realized how good it was, and since I came here, I’ve been using it maybe once a day at least." - U

Both juniors and seniors recognized that having used GenAI or similar tools in academic settings made it easier for younger colleagues to integrate the technology into their workflows.

> *"I think people are curious about it and how to use it, especially because colleagues who are starting now have already used it in their personal lives or during school. So they're naturally interested in how to apply it within Consultica as well." - F*

Notably, openness to AI was not just about experience, but also mindset. Those who viewed change positively seemed more likely to embrace GenAI in their work, often describing themselves as naturally positive toward innovation and change.

> *I think it's partly my experience, but also just my personality. I like change, all the time. Even in my private life, I'm always thinking, 'We need to fix this,' or 'I want to change that.' And it's the same at work. I get tired quickly if things stay the same or if I have to redo tasks over and over. That's why I'm really positive about AI, because it allows for change, improvement, and saving time, so you can focus on more business-relevant things instead." - P*

Some even emphasized that openness to AI was less about age and more about mindset, suggesting that personality plays a stronger role than generational differences.

> *"It's not just about age, it's about mindset. Some partners here are actually really into AI, and some juniors don't touch it at all even if they have previous experience with it." - N*

In contrast, those less inclined toward change often relied more heavily on traditional methods, even when recognizing the potential benefits of GenAI. For them, established habits and routines seemed to create barriers to full engagement.

> *"The reason I don't use the tools so much is because of old habits, I would say. You find your ways of working that you're comfortable with, and then you have to step*

outside your comfort zone and challenge yourself to see what you can actually do with these new tools. " - I

4.4.2 Positive and Negative Interactions

Whether consultants had positive or negative interactions with GenAI tools at Consultica also seemed to play a significant role in shaping their perceptions. Interviewees consistently emphasized that their first interaction had a strong influence on how they continued to view the technology's usefulness. For instance, consultants who had positive first experiences, where the tool delivered helpful outputs, were more likely to remain open and continue using it.

> *"I've actually only used it once so far, that was when I created a Microsoft Form. I had all the questions ready in an Excel sheet, just copy-pasted them in, and it generated the form. It was super convenient. So I'll definitely use it more now that I've seen it's actually good." - D*

In contrast, several consultants shared that an underwhelming or negative first interaction led to disengagement. When the tools generated irrelevant or inaccurate output, it created frustration and reduced motivation to continue exploring.

> *"I've used both Copilot and the AI chat, but I'd say I was a bit… not disappointed, but in the beginning, the chat gave me answers I didn't always agree with. I felt there was some room for improvement, so I actually stopped using it over the last couple of months." - E*

That being said, several consultants expressed a disconnect between the potential of the tools as expressed by management or product demonstrations, and the actual performance of the tools in practice. As one consultant reflected,

> *"I honestly think I'm a little bit underwhelmed by Copilot. I don't think it's that great. Like all the demos are much better than what it can actually do, in my opinion." - O*

5. Analysis

5.1 How Do Management Consultants Perceive GenAI's Impact on Their Work?

Our findings reveal that management consultants' perceptions of GenAI's impact on work can be divided into the three domains outlined by Orlikowski and Gash (1994), revealing both areas of shared understanding and points of divergence. Across the nature-of-technology and technology-strategy domains, consultants showed strong frame congruence, commonly viewing GenAI as a tool to automate routine tasks and enhance human expertise. However, in the technology-in-use domain, significant frame incongruence emerged, particularly regarding its importance, its impact on learning, and the level of trust placed in its outputs.

5.1.1 Streamlining, Not Replacing: Aligned Perceptions

A widely shared perception among the consultants in our study was that GenAI serves primarily to automate repetitive, low-value tasks. This aligns with a significant body of research emphasizing AI's role in boosting efficiency, particularly through the automation of core consulting tasks (Dell'Acqua *et* al., 2023; Oarue-Itseuwa, 2024; Samokhvalov, 2024). This consistency in how GenAI is understood suggests a high degree of alignment - what the TFR framework calls frame congruence - within the nature-of-technology domain (Orlikowski and Gash, 1994). In other words, consultants across all hierarchical levels and functions shared a similar view of what GenAI is and what it can do. Importantly, this perception was not limited to individual experiences, according to interviewees, Consultica's organizational messaging reinforced the same framing, positioning GenAI as a means to increase productivity and efficiency, as noted by interviewee M *"the main reason Consultica has adopted these tools is to give us the possibility to work more efficiently and effectively."* This could indicate a successful case of organizational sensegiving (Gioia & Chittipeddi, 1991), where leadership played an active role in shaping how consultants understand the role and purpose of the technology. The convergence between individual perceptions and strategic communication suggests that top-down messaging has been effective in creating a shared frame around GenAI's capabilities. However, it is also possible that this alignment reflects consultants' internalization of strategic messaging, rather than individually formed beliefs.

Given the organization's strong top-down framing of GenAI, responses may have been altered to fit this message, raising questions about how deeply these views are embedded. As interviewee O pointed out, *"I'm a little bit underwhelmed by Copilot. I don't think it's that great. Like all the demos are much better than what it can actually do"*, suggesting that beneath the surface, skepticism may persist.

In addition to its automating functions, GenAI was also perceived as an augmentative tool, one that enhances rather than replaces human expertise. This perception reflects an increasingly dominant view in the more recent literature on AI in knowledge work, which views GenAI as a complement to human workers (Autor *et* al., 2003; Pettersen, 2019; Alavi *et al.*, 2024; Ritala *et* al., 2024). Participants did not believe that GenAI would take over consulting tasks. Instead, they emphasized that the human element would remain central to consulting, thus agreeing with Blackler (1995) and Alvesson (2004), who emphasize that the most valuable resource in knowledge work are the cognitive capabilities of employees. Interviewee C put it clearly: "*AI can support, but it can't replace that human element."* This view challenges findings by several researchers (Frey and Osborne, 2017; Brynjolfsson and McAfee, 2017), who suggest that AI is increasingly capable of replacing humans, even in strategic tasks. This augmentative view may stem from institutional norms within consulting, which shape how professionals interpret new technologies (Goto, 2022). As highlighted by our interviewees, human judgment and client interaction are and have always been core competencies in consulting, making the idea of full automation feel incompatible with the profession's identity. As Goto explains, institutional norms act as cognitive filters, leading professionals to adopt interpretations that align with established values. In this case, such norms appear to steer consultants toward viewing GenAI as a supportive tool, reinforcing rather than disrupting the people-driven nature of their work. Although, it is important to note that while institutional norms likely influence consultants' interpretations, our data does not allow us to determine the extent to which this view is shaped by these beliefs versus more pragmatic assessments of GenAI's limitations.

Moreover, our findings reinforce the arguments put forward by Lester (2020) and Raisch and Krakowski (2021), who claim that the impact of AI on professional occupations cannot be simply divided into automation or augmentation. Rather, AI technologies like GenAI tend to have a hybrid effect, simultaneously automating some tasks while augmenting human capabilities in others. In our study, consultants acknowledged that GenAI automates some repetitive tasks, yet they consistently framed the technology as augmentative. This dual perception aligns with critiques of Frey and Osborne's (2017) study, which has been challenged for oversimplifying AI's impact by categorizing occupations as either fully automatable or not, ignoring the variability within roles. As Lester (2020) notes, the reality is often more complex, with automation and augmentation often coexisting. One consultant described this dual effect clearly: *"Instead of sitting and thinking about which words to use, or spending time on the layout of a PowerPoint, I can focus more on the recommendations and the thought process behind them."* These findings affirm this more nuanced view, illustrating how GenAI can simultaneously relieve consultants from low-value tasks while empowering them to focus on more strategic contributions, ultimately reshaping rather than replacing professional work.

Across both junior and senior groups, consultants shared similar views on GenAI's capabilities and the firm's strategic rationale for adopting it, reflecting frame congruence in the nature-of-technology and technology-strategy domains (Orlikowski & Gash, 1994). However, as the next section shows, this alignment breaks down in the technology-in-use domain, where perceptions diverge on GenAI's impact on learning, trust and its strategic importance.

5.1.2 Accelerator or Obstacle? Diverging Perceptions

One of the clearest sites of incongruence concerns the perceived impact of GenAI on learning. Our findings revealed two dominant, yet opposing, narratives. The first positioned GenAI as a tool that accelerates learning by offering immediate access to higher knowledge. This aligns with scholarship suggesting that by automating routine work, GenAI enables professionals to engage more deeply in complex problem-solving and innovation (Von Richthofen et al. 2022), thereby fostering more advanced skill development. On the other hand, the second narrative, reflected a more cautious view, emphasizing that over-reliance on GenAI could hinder the development of foundational consulting skills. Tasks considered mundane, they argued, are in fact essential for learning the basics of consulting, reflecting literature that raises concerns about AI's dual trajectory, whereby automation may come at the cost of skill erosion (Shrestha *et* al., 2019). Interestingly, these differing views on its impact reveal intra-group frame incongruences, variations within, rather than strictly between, hierarchical groups (Lundberg *et* al., 2022). This suggests that consultants' sensemaking processes are shaped less by organizational rank and more by individual influences, which will be elaborated on in section 5.2.2.

Yet, these opposing narratives are not uncontested. A number of consultants suggested that traditional models of learning may become increasingly obsolete in a GenAI-integrated work environment, as using GenAI will require new competencies. Scholars such as Dăniloaia and Turturean (2024), and Ritala et al. (2024), similarly argued that future learning will involve acquiring new types of skills, including the ability to interpret, oversee, and collaborate with intelligent systems. This perspective was echoed by participants, who noted that while GenAI might transform traditional learning pathways, it simultaneously demands new forms of capabilities, ones that are better suited to working alongside GenAI. As one consultant noted, *"You need to work together. It's about finding the right people and figuring out how they can work with the system" (P).* This reframing reflects a prospective sensemaking process (Kaplan and Orlikowski, 2013), where consultants not only respond to current shifts but anticipate and adapt to future skill demands. As such, GenAI is not merely disrupting traditional learning models, it is actively reshaping what it means to develop in consulting by prompting a shift toward future-oriented, GenAI-collaboration skillsets.

While consultants' views on GenAI's impact on learning reveal intra-group inconsistencies, our findings also highlight clear frame incongruence between hierarchical groups, within the technology-in-use domain. A notable example concerns trust in GenAI's reliability. Many senior consultants expressed concern about juniors over-relying on GenAI, often treating its outputs as final rather than drafts. They feared this could undermine professional standards in the industry, thus reflecting what Anthony (2021) describes as "black-boxing", where AI outputs are used without full understanding. As Anthony (2021) warns, such blind trust can lead to flawed decisions, particularly when human oversight is weak, a concern clearly reflected by interviewee I, who emphasized that AI outputs must be grounded in human experience and verified against proven practices. Interestingly, juniors challenged this view, suggesting instead that it was sometimes seniors who overestimated the technology's capabilities. Juniors framed themselves as more “tech-savvy,” highlighting that they were more aware of GenAI’s limitations. As interviewee G put it, juniors tend to adopt a more pragmatic view, recognizing GenAI’s strengths and shortcomings, whereas seniors might idealize its potential. This tension between these groups reveal a frame incongruence in the technology-in-use domain (Orlikowski and Gash, 1994), particularly regarding how much the technology should be trusted and the consequences of this. However, within this area, no clear intra-group inconsistencies were observed, pointing to similar views amongst juniors and seniors respectively, reflecting frame incongruence between organizational groups (Davidson, 2006).

Our findings show that frame incongruence exists both between and within organizational groups, with the most salient tensions emerging within the technology-in-use domain. While there appears to be broad alignment regarding GenAI’s functionality and the firm’s strategic rationale for adopting it, the application and implications of the technology remain contested. This is consistent with findings by Nesemeier (2024), who notes that despite widespread recognition of AI’s relevance in consulting, significant ambiguity persists around how it should be used. These incongruences appear to stem from different technological frames and sensemaking processes, shaped by both individual and organizational factors. To unpack the factors shaping perceptions, the following section will combine perceptions, TFR and sensemaking theory, following our theoretical framework (Fig. 2).

5.2 How are management consultant’s perceptions of GenAI shaped?

Our findings suggest that consultants’ perceptions of GenAI are not static, but shaped through an ongoing sensemaking process influenced by both organizational and individual factors. While prior research (Davidson, 2006), highlights the role of experience in shaping technological frames and thus perceptions, our study extends this by showing how the organization, individual and anticipations of the future interact to shape how consultants perceive GenAI’s impact on work.

5.2.1 The Organization

Participants described feeling a degree of pressure to adopt GenAI tools, often attributing this to internal management expectations. It was emphasized that GenAI is not framed as optional, but as a strategic imperative, thereby showing an example of top-down sensegiving, where management attempts to influence consultants' understanding of GenAI into their preferred definition of it (Gioia and Chittipeddi, 1991). As interviewee K noted, management positions GenAI adoption as critical for maintaining competitiveness, especially as competing firms like BCG and McKinsey are already leveraging such technologies. This strategic positioning likely contributes to the pressure consultants feel to adopt GenAI tools. Despite this strategic framing, several participants highlighted a lack of clear guidance on how to apply GenAI in day-to-day consulting work. While some consultants, like interviewee G, described structured initiatives, such as external workshops, others pointed to minimal onboarding and a disconnect between training and consulting tasks. This inconsistency appeared to make it harder to translate strategy into meaningful practice, undermining efforts to build a shared technological frame (Kaplan & Tripsas, 2008). As both Kaplan and Tripsas (2008) and Azad and Faraj (2008) emphasize, collective frames do not emerge from top-down messaging but require ongoing negotiation and interaction. At Consultica, this negotiation and discussion appear to have been constrained by inconsistent support and training, which may have complicated the retention phase of sensemaking (Kudesia, 2017) - the stage where new practices are meant to become embedded into professional identities. Several consultants described challenges in relating GenAI meaningfully to their daily work, suggesting that the lack of consistent reinforcement may have contributed to fragmented adoption. As interviewee D pointed out, *“Instead of just watching a course, we should be required to try AI tools in real tasks. If we had weekly AI challenges, people would actually test it.”* This highlights the importance of practical, hands-on engagement in bridging the gap between strategy and practice. Thus, while sensegiving efforts seem to have successfully shaped shared understandings in the technology-strategy domain, the technology-in-use domain remains fractured. This underscores the importance of focusing on the human aspect and not just the organization, an aspect often overlooked in more technically focused research (Coombs *et* al., 2020).

Moreover, consultants' operational reality also seemed to shape their sensemaking around GenAI. According to Weick's (2005), sensemaking is triggered when individuals notice cues that disrupt existing routines, referred to as the enactment phase. In this study, role based differences seem to influence which cues consultants notice and how they engage with GenAI. For junior consultants, GenAI tools like Copilot became immediately relevant as their daily tasks aligned closely with the tools' capabilities, as highlighted by interviewee W. In contrast, senior consultants, whose work centers on client interaction, and decision-making, encountered fewer relevant cues, as interviewee O observed, *"AI use declines the further up the hierarchy you go. Some seniors only attend meetings all day, and AI can't replace that."* Consequently, seniors seemed to engage more cautiously, often questioning the technology's relevance to their everyday work. This operational reality may help explain some of the variation in how GenAI was perceived across hierarchical levels, particularly within the technology-in-use domain. One could argue that the frame incongruence between juniors and seniors regarding trust in GenAI emerged precisely from these differing sensemaking processes; juniors, regularly engaging with the tool in routine tasks, developed a more pragmatic and informed trust, while seniors, who used it less frequently, tended to view GenAI with greater skepticism. Still, while role differences might help explain some variation, we cannot definitively attribute trust levels to this alone. Other factors, such as attitudes toward innovation and past experiences with digital tools may also shape engagement, and thus warrant further exploration in the following section.

5.2.2 The Individual

In addition to organizational influences, individual-level factors played a central role in shaping how consultants perceived GenAI, with prior experience emerging as a key theme. Supporting Goffman's (1974), framing theory, consultants interpreted GenAI through cognitive schemas rooted in past exposure to similar tools. Rather than encountering GenAI as a neutral phenomenon, they interpreted it through pre-existing frames. For example interviewee L described how his familiarity with GenAI from previous roles made him more confident and proactive with the tools at Consultica, whereas those with limited prior exposure, often senior consultants, tended to describe the tools in more abstract terms and showed greater hesitation toward experimentation. These differences appeared to influence early sensemaking and shaped how readily consultants adopted GenAI in practice. This mirrors Engström et al.'s (2024) findings that employees' sensemaking processes depend heavily on whether the technology is perceived as abstract or concrete: abstract perceptions tend to lead to more cautious use, while concreteness fosters experimentation. As interviewee U noted, it was only after seeing what the tool could do that he began using it regularly, highlighting how concreteness drives engagement. However, while Engström et al. (2024) argue that concreteness fosters adoption, our findings suggest that this alone is insufficient. For instance, despite recognizing GenAI's potential, interviewee L hesitated to use it due to uncertainty about its application to his own work, *"... we need to see clear examples of how we can work with AI, not just general talk about its potential."* This suggests that adoption depends not just on the general visibility of use cases, but on tailored, context-specific guidance.

Beyond experience, participants also highlighted the role of individuals' mindset in shaping their perceptions of GenAI. Several consultants emphasized that interest, curiosity, and a willingness to adapt played a crucial role in shaping how they approached GenAI. As interviewee N put it, "*It's not just about age, it's about mindset.*" While juniors generally had more exposure to GenAI, some senior consultants, despite less familiarity, were equally enthusiastic and eager to experiment. Conversely, a few resisted use, not due to lack of access or understanding, but because of habits. This supports Weick's (1979) idea that sensemaking is anchored in identity, people interpret new technologies in ways that preserve a coherent sense of self. For some, GenAI might have aligned with their self-concept as adaptive professionals; for others, it disrupted routines and was not coherent with oneself.

Finally, our findings suggest that interactions with GenAI, whether positive or negative, played a pivotal role in shaping consultants' perceptions, often acting as anchors during the sensemaking process (Kudesia, 2017). Consultants who experienced immediate value from the tools were more inclined to continue using them, reinforcing frames of usefulness and relevance. Conversely, those who encountered errors or generic outputs, often disengaged and developed skepticism, even when acknowledging the technology's potential in principle. While we cannot determine the extent of these effects, the accounts suggest that early impressions can be particularly influential. This highlights that adoption is not just a matter of access or training, it depends heavily on whether encounters generate concrete, task-relevant value. As such, a positive or negative interaction becomes a key determinant in whether sensemaking processes evolve toward engagement or disengagement and thus a critical moment in the formation of TFR.

These findings not only support Orlikowski and Gash (1994) and Davidson's (2006) view that TFRs are shaped by experience and knowledge, but also help explain the frame incongruence observed in the "technology-in-use" domain. While there was clear alignment across groups on the nature of GenAI and the rationale for its adoption, actual engagement with the tools and perceived relevance to daily tasks varied considerably. This shows that shared organizational messaging does not guarantee shared application, consultants' interpretations are filtered through personal exposure and perceived task relevance. Even within the same implementation strategy, these micro-level differences in sensemaking led to divergent frames, reinforcing why the "technology-in-use" domain remains the most fragmented across our data.

5.2.3 Anticipations of the Future

While traditional sensemaking theory emphasizes how individuals interpret the present through the lens of past experiences (Weick, 1979; Kudesia, 2017), our findings reveal that consultants also engaged in future-oriented sensemaking. Many assessed GenAI's relevance today based on its anticipated future role as an industry standard, reflecting the concept of prospective sensemaking (Kaplan and Orlikowski, 2013). As interviewee M put it, even if GenAI isn't yet fully reliable, experimenting with it now is essential for staying relevant. Their present usage was thus justified by future expectations, suggesting that consultants who perceive GenAI as an inevitable transformation may be more likely to integrate it into their work, ensuring they remain future-ready.

However, this future-focused orientation was accompanied by uncertainty. Several interviewees speculated that tasks traditionally performed by junior consultants may soon be largely automated, leading to a shift in the nature of their responsibilities. This uncertainty seemed to feed back into how GenAI was evaluated in the present. On one hand, the broadly shared belief that GenAI will be strategically important contributed to frame congruence within the technology-strategy domain (Orlikowski & Gash, 1994), as consultants largely agreed on the necessity of its integration. On the other hand, ambiguity about how GenAI will affect daily work and long-term career trajectories could be seen as a factor reinforcing incongruence in the technology-in-use domain. As interviewee B reflected, *"It's possible that we won't need as much junior support in a few years as we did in the past,"* underscoring how this transformation could alter the structure of consulting work in ways that remain uncertain and difficult to navigate. This uncertainty likely contributes to the frame incongruence observed within the "technology-in-use" domain, as consultants grapple with how GenAI should be applied in practice, and what its use today may mean for their future roles and responsibilities.

6. Concluding Discussion

6.1 How Management Consultant's Perceive GenAI's Impact on Their Work

Answering our first research question, we find that consultants primarily perceive GenAI's impact on work positively, emphasizing its ability to automate mundane tasks and augment more strategic and creative activities. Importantly, our findings did not reveal overtly negative perceptions of GenAI's impact on work, rather, consultants tended to view it as a supportive tool that can enhance productivity, and enable a shift toward more meaningful, higher-order tasks. Contrary to dominant narratives in the literature that emphasize job replacement through automation (e.g., Frey and Osborne, 2017), our participants maintained that the human-centered nature of consulting will persist.

However, a deeper analysis using the TFR framework (Orlikowski & Gash, 1994) reveals a more nuanced picture, one that includes both areas of alignment and divergence across consultants. Broadly shared perceptions of GenAI's capabilities and the firm's strategic rationale for its adoption indicate strong frame congruence within the nature-of-technology and technology-strategy domains. Although, our findings also reveal different perceptions of GenAI within the technology-in-use domain, indicating frame incongruence. Here, perceptions of its impact were more divergent, especially with regards to its impact on learning, reliability and the industry as a whole. This means that although consultants seem to have similar perceptions of *what* GenAI is and *why* it has been adopted, they have very different ideas of how it should be used in daily work. This underscores the importance of examining different frame domains in order to find areas of divergence. Addressing these divergent interpretations will be key to successful GenAI integration (Kaplan and Tripsas, 2008).

6.2 How Management Consultants' Perceptions of GenAI are Shaped

Applying our theoretical framework, we find that consultants' perceptions of GenAI are shaped by individual factors, organizational influences, and future anticipations. At the individual level, prior experience, personal openness and positive/negative interactions proved central to consultants' sensemaking processes. For instance, consultants who reported positive initial experiences with the tools were also more likely to report positive perceptions of GenAI's usefulness. Organizationally, one of the key findings is that sensegiving efforts, such as strategic messaging, may have been effective in fostering a shared understanding around GenAI's strategic relevance and core capabilities, contributing to frame congruence in the nature-of-technology and technology-strategy domains. However, inconsistent support and operational realities seem to have caused fragmentation in the technology-in-use domain. The absence of tailored, task-specific guidance seemed to make it challenging for some consultants to translate strategic messages into concrete day-to-day practices, ultimately undermining the development of a shared frame in the technology-in-use domain. This helps explain the divergent perceptions regarding GenAI's importance, its impact on learning, and the degree of trust placed in its outputs. Finally, our findings show that future anticipations also seem to influence present perceptions. Many consultants interpreted GenAI through a forward-looking lens, engaging with it not only for current utility but as preparation for its expected future role, adding a temporal dimension to how technological frames are constructed. Ultimately, our findings suggest that consultants' perceptions of GenAI's impact on work is closely connected to their technological frames which have been constructed through individual sensemaking processes. These processes, in turn, are shaped by both the individual, organization and future anticipations - as visualized in our developed theoretical framework.

6.3 Implications for Consultica

The way consultants perceive GenAI, has direct implications for how the technology is engaged with in daily work. Thus, the identified variability in perceptions within the technology-in-use domain may cause different usage patterns across the organization, limiting the organization's ability to enact a successful GenAI implementation. While the firm's strategic sensegiving efforts seem effective in establishing why GenAI matters and its possibilities, they seem to have fallen short in clarifying how consultants should practically incorporate it into their workflows. This gap calls for other measures to ensure alignment in perceptions across all frame domains, which will be elaborated on in section 6.6.

6.4 Developed Theoretical Framework

By integrating our empirical findings into the framework introduced in Figure 2, we extend and refine our theoretical framework, as visualized in Figure 4. Specifically, it illustrates how consultants' perceptions of GenAI are shaped through individual sensemaking processes (Kudesia, 2017), which in turn give rise to either congruent or incongruent technological frames of reference (Orlikowski & Gash, 1994). The model shows how organizational factors, individual influences and future anticipations shape consultants' enactment, selection, and retention processes, influencing whether shared or divergent frames emerge. While this process unfolds at the individual level, the resulting frames are best understood at the organizational level, as alignment or misalignment can only be understood through comparison across individuals. These frames, in turn, give rise to both similar and divergent perceptions of GenAI's impact on work.

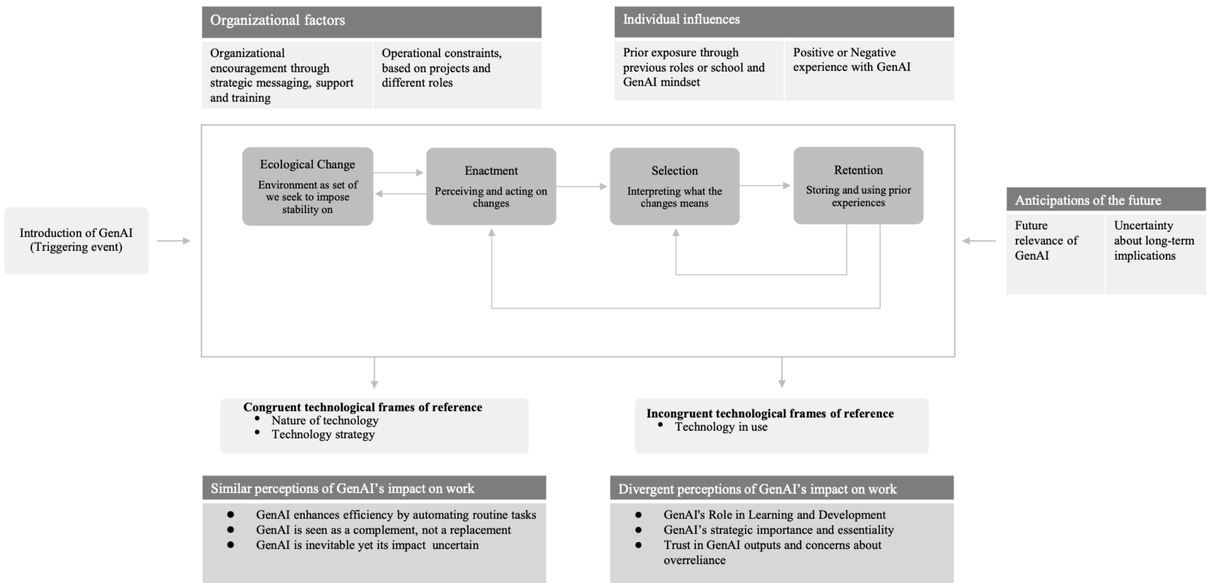


Figure 4. Developed Theoretical Framework

6.5 Theoretical Contributions

This study offers two main theoretical contributions to the literature on GenAI adoption and knowledge work. First, by combining sensemaking theory (Weick, 1979) with the TFR framework (Orlikowski & Gash, 1994), we develop a model that explains how individual perceptions of GenAI are constructed. While prior research has examined sensemaking and TFR independently, our framework bridges them, illustrating how sensemaking processes shape the development of technological frames, and ultimately, how consultants perceive GenAI's impact on work. In doing so, we show that perceptions of GenAI are shaped by organizational, individual, and anticipatory factors, offering a more granular understanding of why technology perceptions may vary within the same organizational context. Additionally, while previous research has primarily explored frame incongruence between organizational groups (Orlikowski & Gash, 1994; Davidson, 2006), we extend TFR theory by demonstrating that frame domains are much more nuanced and can contain multiple, layered points of divergence, not only between groups, but also within.

Second, we address the research gap outlined in section 2.4 by shifting attention from technological functionality and strategic adoption to the human experience of GenAI integration. In doing so, we respond to calls for research that centers on the role of employee perceptions in AI integration (Coombs *et* al., 2020). Here, we add nuance by showing that while consultants broadly agree on GenAI's purpose and potential, their perceptions diverge significantly in the technology-in-use domain. This highlights that the key adoption challenge lies not in understanding what GenAI is, but in how it should be applied in practice and what it means for the future of consulting work.

6.6 Practical Implications

This study offers several practical implications for firms, especially knowledge-intensive organizations, integrating GenAI. Since employee perceptions directly influence adoption (Nesemeier, 2024), identifying where these perceptions diverge can help organizations anticipate and address potential implementation challenges more effectively. First, organizations should move beyond broad strategic messaging and invest in targeted, task-specific training that demonstrates how GenAI can be applied in actual workflows. Our findings show that while many consultants understand the strategic rationale for adopting GenAI and its capabilities, uncertainty persists around how to use it meaningfully in practice, reflected in the frame incongruence observed within the technology-in-use domain. Providing clear, role-relevant use cases and hands-on opportunities for experimentation (e.g., 'AI challenges' as suggested by one interviewee) can foster deeper engagement and reduce skepticism, ultimately ensuring a smoother implementation process. Second, managers should recognize that GenAI is often perceived as more relevant to junior roles, contributing to disengagement and skepticism among senior consultants, as highlighted in our findings. To drive adoption across all levels, organizations should highlight how GenAI can support higher-order activities such as strategic decision-making and client interaction. This calls for differentiated support strategies tailored to the realities of each role. Finally, our findings suggest that professional norms - particularly the belief that consulting is a human-centric profession - shape how new technologies are understood. While this may ease concerns about job displacement, it can also create blind spots that limit recognition of GenAI's transformative potential. Thus, to foster more forward-thinking adoption, firms should engage with these norms and encourage reflection on how the profession and GenAI can evolve together. Given that consultants' perceptions are also shaped by future expectations, as shown in our findings, organizations should frame GenAI not only as a current productivity tool but as a key enabler of long-term professional development in an evolving industry.

6.7 Limitations and Suggestions for Future Research

While this study offers timely insights into how management consultants perceive GenAI and what shapes these perceptions, several limitations warrant consideration and foundation for future research. First the single-case study design enabled deep contextual understanding relevant given the cognitive nature of our research question. However, it limits the generalizability of the findings across firms, industries or geographies. As organizational culture, digital maturity, and national context likely influences GenAI perception and adoption, future studies may consider cross-case or comparative research designs to explore these variations. Second, despite emphasizing the processual nature of sensemaking, the study itself was cross-sectional in design, capturing perceptions at a specific point in time. Given the fast-evolving nature of GenAI, longitudinal research could offer insights into how perceptions evolve over time. Third, relying on qualitative interview data, this study captures articulated experiences and interpretation, however future research could complement this with ethnographic observation or quantitative measures as digital trace data to assess how practice aligns with perception.

In summary, this study offers an initial step toward understanding how GenAI is perceived within the consulting profession. Future research can continue to explore the temporal, relational, and institutional dimensions of these perceptions, and in doing so, contribute to a more comprehensive understanding of what it means to work, learn, and lead in the age of intelligent technologies.

7. References

Alavi, M., Georgia Institute of Technology, Leidner, D. E., University of Virginia, Mousavi, R., & University of Virginia. (2024). Knowledge Management Perspective of Generative Artificial Intelligence. *Journal of the Association for Information Systems*, *25*(1), 1–12. https://doi.org/10.17705/1jais.00859

Alvesson, M. (2004). *Knowledge work and knowledge-intensive firms* (1st ed.). Oxford University Press.

Alvesson, M., & Deetz, S. (2021). *Doing Critical Research*. SAGE Publications Ltd. https://doi.org/10.4135/9781529682649

Alvesson, M., & Kärreman, D. (2007). Constructing Mystery: Empirical Matters in Theory Development. *Academy of Management Review*, *32*(4), 1265–1281. https://doi.org/10.5465/AMR.2007.26586822

Anthony, C. (2021). When Knowledge Work and Analytical Technologies Collide: The Practices and Consequences of Black Boxing Algorithmic Technologies. *Administrative Science Quarterly*, *66*(4), 1173–1212. https://doi.org/10.1177/00018392211016755

Anthony, C., Bechky, B. A., & Fayard, A.-L. (2023). "Collaborating" with AI: Taking a System View to Explore the Future of Work. *Organization Science*, *34*(5), 1672–1694. https://doi.org/10.1287/orsc.2022.1651

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Azad, B., & Faraj, S. (2008). Making e-Government systems workable: Exploring the evolution of frames. *The Journal of Strategic Information Systems*, *17*(2), 75–98. https://doi.org/10.1016/j.jsis.2007.12.001

Bai, S., Zhang, X., Yu, D., & Yao, J. (2024). Assist me or replace me? Uncovering the influence of AI awareness on employees' counterproductive work behaviors. *Frontiers in Public Health*, *12*, 1449561. https://doi.org/10.3389/fpubh.2024.1449561

Bell, E., Bryman, A., & Harley, B. (2022). *Business research methods* (Sixth edition). Oxford University Press.

Blackler, F. (1995). Knowledge, Knowledge Work and Organizations: An Overview and Interpretation. *Organization Studies*, *16*(6), 1021–1046. https://doi.org/10.1177/017084069501600605

Brynjolfsson, E., & McAfee, A. (2017). The Business of Artificial Intelligence. *Harvard Business Review*. https://hbr.org/2017/07/the-business-of-artificial-intelligence

Coombs, C., Hislop, D., Taneva, S. K., & Barnard, S. (2020). The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review. *The Journal of Strategic Information Systems*, *29*(4), 101600. https://doi.org/10.1016/j.jsis.2020.101600

Cornelissen, J. P., & Werner, M. D. (2014). Putting Framing in Perspective: A Review of Framing and Frame Analysis across the Management and Organizational Literature. *The Academy of Management Annals*, *8*(1), 181–235. https://doi.org/10.5465/19416520.2014.875669

Curasi, C. F. (2001). A Critical Exploration of Face-to Face Interviewing vs. Computer-Mediated Interviewing. *International Journal of Market Research*, *43*(4), 1–13. https://doi.org/10.1177/147078530104300402

Dăniloaia, D.-F., & Turturean, E. (2024). Knowledge Workers and the Rise of Artificial Intelligence: Navigating New Challenges. *SEA - Practical Application of Science*, 111–121. https://doi.org/10.70147/s35111121

Davidson, E. (2006). A Technological Frames Perspective on Information Technology and Organizational Change. *The Journal of Applied Behavioral Science*, *42*(1), 23–39. https://doi.org/10.1177/0021886305285126

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4573321

Edmondson, A. C., & McManus, S. E. (2007). Methodological Fit in Management Field Research. *The Academy of Management Review*, *32*(4), 1155–1179. https://doi.org/10.5465/AMR.2007.26586086

Engström, A., Pittino, D., Mohlin, A., Johansson, A., & Edh Mirzaei, N. (2024). Artificial intelligence and work transformations: Integrating sensemaking and workplace learning perspectives. *Information Technology & People*, *37*(7), 2441–2461. https://doi.org/10.1108/ITP-01-2023-0048

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, *66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Flyvbjerg, B. (2006). Five Misunderstandings About Case-Study Research. *Qualitative Inquiry*, *12*(2), 219–245. https://doi.org/10.1177/1077800405284363

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gînguță, A., Ștefea, P., Noja, G. G., & Munteanu, V. P. (2023). Ethical Impacts, Risks and Challenges of Artificial Intelligence Technologies in Business Consulting: A New Modelling Approach Based on Structural Equations. *Electronics*, *12*(6), 1462. https://doi.org/10.3390/electronics12061462

Gioia, D. A., & Chittipeddi, K. (1991). Sensemaking and sensegiving in strategic change initiation. *Strategic Management Journal*, *12*(6), 433–448. https://doi.org/10.1002/smj.4250120604

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, *16*(1), 15–31. https://doi.org/10.1177/1094428112452151

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory : strategies for qualitative research*. Aldine.

Goffman, E. (1974). *Frame analysis: An essay on the organization of experience*. Harvard University Press.

Goldman Sachs. (2023, April 5). Generative AI could raise global GDP by 7%. Goldman Sachs. Retrieved April 10. 2025, from https://www.goldmansachs.com/insights/articles/generative-ai-could-raise-global-gdp-by-7-percent

Goto, M. (2022). Accepting the future as ever-changing: Professionals' sensemaking about artificial intelligence. *Journal of Professions and Organization*, *9*(1), 77–99. https://doi.org/10.1093/jpo/joab022

Safiulina, I & Rabii, H. (2025). Predicting Employee Turnover in Consulting Firms: A Machine Learning Approach to Multi-Parameter Satisfaction Modeling. *Proceedings of The International Conference on Research in Human Resource Management*, *1*(1), 35–51. https://doi.org/10.33422/icrhrm.v1i1.747

Kaplan, S., & Orlikowski, W. J. (2013). Temporal Work in Strategy Making. *Organization Science (Providence, R.I.)*, *24*(4), 965–995. https://doi.org/10.1287/orsc.1120.0792

Kaplan, S., & Tripsas, M. (2008). Thinking about technology: Applying a cognitive lens to technical change. *Research Policy*, *37*(5), 790–805. https://doi.org/10.1016/j.respol.2008.02.002

Kudesia, R. S. (2017). Organizational Sensemaking. *Oxford Research Encyclopedia of Psychology*. Retrieved April 13. 2025, from https://oxfordre.com/psychology/view/10.1093/acrefore/9780190236557.001.0001/acrefore-9780190236557-e-78.

Lester, S. (2020). New Technology and Professional Work. *Professions and Professionalism*, *10*(2). https://doi.org/10.7577/pp.3836

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry.* Sage.

Lobe, B., Morgan, D. L., & Hoffman, K. (2022). A Systematic Comparison of In-Person and Video-Based Online Interviewing. *International Journal of Qualitative Methods*, *21*, 16094069221127068. https://doi.org/10.1177/16094069221127068

Lundberg, O., Nylén, D., & Sandberg, J. (2022). Unpacking construction site digitalization: The role of incongruence and inconsistency in technological frames. *Construction Management and Economics*, *40*(11–12), 987–1002. https://doi.org/10.1080/01446193.2021.1980896

Maitlis, S., & Christianson, M. (2014). Sensemaking in Organizations: Taking Stock and Moving Forward. *The Academy of Management Annals*, *8*(1), 57–125. https://doi.org/10.1080/19416520.2014.873177

Makri, C., & Neely, A. (2021). Grounded Theory: A Guide for Exploratory Studies in Management Research. *International Journal of Qualitative Methods*, *20*, 16094069211013654. https://doi.org/10.1177/16094069211013654

Malatji, W. R., Eck, R. V., & Zuva, T. (2020). Understanding the usage, Modifications, Limitations and Criticisms of Technology Acceptance Model (TAM). *Advances in Science, Technology and Engineering Systems Journal*, *5*(6), 113–117. https://doi.org/10.25046/aj050612

Marr, B. (2023). *The Difference Between Generative AI And Traditional AI: An Easy Explanation For Anyone*. Forbes. Retrieved April 20, 2025, from https://www.forbes.com/sites/bernardmarr/2023/07/24/the-difference-between-generative-ai-and-traditional-ai-an-easy-explanation-for-anyone/

Mayer, H., Yee, L., Chui, M., & Roberts, R. (2025). *Superagency in the workplace: Empowering people to unlock AI's full potential.* McKinsey & Company. Retrieved

March 25, 2025, from https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/superagency-in-the-workplace-empowering-people-to-unlock-ais-full-potential-at-work

Mohan, S. K. (2024). Management Consulting in the Artificial Intelligence – LLM Era. *Management Consulting Journal*, *7*(1), 9–24. https://doi.org/10.2478/mcj-2024-0002

Nesemeier, D. (2024). GenAI Acceptance in Professional Services: The Case of Management Consulting. *International Conference on AI Research*, *4*(1), 313–321. https://doi.org/10.34190/icair.4.1.3021

Oarue-Itseuwa, E. (2024). Artificial Intelligence's Impact of the Management Consultancy Sector over the Next Five Years. *Management Consulting Journal*, *7*(1), 49–58. https://doi.org/10.2478/mcj-2024-0005

Orlikowski, W. J., & Baroudi, J. J. (1991). Studying Information Technology in Organizations: Research Approaches and Assumptions. *Information Systems Research*, *2*(1), 1–28. https://doi.org/10.1287/isre.2.1.1

Orlikowski, W. J., & Gash, D. C. (1994). Technological frames: Making sense of information technology in organizations. *ACM Transactions on Information Systems*, *12*(2), 174–207. https://doi.org/10.1145/196734.196745

Pettersen, L. (2019). Why Artificial Intelligence Will Not Outsmart Complex Knowledge Work. *Work, Employment and Society*, *33*(6), 1058–1067. https://doi.org/10.1177/0950017018817489

Qu, S. Q., & Dumay, J. (2011). The qualitative research interview. *Qualitative Research in Accounting & Management*, *8*(3), 238–264. https://doi.org/10.1108/11766091111162070

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *The Academy of Management Review*, *46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Ritala, P., Ruokonen, M., & Ramaul, L. (2024). Transforming boundaries: How does ChatGPT change knowledge work? *Journal of Business Strategy*, *45*(3), 214–220. https://doi.org/10.1108/JBS-05-2023-0094

Rubin, H., & Rubin, I. (2005). *Qualitative Interviewing: The Art of Hearing Data* (2nd ed.). Sage. https://doi.org/10.4135/9781452226651

Samokhvalov, K. (2024). The Transformative Impact of Artificial Intelligence on the Management Consultancy Sector. *Management Consulting Journal*, *7*(1), 59–68. https://doi.org/10.2478/mcj-2024-0006

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational Decision-Making Structures in the Age of Artificial Intelligence. *California Management Review*, *61*(4), 66–83. https://doi.org/10.1177/0008125619862257

Singla, A., Sukharevsky, A., Yee, L., Chui, M., & Hall, B. (2025). *The state of AI: How organizations are rewiring to capture value.* McKinsey & Company. Retrieved March 28, 2025, from https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai#/

Stake, R. E. (1995). *The art of case study research*. Sage Publications, Inc.

Susskind, R., & Susskind, D. (2017). *The future of the professions : how technology will transform the work of human experts*. Oxford University Press.

Tavoletti, E., Kazemargi, N., Cerruti, C., Grieco, C., & Appolloni, A. (2022). Business model innovation and digital transformation in global management consulting firms. *European Journal of Innovation Management*, *25*(6), 612–636. https://doi.org/10.1108/EJIM-11-2020-0443

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Von Richthofen, G., Ogolla, S., & Send, H. (2022). Adopting AI in the Context of Knowledge Work: Empirical Insights from German Organizations. *Information*, *13*(4), 199. https://doi.org/10.3390/info13040199

Weick, K. E. (1979). *The social psychology of organizing* (2. ed.). Addison-Wesley.

Weick, K. E. (1995). *Sensemaking in organizations*. Sage.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the Process of Sensemaking. *Organization Science (Providence, R.I.)*, *16*(4), 409–421. https://doi.org/10.1287/orsc.1050.0133

Woodruff, A., Shelby, R., Kelley, P. G., Rousso-Schindler, S., Smith-Loud, J., & Wilcox, L. (2024). How Knowledge Workers Think Generative AI Will (Not) Transform Their Industries. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–26. https://doi.org/10.1145/3613904.3642700

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change*, *201*, 123251. https://doi.org/10.1016/j.techfore.2024.123251

Yin, R. K. (2013). Validity and generalization in future case study evaluations. *Evaluation (London, England. 1995)*, *19*(3), 321–332. https://doi.org/10.1177/1356389013497081

8. Appendices

Appendix A. Interviewee Overview

Interviewee	Team	Role	Role Classification	Type of interview	Date
Interviewee A	A	5	Senior	Prep	2025-01-28
Interviewee B	B	2	Junior	Prep	2025-02-07
Interviewee C	A	1	Junior	Prep	2025-02-07
Interviewee D	C	1	Junior	Prep	2025-02-10
Interviewee E	A	3	Senior	Prep	2025-02-11
Interviewee F	B	3	Senior	Main	2025-02-13
Interviewee G	B	1	Junior	Main	2025-02-13
Interviewee H	C	3	Senior	Main	2025-02-17
Interviewee I	A	4	Senior	Main	2025-02-18
Interviewee J	C	2	Junior	Main	2025-02-19
Interviewee K	A	1	Junior	Main	2025-02-20
Interviewee L	A	2	Junior	Main	2025-02-20
Interviewee M	B	1	Junior	Main	2025-02-21
Interviewee N	A	5	Senior	Main	2025-02-25
Interviewee O	A	3	Senior	Main	2025-02-25
Interviewee P	A	4	Senior	Main	2025-02-25
Interviewee Q	C	1	Junior	Main	2025-02-27
Interviewee R	A	3	Senior	Main	2025-02-27
Interviewee S	A	4	Senior	Main	2025-03-03
Interviewee T	A	3	Senior	Main	2025-03-11
Interviewee U	C	1	Junior	Main	2025-03-12
Interviewee V	A	3	Senior	Main	2025-03-12
Interviewee W	A	1	Junior	Main	2025-03-14
Seniors:	*12*				
Juniors:	*11*				

Appendix B. Interview guide (Preparatory study)

Introduction

- Presentation of ourselves and our thesis.
- Ask if they are ok with recording and transcribing the interview.
- Ask if they have any questions for us before beginning.

Warm-up and background

- Tell us a bit about yourself and your role.
- How long have you been working at Consultica, and within your current role/team?
- What did you do before you started at Consultica? (Education, Previous roles)

GenAI in practice at consultica

- What types of AI tools are available in your department and what are their functions?
    - In what situations do you encounter these tools in your daily work?
- How do you and your colleagues use these tools?
- What do you think is the company's objective for implementing GenAI tools?
- What are your reasons for using GenAI tools?
- Do you mostly see GenAI as an opportunity or threat?
- Have you encountered or worked with GenAI tools in any previous roles/school?
- What type of support (training, leadership, prior experience) have you received?

Perceptions and looking forward

- Has GenAI influenced how you see your role as a consultant?
- What excites you about GenAI, and what concerns do you have?

Closing reflections

- What are some things you think humans will always do better than GenAI?
- In your view, could GenAI ever replace consultants?
- Is there anything you would like to add that we have not discussed during this interview?

Appendix C. Interview guide (Main study)

Introduction

- Presentation of ourselves and our thesis.
- Ask if they are ok with recording and transcribing the interview.
- Ask if they have any questions for us before beginning.

Warm-up and background

- Tell us a bit about yourself and your role.
- How long have you been working at Consultica, and within your current role/team?
- What did you do before you started at Consultica? (Education, Previous roles)
- What roles have you had at the company?

Introduction to GenAI

- How would you describe your first encounter with GenAI?
- Has your understanding of GenAI changed over time?
  - If yes, what influenced this change?
- What are the biggest misconceptions you think exist about GenAI in consulting?

Perceptions of GenAI

- Do you mostly see GenAI as an opportunity or threat?
- Do you think GenAI will fundamentally change the consulting industry?
- What are some advantages and disadvantages with using GenAI?
- How do you think GenAI impacts junior vs. senior consultants differently?
- What consulting tasks do you find GenAI most useful for?
- How did you learn to use the GenAI tools effectively?
  - Did you receive any formal training?
- Do you ever feel that consultants trust AI outputs too much?

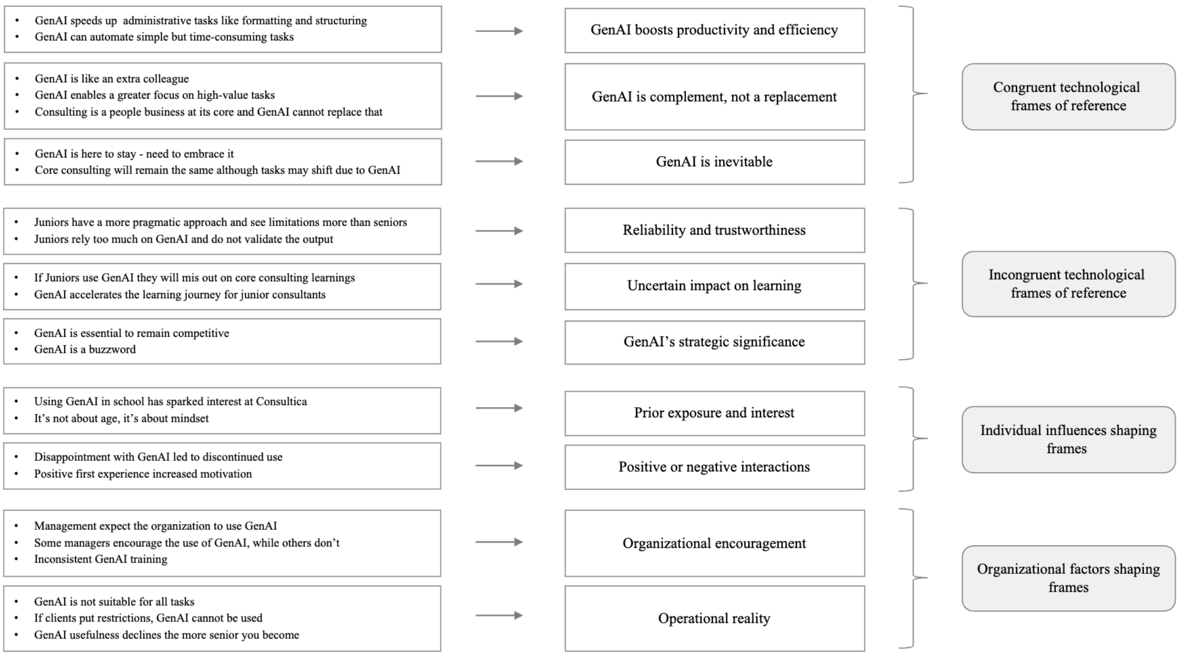
Future outlook

- How do you see GenAI and digital technologies evolving at Consultica in the near future?
- What areas of consulting do you believe will be most affected by GenAI, and why?
  - Are there areas that you believe will not be affected?
- What aspects of GenAI makes you excited, and what makes you concerned?
- What could Consultica do differently in how GenAI tools are introduced or supported?

Concluding reflections

- Looking ahead five years, how do you think GenAI will reshape the consulting industry?
- In your view, could GenAI replace consultants in the future?
- What do humans do better than GenAI?
- Is there anything you would like to add that we have not discussed during this interview?

Appendix D. Methodological Approach



Appendix E. Interview Invitation Email

Subject: Interview Invitation for Our Master's Thesis Study

Dear [Interviewees name]

We hope this email finds you well.

We are Lina Johansson and Clara Gille, Master's thesis students currently pursuing our last semester of studies in Business and Management at SSE. Our research focuses on understanding how AI is impacting the management consulting industry and how these changes are perceived across different roles. Through a case study approach at Consultica, we aim to explore how these perceptions differ between roles, and how this might influence AI adoption and usage.

We are currently conducting interviews with key individuals who can provide insights into this topic and we would be delighted if you would consider participating. If you have any preferred time slots, we'd be happy to accommodate your availability.

Below, we have outlined the key themes that will be covered in the interview. However, we prefer not to share the exact questions in advance, as we aim to capture your spontaneous reactions and genuine perspectives. If you would feel more comfortable reviewing the specific questions beforehand, please let us know, and we would be happy to accommodate your preference.

1. Background and role at Consultica
2. GenAI tools used in the department
3. GenAI's impact on individual roles and tasks
4. The future of GenAI and its long-term impact on roles/tasks

The interview will be held online, making participation convenient, and will be scheduled for approximately 45 minutes. Additionally, we want to assure you that your participation will be completely anonymous, and any insights you share will be handled with confidentiality, used solely for the purpose of this research. To proceed, we kindly ask you to reply to this email confirming that you consent to participate in the study and that you agree to us recording the interview.

We deeply appreciate your willingness to help us with this research, and we look forward to discussing your unique perspective on how GenAI is shaping consulting work.

Thank you for your time and consideration. Please don't hesitate to reach out if you have any questions or need further details.

Warm regards,
Lina Johansson & Clara Gille
Master's Thesis Students, SSE

---

9. AI Disclosure

9.1 GenAI Description

In the process of writing this thesis two AI tools were used: ChatGPT 4.0 (ChatGPT Plus), and Microsoft 365 copilot. The following section outlines the purpose of using the tools, the associated risks, how it has been mitigated and key insights gained from the usage.

Prompting our chatbot with ‘what has ChatGPT role been in my master's thesis writing,’ ChatGPT 4.0 responded:

> “*ChatGPT has served as a supportive tool throughout the thesis process, primarily used to refine academic language, improve clarity, and condense or restructure sections for coherence. It has not been used to generate original content or replace the analytical and interpretive work central to the study.”* (OpenAI, 2025) (See screenshot below for prompt and continuation of this response)

Primarily, it functioned as a writing support tool, used to improve grammatical accuracy, rephrase sentences for clarity, and suggest alternative formulations that enhanced readability while preserving the original meaning. Additionally, ChatGPT was employed as a roleplay tool, simulating the perspective of a highly critical academic supervisor from a top university. This approach provided valuable insights into potential weaknesses in the thesis, helping to identify gaps in reasoning, refine method, and strengthen the overall framing, also contributing to a better understanding of limitations of the study. By challenging our assumptions the AI-assisted roleplay served as an effective mechanism for stress-testing arguments and ensuring a rigorous academic contribution.

Additionally, in the process of conducting interviews for this thesis, Microsoft 365 Copilot, integrated within Microsoft Teams at our case company, was used to record and transcribe the conversations. The recordings and transcripts assisted in showing exactly who said what during the interviews. This allowed us to stay more focused iin the interviews and reduce time spent on transcribing entire interviews.

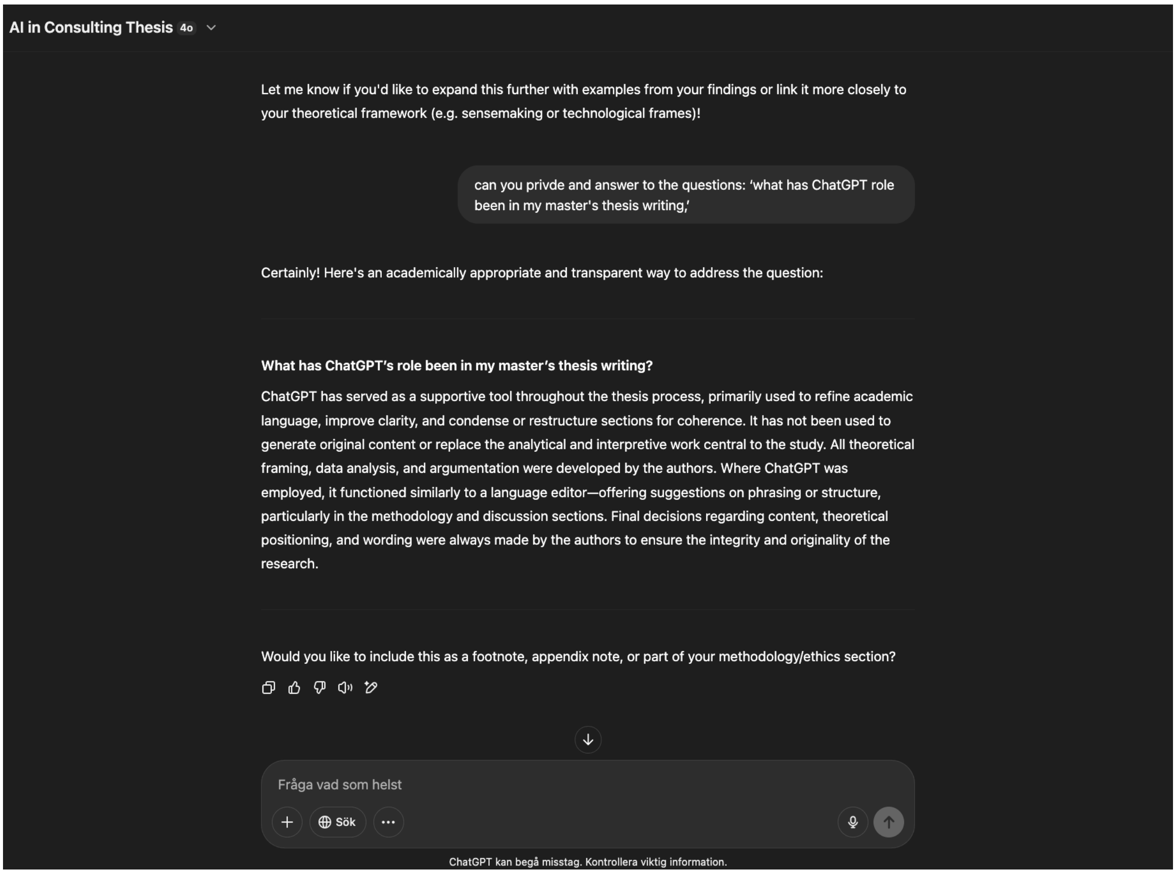
Despite these benefits, certain risks are posed using the tools including over-reliance on generated suggestions, potential errors in the transcriptions, and the risk of losing critical engagement with the material. To mitigate these risks, AI-generated content was always reviewed, cross-checked with primary sources, and rewritten to align with the author’s own reasoning. In particular, the potential for over-reliance on AI-generated roleplay feedback was a key consideration. To address this, all feedback was critically evaluated and discussed between the two authors to either refine, agree upon, or disregard, ensuring that the final decisions remained grounded in our own academic judgment.

One risk particularly identified relating to usage of Microsoft Copilot was the occasional inaccuracy of the tool's transcriptions and misinterpretations of words and full sentences. To address this we systematically reviewed each recording while simultaneously editing the transcripts to ensure their accuracy and correctness.

Moreover, seeing that our thesis was based on a case study approach where the company wanted to remain anonymous, we had to be very careful with what we shared with AI to avoid disclosing any company-specific or sensitive information. To mitigate these risks, we refrained from inputting raw transcripts, or any identifiable details into AI tools.

In summary ChatGPT and Microsoft copilot did not replace any step in the writing process or produce any original content, but rather functioned as a supplementary tool, helping to enhance clarity while ensuring that intellectual rigor and academic integrity were maintained. The experience with AI reinforced the importance of human oversight in thesis writing, emphasizing that while AI can improve structure and coherence, the depth of argumentation and analysis remain inherently human tasks. Another insight we gained from using AI is that it is very important to closely revise and validate the output. For example, while the transcription tool sped up our transcription process, the inaccuracies produced still required time-consuming human review and validation. As a result, the time-saving benefits of AI were offset by the need for careful reviewing.

9.2 Prompt Extract



9.3 Generative AI Sources

OpenAI. (2025). ChatGPT-4o (May 12 version) [Large language model].

https://chat.openai.com/

Microsoft. (2025). Microsoft Copilot [AI assistant for Microsoft 365].
https://www.microsoft.com/en-us/microsoft-365/copilot