The problem solvers’ problem-solver

An exploratory qualitative study of Management Consultants' adoption of Generative AI

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Abstract

The management consulting industry, historically resilient to technological disruptions, faces a potential paradigm shift due to rapid advancements in Generative Artificial Intelligence (GenAI). GenAI's ability to perform a broad range of language tasks and achieve complex reasoning distinguishes it from previous technological disruptions. This exploratory study examines what influences management consultants' adoption of GenAI. The extended Technology Acceptance Model (TAM2) is leveraged as a framework to understand the decision-making process. Using a qualitative approach, semi-structured interviews were conducted with 21 management consultants from different firms in Sweden. The empirical results from the inductive thematic coding reveal four themes that influence a consultant's adoption: role-specific aspects, technological factors, social dynamics, and identity threat and opportunity. Key takeaways include the relevance of GenAI in enhancing productivity and cognitive expansion, particularly for junior consultants. Moreover, the chat interface of GenAI increases accessibility, though manual oversight and concerns about sensitive data act as barriers. Furthermore, the perceptions of peers and support from the firm influence individual consultants' adoption decisions. Lastly, consultants perceive threats and opportunities to their identities, striving to stay relevant and competitive while maintaining control over their creative processes. Our analysis shows that TAM2 can effectively explain and enhance our understanding of what influences the adoption of GenAI, providing a robust framework for exploratory qualitative studies. Additionally, our study suggests the contribution of identity as a determinant, which is not addressed by TAM2. This warrants further investigation into how management consultants and, more broadly, knowledge workers perceive threats and opportunities to their identities in the context of GenAI.

Keywords: Management Consulting, Generative Artificial Intelligence, Technology Adoption, Technology Acceptance Model, Knowledge Work

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Definitions and abbreviations

Artificial Intelligence (AI)	An umbrella term for "the science and engineering of making intelligent machines" (Haenlein & Kaplan, 2019)
Augmentation	Humans closely collaborate with machines to perform a task (Raisch & Krakowski, 2021)
Automation	Machines taking over human tasks (Raisch & Krakowski, 2021)
Conversational AI	AI systems interact with users through a chat interface (Ritala et al., 2023)
Deep learning (DL)	A subset of machine learning that models data through layers of artificial neural networks, inspired by the neurons found in the human brain. (Goodfellow et al., 2016).
Generative AI (GenAI):	AI that can generate human-like content, such as text and images, in response to given prompts (a question or instructions) (Lim et al., 2023)
Knowledge Work	A cognitive process where new knowledge is generated and used (Iazzolino et al., 2017).
Large language models (LLMs)	DL models which are trained on massive amounts of text data available on the public internet and in databases, allowing them to learn language patterns, grammar, and context. (Ritala et al., 2023; Orrù et al., 2023)
Management Consultant	“Someone whose job it is to advise companies about the best way of managing and improving their businesses.” (Cambridge Dictionary, n.d)
Technology Adoption	“A decision to make full use of an innovation as the best course of action available” (Rogers, 2003)
Technology Acceptance	Attitude towards technology, the first step of adoption (Granić, 2023)
TAM2	The extended technology acceptance model (Venkatesh & Davis, 2000)

1. Introduction

The introduction chapter provides a background on the subject, followed by the purpose of our research. Next, the research question and delimitations of this study are presented.

1.1 Background

Since the creation of the first management consulting firm Arthur D. Little in 1886, the management consulting industry has been rather unaffected by changes and developments affecting other facets of the economy (Sayyadi et al., 2023). The business model, where consultants are sent to clients' organizations to find a problem and deliver subsequent solutions, has remained the same since the profession's origin. However, despite a century-long resilience, the management consulting industry may now be on the verge of disruption due to the rapid advancements in Generative Artificial Intelligence (GenAI). GenAI's ability to perform a broad set of language tasks and achieve complex reasoning sets it apart from previous technological disruptions, seriously challenging knowledge work (Berg et al., 2023; Orrù et al., 2023). Management consulting represents the epitome of the knowledge work industry, constantly switching between projects and having considerable downstream effects on the thousands of employees in the business they advise (Cemaloglu et al., 2019). While all knowledge-work industries are expected to be impacted by GenAI in some capacity, management consulting is the knowledge-work industry that has the highest exposure to GenAI applications (British Department of Education, 2023; Felten et al., 2023). Considering the imminent disruption due to GenAI, there is an urgent need to understand how and why management consultants adopt the technology.

Studying why individuals and organizations choose to adopt new technologies has been an area of interest for researchers and practitioners since the first Information Technology (IT) systems in the 1970s. This research domain, called Technology Adoption, has evolved significantly, primarily focusing on organizational settings and giving rise to many theories. Among these, the Technology Acceptance Model (TAM), introduced by Davis (1989), stands out as one of the most cited and rigorously tested theories in technology adoption research

(Bagozzi, 2007). As technology continues to reshape society, understanding the factors influencing technology adoption has become increasingly important, especially with the rise of Generative Artificial Intelligence (GenAI). Therefore, it is problematic that existing theories, including TAM, haven't been tested as they need to catch up with the rapid advancements in the technologies they seek to explain.

Despite the growing body of literature advocating for GenAI's disruptive potential in knowledge work, particularly within management consulting, there is a need for increased academic exploration of its adoption in a real-world setting. Understanding how management consultants decide to adopt GenAI remains underexplored but is critical as more firms look to integrate the technology. Moreover, GenAI's unparalleled ability to create content and reason complicates the adoption process, as it could potentially replace tasks we consider deeply human. This complexity necessitates further investigation into whether existing adoption theories can address the nuances of this revolutionary technology.

1.2 Purpose

The purpose of this exploratory thesis is twofold. Firstly, we aim to provide readers with a nuanced and comprehensive understanding of management consultants' decision-making process regarding adopting GenAI. This is done through interviews conducted with management consultants from various firms in Sweden. In doing so, we are venturing into the unexplored territory of primary research of management consulting and GenAI adoption. Here, management consulting serves as a lens to more broadly explore how and why knowledge workers adopt GenAI, comparing and contrasting this with the limited existing literature on the subject.

Secondly, we aim to identify new areas of interest for future research, in regards to GenAI adoption within knowledge work". Given the fundamental differences between GenAI and the technologies previously examined by adoption theories, it cannot be presumed that these theories remain relevant. By qualitatively comparing our empirical findings to the well-established extended Technology Adoption Model (TAM2), we can uncover aspects the existing model does not explain. In doing so, this thesis contributes valuable research directions regarding one of the most significant technological disruptions in knowledge work, ensuring that technology adoption theory remains relevant in the emerging era of GenAI.

1.3 Research Question

Motivated by the above reasoning, the following research question has been formulated:

What influences management consultants' *adoption of Generative AI?*

1.4 Delimitations

This study has three main delimitations that help to scope this study. First, this thesis is narrowed down to only encompass conversational GenAI chatbots and not any other type of AI. As such, this study does not explore the broader usage of AI and the implications of adopting such technologies. Secondly, this study is limited to specifically management consultants due to time and resource constraints. This limitation is motivated by research indicating the profession will be heavily impacted by GenAI. Lastly, the study has a geographical delimitation and focuses on management consultants in Sweden. While consultants from different firms in Sweden were interviewed to get a broad perspective, the results should not be seen as generalizable across the industry.

2. Literature review

This chapter covers a review of the Technology Adoption literature and presents the various theories that have emerged. Furthermore, Artificial Intelligence is explored in detail along with its several subsets, arriving at Generative AI. That is followed by an investigation of the existing literature about AI and GenAI in the realm of knowledge work. Lastly, a synthesis is presented to showcase the literary gap this thesis aims to fill.

2.1 Technology Adoption Theory

Research on technology adoption has been ongoing since firms started implementing IT systems to enhance white-collar performance (Davis, 1989). The most influential theories regarding Technology Adoption have their origins in social psychology and research on information systems (IS) (Ajzen, 1985; Davis et al., 1989). The Theory of Reasoned Action (TRA) was first introduced by Fishbein and Ajzen (1975) and laid the groundwork for further technology adoption research. New theories have been introduced, such as the Technology Acceptance Model (TAM), pioneered by Davis (1989), the Theory of Planned Behavior (TPB) created by (Ajzen, 1991), and the Diffusion of Innovation (DOI), which was first published in by Rogers in 1962, but was later modified to more closely align with adoption theory by Rogers (1995). These theoretical frameworks all aim to comprehend the factors influencing an individual's decision to adopt a new technology. One of the most recent addition to this body of literature is the Unified Theory of Acceptance and Use of Technology (UTAUT) as proposed by Venkatesh et al. (2003) which builds upon many of the previous theories but adds new independent variables to address context (see figure 1 for a more detailed description of the theories). Arguably the most widespread framework in this domain is the Technology Acceptance Model (TAM), pioneered by Davis (1989), where technology acceptance specifically relates to an individual's attitude toward a technology. TAM suggests that attitudes and behavioral intentions predict technology adoption through two primary perspectives: perceived ease of use and perceived usefulness. Expanding upon Davis's work, Davis and Venkatesh (2000) have further developed TAM into the extended Technology Acceptance

Model (TAM2), which incorporates social influences and cognitive factors. TAM and TAM2 will be further elaborated and discussed in the theory section of the thesis.

Technology Adoption Theories		
Theory	**Authors**	**Description**
Theory of Reasoned Action (TRA)	Fishbein & Ajzen (1975)	Predicts and explains human behavior by considering three primary cognitive components: attitudes, social norms, and intentions.
Technology Acceptance Model (TAM)	Davis (1989)	TAM explains user motivation through three factors: perceived usefulness, perceived ease of use, and attitude toward use.
Theory of Planned Behavior (TPB)	Ajzen (1991)	Perceived behavioral control (PBC) emerges as a novel variable. PBC is shaped by the accessibility of resources, opportunities, and skills and the perceived significance of these elements in achieving desired outcomes.
Diffusion of Innovation (DOI)	Rogers (1995)	The DOI model explores various innovations by introducing four factors (time, communication channels, the innovation itself, and the social system) influencing the dissemination of a new idea.
Extended Technology Acceptance Model (TAM2)	Venkatesh & Davis (2000)	TAM2 was introduced by incorporating two sets of constructs – social influence (image, subjective norms, and voluntariness), and cognitive factors (result demonstrability, job relevance, and output quality) – into TAM, aimed at enhancing the predictive capacity of perceived usefulness.
Unified Theory of Acceptance and Use of Technology (UTAUT)	Venkatesh et al (2003)	UTAUT identified four antecedents for information system acceptance, derived by refining fourteen initial constructs from eight acceptance theories. The key constructs include effort expectancy, performance expectancy, social influence, and facilitating conditions. Moderating variables are; Gender, experience, age, and voluntariness of use.
Technology Acceptance Model 3	Venkatesh & Bala (2008)	TAM 3 extends the TAM2 model by adding additional determinants to perceived ease of use; computer self-efficacy, computer anxiety, computer playfulness, and perceptions of external control.
Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)	Venkatesh et al (2012)	UTAUT2 extends the UTAUT model by adding; Hedonic motivation, Price value and Habit.

Figure 1. Technology Adoption Theories

Using the theories mentioned above as a lens, previous research on technology adoption has explored various industries, including manufacturing (Chao & Kozlowski, 1986; Venkatesh & Davis, 2000; Kim & Kim, 2018), education (Talukder, 2012), media (Jones, 1999; Karimi & Walter, 2015), and financial services (Brown et al., 2002; Veiga et al., 2014). Although previous literature regarding technology adoption covers a range of industries, it is mainly focused on IT systems, such as digital accounting and reporting, Customer Relationship Management (CRM), and Enterprise Resource Planning (ERP) (Kim et al., 2017; Dutta & Borah, 2018). With recent technological advancements, industries currently experiencing disruption differ from those impacted in the past by the emergence of IT systems. As such, there has been a transition from low-skilled to knowledge-intensive industries affected by new technology (Faraj et al., 2018; Susskind & Susskind, 2015; Ågerfalk, 2020). Considering the unique characteristics of GenAI and the industries it impacts, which are different from previous instances of technology adoption, there is a need to reassess existing adoption theories. Therefore, established theories have to be evaluated based on their relevance and effectiveness in understanding the factors impacting the adoption of new technologies.

2.2 Artificial Intelligence

Artificial Intelligence (AI) is an umbrella term that encompasses a variety of concepts. The discipline of AI officially emerged in 1956 during the Dartmouth conference, where John McCarthy, a professor at Stanford, characterized AI as "the science and engineering of making intelligent machines" (Haenlein & Kaplan, 2019). This involves machines learning, adapting, and solving problems autonomously in uncertain environments (Manning, 2022). There is no unanimous definition of AI; perspectives vary significantly with some emphasizing thought processes and reasoning, while others focus on observable behavior (Russell & Norvig, 2012). Just as there are numerous definitions, there are also many subfields within AI. These range from natural language processing, which analyses the structure and meaning of text (Russell & Norvig, 2012), to machine learning, which enables computers to understand patterns (Manning, 2022). Today, AI is an essential component of daily life, driving innovations such as voice assistants, smart speakers, and autonomous vehicles (Haenlein & Kaplan, 2019). Given that this thesis aims to investigate the adoption of GenAI, the following sections will concentrate on outlining and explaining some of the key technological advancements that led to its evolution (figure 2).

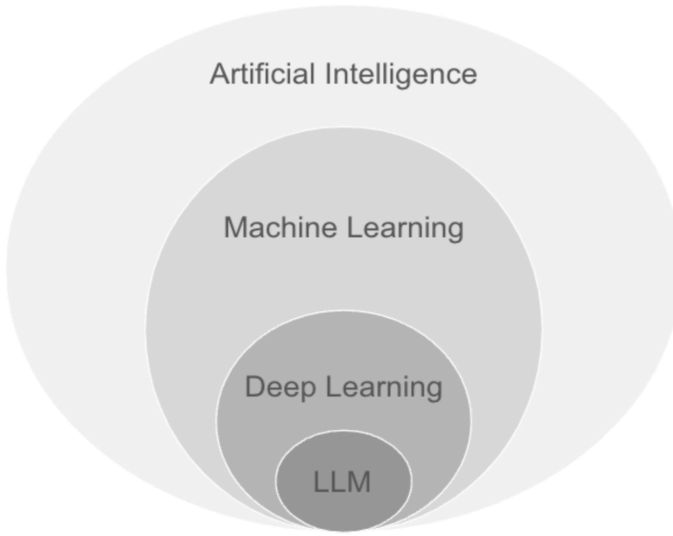

Figure 2. Technologies that enabled the GenAI revolution

The first significant leap started already in the 1950s with machine learning. Machine learning (ML) is a subset of AI, focusing on a computer's capacity to improve its prediction accuracy through exposure to data and experience. This approach allows systems to gradually increase performance over time, enabling a wide range of applications (Russell & Norvig, 2012). ML is categorized into three main types: supervised learning, where models make predictions based on human-labeled data; unsupervised learning, which involves identifying patterns and relationships in data without pre-assigned labels; and reinforcement learning, where a model learns to make decisions through trial and error, guided by a reward function decided by a human (Manning, 2022).

The next step in the evolution was Deep Learning (DL). DL is a subset of machine learning that models data through layers of artificial neural networks, inspired by the neurons found in the human brain. DL becomes powerful and flexible because it learns to view the world as a hierarchy of concepts, allowing the model to learn complicated concepts by building on simpler ones (Goodfellow et al., 2016). This approach allows the system to learn complex patterns from large volumes of unstructured data. DL has revolutionized fields such as image recognition and natural language processing, enabling machines to learn to perform tasks with increasing accuracy and human-like intuition (Goodfellow et al., 2016).

Building on the principles of DL, Large Language Models (LLMs) have been developed specifically to understand and generate human language. The models are trained on extensive collections of text, allowing them to learn language patterns, grammar, and context. One of the breakthroughs that enabled this training was the transformer architecture. Introduced by Vaswani et al. (2017) at Google Brain, transformers incorporate a novel attention mechanism that selectively concentrates on various segments of the input during processing, enhancing its ability to comprehend relationships between words and phrases. For instance, it enables the understanding that in the sentence "the teacher admired by the students is retiring," the phrase "is retiring" applies to "the teacher" and not to "the students" (Orrù et al., 2023). LLMs are different from traditional ML and DL approaches, not only predicting patterns but also generating entirely new data based on the original training datasets (Prasad, 2023). This capability enables LLMs to perform a broad set of language tasks, including translation, summarization, and complex reasoning (Orrù et al., 2023). This marks a revolution in artificial intelligence, shifting from narrow AI, designed for specific use cases like facial or speech recognition (Manning, 2022), to general AI, which aims to address a broad set of use cases by mimicking human thinking and reasoning (Ang et al., 2023). New GenAI chatbots show a higher degree of general intelligence compared to earlier AI models. They excel in language mastery and perform similarly to humans in various complex tasks such as coding, medicine, and law (Bubeck, 2023). Therefore, GenAI shows sparks of general intelligence from its broader capabilities while still not being close to achieving the versatility of human intelligence (Bubeck, 2023).

The pivotal moment for LLMs and GenAI came in November 2022 with the introduction of ChatGPT, based on OpenAIs LLM GPT3 (OpenAI, 2022). ChatGPT reached 100 million users two months after its launch, making it the fastest-growing consumer app ever and paving the way for the GenAI revolution (Milmo, 2023).

2.3 Generative AI and Chat Interfaces

Generative AI (GenAI) chatbots like ChatGPT are in essence trying to produce a "reasonable continuation" of whatever one might expect a human to write, based on billions of text inputs the LLM has been trained on (Wolfram, 2023). It is therefore a probabilistic model where the most likely next word is being presented, similar to how an auto-complete function can guess the next work you want to write. For example, if we have the sentence "The best thing about AI is its ability to…", the word "learn" will have the highest probability of being chosen (Wolfram, 2023).

What sets GenAI chatbots apart is their unique generative and conversational capabilities, increasing their ease of use and making them more broadly accessible (Ritala et al., 2023). Its generative capabilities enable it to create "original" content, imitating human creativity (Dwivedi et al., 2023; Ritala et al., 2023). Meanwhile, its conversational capabilities facilitate interactions in the most natural manner possible, through human language, making it more accessible and intuitive. This interaction not only allows for straightforward communication but also enables the AI to adapt its output based on direct user feedback, creating a dynamic of mutual learning (Ritala et al., 2023). The combined generative and conversational capabilities significantly enhance GenAI's applicability in fields that demand creativity and knowledge-intensive work (Berg et al., 2023).

As GenAI chatbots are steered by natural language, the specificity of the instruction or question to the model becomes important to ensure high-quality output (OpenAI, n.d). The process of guiding GenAI models to achieve desired outcomes is called Prompt Engineering (OpenAI, n.d). To get the most relevant output from questions, also called prompts, the user can specify the format, tone of voice, background, and context. The chat interface allows humans to follow up with feedback to the model, allowing iterations to find the desired output (OpenAI, n.d).

While GenAI poses significant possibilities, it also has inherent limitations grounded in how LLMs are built on prediction. One such limitation is what is called "hallucinations", where the model confidently gives a factually false answer. As the model can confidently present the information, it creates a higher likelihood of humans thinking the information is correct (Edelman and Abraham, 2023). Another challenge that LLMs pose for organizations is that some applications train their models on the data input. Therefore, sensitive or confidential client data should not be included when using a GenAI tool that trains on the input. However, this limitation is expected to disappear in future enterprise versions of GenAI software (Ritala et al., 2023).

2.4 Artificial Intelligence and Knowledge Work

The disruptive potential of AI has become increasingly evident in recent years, prompting an expansion of the research landscape. Scholars have highlighted how modern AI systems will affect not only routine low-skilled workers but also knowledge workers (Faraj et al., 2018; Susskind & Susskind, 2015; Ågerfalk, 2020). Knowledge work is the cognitive process where new knowledge is generated and used (Iazzolino et al., 2017). A knowledge worker's task is to leverage their knowledge to produce new knowledge as an output, which can be in the context of a service or product (Mládková et al, 2015). The impact of AI in knowledge work differs significantly from that in industries such as manufacturing, where data serves as the primary source of automation (Agostini & Nosella., 2020). Instead, in knowledge work, the automation and augmentation by AI primarily target human tasks of a more cognitive and analytical nature (Huang et al., 2019; Alavi & Westerman, 2023).

Given the complex nature of knowledge work, integrating AI into organizations providing knowledge-intensive services has proven challenging. Global surveys with senior managers across industries indicate a low adoption rate, with efforts to introduce AI often encountering obstacles (Zolas et al., 2020; Brock & von Wangenheim, 2019). While the full scope of this resistance remains to be fully understood, insights from knowledge work in the healthcare sector suggest several factors such as inadequate data availability, employee resistance, and a lack of internal competencies (Dwivedi et al., 2021; Sun et al., 2019). Furthermore, scholars have suggested that in knowledge work, due to the cognitive processing of information and the advanced training required, AI is unlikely to be able to completely replace human workers (Pettersen, 2019; von Richthofen et al., 2022.)

Several researchers have explored the augmentative potential of AI, portraying augmentation as the optimal scenario wherein humans are supported and enhanced by AI rather than substituted by it (Raisch & Krakowski, 2021; Henkel et al., 2020; Davenport et al., 2020). While knowledge work presents unique characteristics, the concept of AI augmentation remains consistent, encapsulated in knowledge work literature as: "Just AI won't replace you, but a person using AI will" (Lakhani, 2023). Research indicates that knowledge workers are indeed being augmented by AI, enabling more efficient work and a shift towards activities that contribute greater value (von Richthofen et al., 2022; Ritala et al., 2023).

2.4.1 Generative AI in Knowledge Work

The emergence of GenAI has fundamentally transformed our understanding of what tasks can be augmented or automated. In the realm of knowledge work, AI has traditionally operated behind the scenes within enterprise software, playing a supportive role. However, the advancement of GenAI applications, such as ChatGPT, signifies a distinct evolution in the interaction between humans and machines (Ritala et al., 2023). GenAI applications can significantly enhance the productivity of knowledge workers by improving information search processes and aiding in the creation process of tasks such as emails, proposals, and reports (Dwivedi et al., 2023). Furthermore, GenAI is particularly beneficial at the novice stage of learning a new domain, making the process simpler and quicker (Ritala et al., 2023). According to recent research, 19% of workers in the US are in an occupation where over half of their tasks are labeled as exposed, meaning that the time required to finish the task can be reduced by 50% (Eloundou et al., 2023). Knowledge work occupations were highest, with professions like auditors, journalists, and financial analysts. Contrary to prior findings of AI exposure in the area of machine learning, occupations offering higher wages show greater overall exposure than lower-income workers (Brynjolfsson et al., 2023). Writing and programming skills have a strong exposure to GenAI replacement while science and critical thinking skills have a low exposure (Eloundou et al., 2023). Although the replacement of tasks might seem negative, research indicates that 41% of a knowledge worker's time is spent on activities that offer little personal satisfaction (Birkinshaw & Cohen, 2013), highlighting the potential of GenAI to enable greater worker satisfaction and more time spent on value-adding activities.

The literature on GenAI adoption in knowledge work is understandably sparse due to its recent emergence (Brynjolfsson et al., 2023). Brynjolfsson et al. (2023) provide one of the first studies of the impact of GenAI deployed at scale in the workplace. Investigating the integration of a GenAI tool providing conversational guidance for human customer support agents, the study found a 14% increase in productivity. GenAI benefited novice and lower-skilled workers more, boosting their productivity by 35%, whereas experienced workers saw minimal impact. This contradicts prior research showing that computer technology complements higher-skilled workers more effectively (Autor et al., 2003; Bresnahan et al., 2002; Bartel et al., 2007). Brynjolfsson et al. (2023) theorize that this difference stems from GenAI's ability to capture the behavioral patterns of the most efficient humans, and then advise novice workers. Additionally, lasting learning effects were noticed among agents who interacted with AI recommendations, as productivity improvements were sustained during software outages (Brynjolfsson et al., 2023).

Woodruff et al. (2023) conducted a study examining the impact of Generative AI on knowledge worker professions. Within the law profession, GenAI can aid research if given professional oversight, potentially replacing entry-level roles but not skilled professionals. There is also a fear of clients beginning to use GenAI tools for some legal tasks, affecting profits. Moreover, in advertising, some tasks are likely to be under threat immediately, like copywriting and photography production. In other tasks, GenAI acts as a brainstorming tool, with creative oversight remaining the norm to check for any violations of brand standards or copyright. Furthermore, in business communication, GenAI can handle routine tasks like drafting disposable communication such as emails and proposals. While in software development, GenAI will likely automate routine tasks and affect entry-level roles, limiting some entry paths. There is also some fear that GenAI will replace meaningful problem-solving tasks, leading to demotivation. Overall, employees in several professions feel the need to learn about GenAI to stay relevant and protect their careers. Many feel uncertain about how their roles will change and feel pressured to adapt (Woodruff et al, 2023).

In another study, Russo (2024) investigates the factors influencing the adoption of GenAI in software engineering, using established theories like the Technology Acceptance Model and

Social Cognitive Theory. The study finds that users tend to view GenAI as a tool that complements human expertise and judgment, highlighting the crucial balance between the advantages of GenAI and the necessity for human oversight, influencing the overall perceived usefulness. The applicability is limited because code review and comprehension are still necessary, aligning with the TAM literature that emphasizes a technology's perceived usefulness is shaped not only by its benefits but also by its inherent limitations (Venkatesh et al., 2003). Furthermore, the user-friendly interface and easy learning curve associated with GenAI tools are key factors impacting ease of use (Russo, 2024). However, the ease of use of GenAI depends on the complexity of the task. Moreover, Russo (2024) demonstrates, from the perspective of Social Cognitive Theory, that peer influence affects GenAI technology adoption. Engineers are motivated to adopt cutting-edge technology to enhance their reputation and to demonstrate their ability to use new technologies that effectively solve problems or meet client needs. Additionally, environmental factors play a role where a supportive organizational culture that encourages and invests in new technology impacts adoption (Russo, 2024).

2.4.2 AI in Management Consulting

As GenAI begins to penetrate the management consulting industry, literature within this sector remains limited. Existing research predominantly centers on exploring the potential implications of GenAI rather than primary data on how consultants perceive the technology.

In a recent study, being among the first to explore GenAI in the context of management consultants using primary data on a large scale, Dell’Acqua et al. (2023) examined 758 consultants at Boston Consulting Group (BCG). The authors suggest the existence of a "Jagged Technological Frontier," where several common tasks of management consultants can be performed by AI while others cannot. Hypothetical business cases touching on creativity, analytical thinking, writing proficiency, and persuasiveness were used to test the consultant's performance. The frontier delineates tasks that fall within or outside the current capabilities of GenAI. The findings indicate that management consultants utilizing GenAI are significantly more productive, completing 12.2% more tasks at a 25.1% higher pace. Moreover, consultants incorporating GenAI in their tasks produce results of over 40% higher quality, with those performing below the average threshold improving their performance by 43%. However, management consultants face challenges in determining what falls within the jagged frontier and often rely too heavily on GenAI, which tends to make mistakes on tasks outside this frontier. Consequently, consultants using GenAI are 19% less likely to generate the correct solution than those not using GenAI (Dell'Acqua et al., 2023).

While the findings of Dell'Acqua et al. (2023) suggest that GenAI significantly impacts management consultants' productivity and ability to produce quality output, a study conducted by Sayyadi et al. (2023) presents a contrasting perspective. Through interviews with 81 senior management consultants from several prominent global firms, their research reveals a perception that somewhat downplays the disruptive potential of AI and overconfidence in the historical ways of working. These insights provide a unique and compelling viewpoint on how management consultants view AI, diverging significantly from the prevailing discourse within the industry as evidenced by existing research (Dell'Acqua et al., 2023; Mohan, 2024; Ritala et al., 2023).

Mohan (2024) examines the various processes involved in the work of management consultants, highlighting the potential for different tasks to be either augmented by AI, led by AI, or led exclusively by humans. In this framework, tasks such as "data analysis" and "searching for possible solutions" are identified as likely to be AI-led. Conversely, tasks like "providing feedback to clients" and "presenting action proposals to clients" are indicated as the exclusive domain of human experts. Mohan (2024) emphasizes that management consulting is fundamentally a people-centric business, where client engagement remains an area beyond AI's current capabilities.

Contrasting the view that GenAI will lead in the search for solutions, Cemaloglu et al. (2019) discuss the concept of "thinking agency" versus "execution agency" in consulting. Thinking agency refers to the capacity to generate ideas freely, while execution agency is the capability to act upon or implement those ideas. The study finds that while management consultants are willing to give up some control over the "execution agency" to AI, they are not willing to give up control over the thinking agency. This perspective is particularly interesting given that it predates the rise of GenAI and highlights the evolving perception of GenAI’s capabilities. Moreover, Cemaloglu et al. (2019) state that although AI and automation are often seen as threats to human labor when strategically implemented, they can relieve individuals from the monotonous tasks that typically dominate the average workday, allowing for greater focus on creative and cognitive tasks.

Samokhvalov (2024) investigates the potential transformation in business models and the evolving role of management consultants in this new era. GenAI has the potential to significantly transform the consulting industry by accelerating data analysis and creating presentations, thereby reducing costs. This likely means that the value of consultants will shift towards more strategic input from senior consultants rather than number crunching. Traditional business models based on billable hours for labor-intensive work may need to evolve. However, despite standardized frameworks, trust and social interaction with clients remain crucial, especially in managing complex organizational changes. Additionally, Samokhvalov (2024) predicts significant client and consultant resistance to completely outsourcing consulting tasks to AI. Human judgment will continue to control decision-making, while AI will focus on automating underlying processes.

The limited research on AI within management consulting underscores two primary aspects. Firstly, there is a consensus among researchers regarding the transformative impact that AI will have on the consulting industry, with scholars advocating for further investigation to better understand its role in the industry (Mohan, 2024; Samokhvalov, 2024). Secondly, existing literature largely adopts an industry perspective grounded in secondary data analysis. However, the few studies based on primary data offer conflicting findings: while some management consultants underestimate AI's potential, others report significant gains in productivity and quality when using it. This conflicting view warrants further research, utilizing primary data analysis to truly discern the thoughts and reasoning of management consultants regarding GenAI.

2.5 Synthesis

Although the technology adoption literature has been around for a long time and is extensive, it is scarce in exploring GenAI, and even more so in the context of management consulting. Hence, there is a gap in the literature where these three subjects intersect (figure 3), and to the best of the author's knowledge, there is no current research exploring the adoption of GenAI within the management consulting industry. As such, this thesis aims to contribute to the literature by combining the three subjects to bring clarity to what this intersection entails.

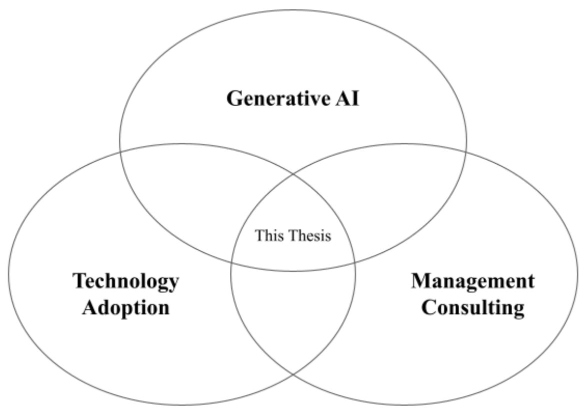

Figure 3. Scope of the thesis

3. Theoretical framework

This section of the thesis presents the theoretical framework chosen to answer the research question. First, TAM is briefly discussed, followed by a longer discussion of the extended TAM (TAM2), the theoretical lens utilized in this study. Lastly, possible limitations of TAM2 are delved into as well as the implications of using the model in qualitative research.

3.1 Technology Acceptance Models

The original TAM model was developed by Fred Davis in 1989 to predict an individual's acceptance and use of new technologies in a work context. Davis (1989) notes that information technology has significant potential to improve white-collar performance, but barriers to users accepting and using available systems are hindering this potential gain. Therefore, it is of utmost priority for researchers and practitioners to understand the predictors of user acceptance. Over the years, the original model has been extended several times, most notably the TAM2 extension by Venkatesh and Davis (2000), as well as TAM3 by Venkatesh and Bala (2008). There has also been extensive focus on analyzing TAM in the context of new technologies (Vogelsang et al., 2013).

3.1.1 TAM

The TAM model (figure 4) suggests two main determinants that influence system use based on previous research. Firstly, *perceived usefulness* is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989). Assuming that individuals are driven by gaining monetary rewards, promotions, and other recognition by improving their performance, perceived usefulness should positively impact technology acceptance. Secondly, *perceived ease of use* is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989). As individuals have limited time allocation, the ease of using a system likely impacts the acceptance of such a system.

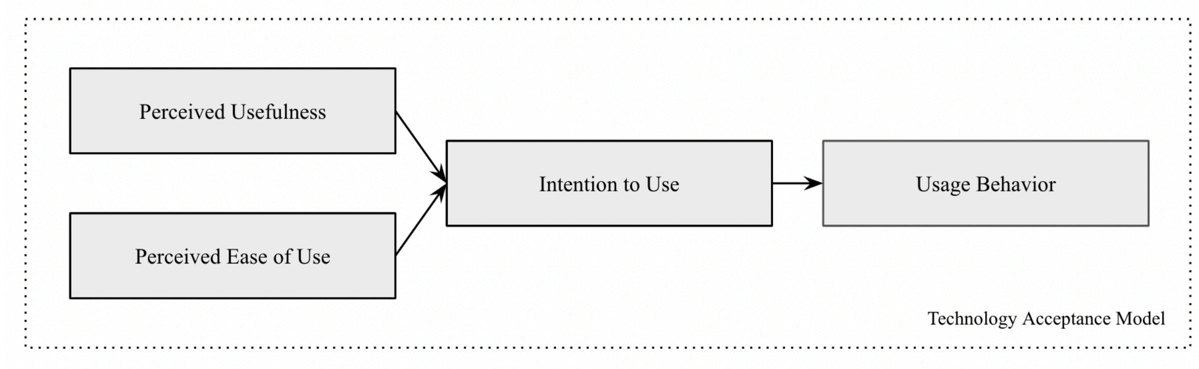

Figure 4. Technology Acceptance Model by Davis (1989)

While the model seems simplistic, which is one of its advantages, empirical studies have shown that TAM explains a significant proportion of the variance in different contexts, typically around 40%. However, one of the model's main criticisms is the lack of focus on social and subjective norms that impact the acceptance of technology (Venkatesh & Davis, 2000). In 2000, Venkatesh & Davis (2000) set to address these criticisms by extending the model.

3.1.2 TAM2

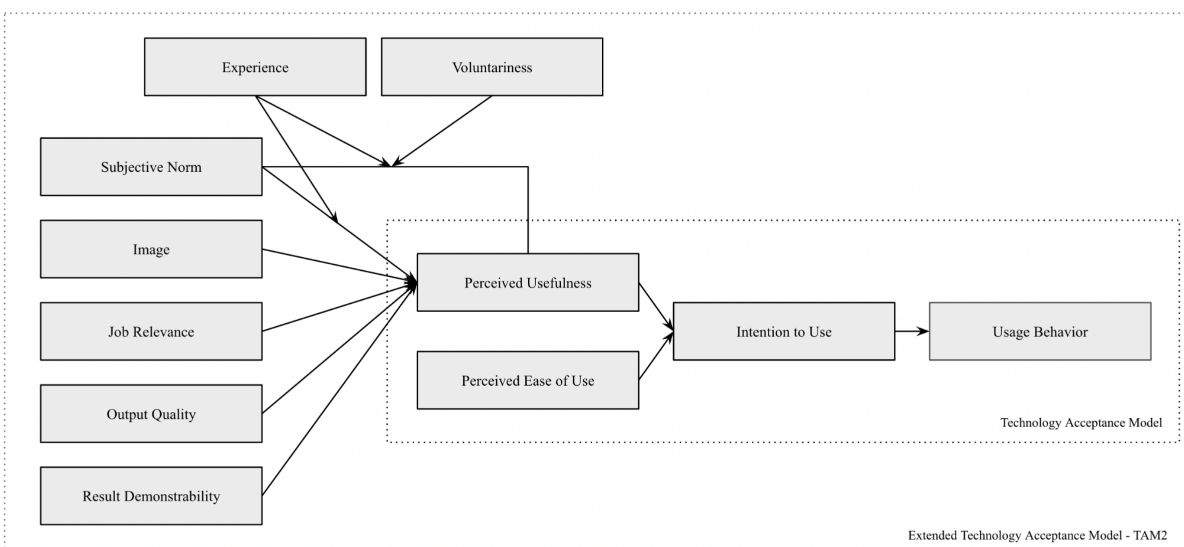

Figure 5. Extended Technology Acceptance Model (TAM2) by Venkatesh & Davis (2000)

TAM2 (figure 5) extends the original model by integrating three interconnected social influence processes that impact an individual's decision to adopt a new system: subjective norm, voluntariness, and image (Venkatesh & Davis, 2000). *Subjective norm* is defined as a "person's perception that most people who are important to oneself think one should or should not perform the behavior in question" (Fishbein and Ajzen, 1975). Stemming from earlier models like TRA and TPB (see figure 1 in section 2.1) the concept holds importance by proposing that individuals may accept a technology despite not having a favorable attitude if they perceive that influential individuals around them endorse its use.

Furthermore, *voluntariness* acts as a moderating variable, influencing the relationship between subjective norm and intention of use, depending on whether system usage is mandatory or voluntary (Venkatesh & Davis, 2000). Referred to as compliance, TAM2 finds a direct effect on intentions in mandatory environments, but not in voluntary ones. Moreover, TAM2 proposes an indirect impact on intentions called internalization. This implies that subjective norm influences perceived usefulness, because if peers and superiors advocate that a system is useful, you are more likely to start believing it, thus creating intentions to use it. This aligns with French and Raven's (1959) bases of power taxonomy, where internalization, called expert power, creates influence.

Lastly, TAM2 suggests that subjective norm positively impacts *image*, defined as "the extent to which the use of an innovation is perceived to enhance one's status within a social system" (Venkatesh & Davis, 2000). In a typical work environment where people depend on each other to complete tasks, having a higher status within the group gives a person more power, also called referent power (French and Raven, 1959). This sort of power often comes from social exchanges and the forming of coalitions. Therefore, someone might think that using a new system will indirectly boost their job performance by improving their image, along with any direct benefits from the system (Venkatesh & Davis, 2000).

In addition to social influences, TAM2 includes three new cognitive instrumental processes that determine perceived usefulness: job relevance, output quality, and result demonstrability. *Job relevance* is defined as an "individual's perception regarding the degree to which the target system applies to his or her job" (Venkatesh & Davis, 2000). In essence, an individual assesses the match between the technical capability of a technology and the job requirements. *Output quality* is defined as how well the system performs the tasks seen as relevant to the job. Lastly, *Result demonstrability* is defined as the "tangibility of the results of using the innovation" (Moore & Benbasat, 1991), meaning that user acceptance is more likely if it is easier to attribute job improvements to the specific technology. Overall, TAM2 offers an in-depth explanation of the primary factors influencing acceptance, explaining 60% of the variance in the intentions to use a technology (Venkatesh & Davis, 2000).

3.1.3 Limitations

Several scholars have identified limitations in the Technology Acceptance Model. One important constraint is its failure to consider external factors, such as age and education, which could influence individual acceptance (Burton & Hubona, 2006). These moderating variables are addressed in alternative models, such as the Unified Theory of Acceptance and Use of Technology (figure 1 in section 2.1) (Venkatesh et al., 2003). Secondly, Lee et al. (2003), argue that the TAM framework is limited in its practical applicability for managers. Simply stating that a technology needs to be perceived as useful and easy to use provides limited guidance for managers on product design or understanding user perceptions. Even with the enhancements introduced in TAM2, which expands on the original model's determinants, there remains a significant gap in its ability to explain user behavior comprehensively (Lee et al., 2003). The limitation in TAM's simplicity is further acknowledged by Bagozzi (2007), highlighting that the model provides an overly simplistic perspective on rather complex decision-making processes. Conversely, the extensions into TAM2 and TAM3, which introduce additional determinants and assumptions about moderating effects, instead complicate its application.

3.1.4 Using TAM2 with a Qualitative Research Approach

Since its inception in 1989, TAM has been predominantly applied through quantitative methods. Vogelsang et al. (2013) argue that qualitative methods using the TAM2 model could be used to better understand the intricacies and nuances of interactions between man and technology. In the limited number of studies employing qualitative methodologies, researchers have uncovered findings that extend beyond conventional theories. Studies have for example investigated the influence of personality (Ouadahi, 2008) and leadership (Kavanagh & Ashkanasy, 2006) on technology acceptance. Using a qualitative approach, novel acceptance factors not covered by existing literature can be found, creating the potential for expanding the theory further (Vogelsang et al., 2013). The richness of qualitative data allows for a detailed exploration without the need to simplify it into quantitative scales. Moreover, a manageable number of qualified interviewees can be carefully chosen, ensuring insights about the real use of the technology instead of relying on an unqualified sample (Vogelsang et al., 2013).

As this thesis aims to explore what influences adoption decisions, we have chosen a qualitative approach based on the TAM2, following the methodology of Vogelsang et al. (2013). This approach allows for a deeper examination of the reasoning behind decision-making rather than focusing on prediction accuracy or generalizability. In the context of the GenAI era, understanding the motivations behind human-technology interaction requires a more nuanced investigation than what quantitative, questionnaire-based surveys can provide. Additionally, this qualitative framework enables the development of comprehensive managerial recommendations, improving practical relevance (Vogelsang et al., 2013).

4. Methodology

This chapter explains the research approach used to conduct the study. It also presents the research process, both for the pre-study and the subsequent main study. Lastly, the methodology is discussed from a quality and trustworthiness standpoint.

4.1 Research Approach

4.1.1 Methodological Fit

This thesis aims to examine what influences management consultants' adoption of GenAI using an exploratory qualitative methodology. The study was conducted with an exploratory purpose in which preliminary data was gathered to provide direction and insights for future research (Makri & Neely, 2021). As elaborated in the literature review, GenAI in the workplace is a relatively new phenomenon, so prior research on the topic is scarce. Therefore, a qualitative method was deemed suitable for such a nascent research area (Edmondson & McManus, 2007). Additionally, a qualitative approach was appropriate given the aim of the study; to understand the research subject's reasoning, experiences, and feelings about GenAI which subsequently drives or prevents adoption. To capture such abstract concepts, a qualitative approach is significantly more fitting than a quantitative one (Bell et al., 2019). Following the methodology of Vogelsang et al. (2013), using the TAM2 model qualitatively was deemed the most appropriate approach for our research. The newer TAM3 model was considered less suitable, as it introduces determinants of computer use that add unnecessary complexity without providing additional value, which was confirmed during our pre-study.

4.1.2 Research Design

An abductive study was deemed most appropriate to achieve our dual purpose of both inductively understanding management consultant's adoption decisions and then explaining these decisions based on a well-established model. This approach facilitates an iterative process of integrating theory and data to formulate explanations for observations and comprehend the factors influencing specific concepts (Bell et al., 2019). The interview guide (see Appendix 3) was created based on the qualitative research approach of Vogelsang et al.

(2013) using the TAM2 model. As part of the iterative process, the interview guide was continuously updated to capture various emerging phenomena. For instance, the guide was revised following the pre-study to allow the exploration of interesting themes. Moreover, additional themes were added later as the authors wanted to dive deeper into certain insights.

4.1.3 Data Collection

As will be detailed in section 4.2, this study incorporates data obtained from both an initial pre-study and a subsequent main study. In both phases, semi-structured interviews were conducted with participants to understand their perspectives on adopting GenAI, thus addressing the research question. The use of semi-structured interviews, guided by an interview protocol, facilitates responses that are codifiable yet yield comprehensive and nuanced insights (Bell et al., 2019). The interview guide was crafted based on inspiration from the theoretical framework employed in this study, TAM2, which encompasses various facets of technology adoption. The interview guide served primarily as a conversational tool to explore relevant topics and it was continuously refined to accommodate emerging themes, enabling the researchers to adapt swiftly (Bell et al., 2019).

At the start of each interview, the authors provided an overview of the study, highlighting its focus on GenAI. This approach allowed interviewees to seek clarification on any uncertainties regarding the classification of GenAI, thereby ensuring that discussions remained focused on the research question, ultimately enhancing the efficiency of the interviews. Utilizing the interview guide as a starting point (Dilley, 2000), participants were initially asked about their roles, daily tasks, and experiences with GenAI. Subsequently, they were faced with more open-ended questions stemming from TAM2 to understand their decision-making process more deeply.

To ensure accurate capture of participants' reflections and responses, all interviews were recorded and automatically transcribed in Microsoft Teams, with participants' consent. One author primarily focused on note-taking during interviews to mitigate reliance solely on automatic transcription and ensure high quality, while the other led the discussion. This approach allowed the authors to compare their notes with the automatically generated transcripts after each interview, uncovering any insights that might have been overlooked or omitted during the interview.

4.2 Research Process

As shown in Figure 6 below, the research process consisted of two phases: a preparatory pilot study and a subsequent main study.

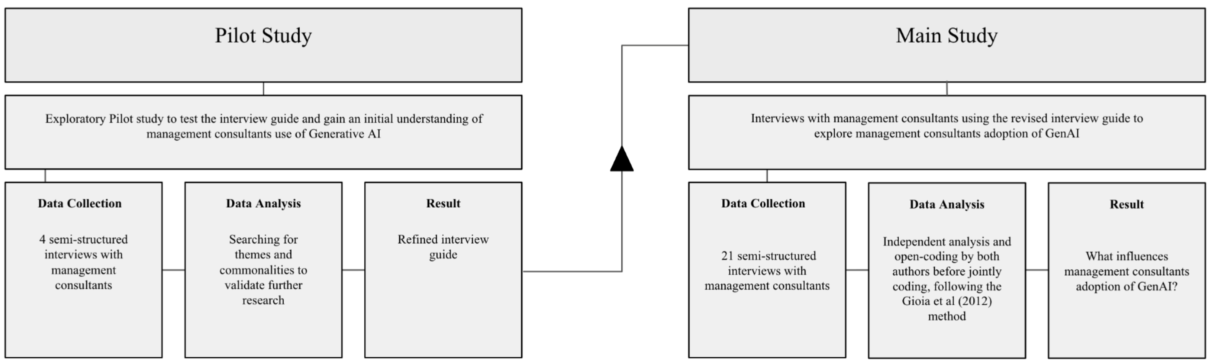

Figure 6. The Research Process

4.2.1 Pre-study

To start the research process, a pre-study was conducted to get a glimpse into the world of management consulting and thereby unravel the role that AI and GenAI currently have in the industry. The pre-study consisted of four semi-structured interviews with interviewees from four different companies of various sizes (see Appendix 1). The interviews provided insights used to validate the frequency of the phenomena within the specific context under investigation, aligning with the objective of the pre-study (Bell et al., 2019). In the context of this thesis, this entailed confirming the prevalence of GenAI usage within the management consulting industry. The pilot interviews were conducted between the 12th and 16th of February 2024 and covered questions about the interviewee's experience with, and perception, of GenAI in their work environment (see Appendix 2). Following the initial interviews, the interview guide was revised for the main study (see Appendix 3), resulting in changes to the questions for more openness and clarity to enhance the quality of the subsequent interviews (Bell et al., 2019). The pre-study interviews unveiled an interesting dynamic, at times revealing a discrepancy between the communication within the firm regarding GenAI usage and the actual experiences reported by interviewees. Additionally, the interviews shed light on how the use of GenAI influenced individuals' status in the workplace, occasionally enhancing it while at other times creating doubts about the quality of their work. Despite the interviewees' diverse experiences with GenAI, there was unanimous agreement among participants that GenAI would undoubtedly become an important industry element in the near future. The diverse, and sometimes contradictory, implications of and reasons for adopting or not adopting GenAI, along with the consensus regarding GenAI's future role within the industry, provided the validity required to proceed to the main study. The main study aimed to further investigate what influences the adoption of GenAI.

4.2.2 Main Study

Following the pre-study, the authors proceeded to the main study, as the insights from the initial interviews validated further studies. This section discusses the interview sample, the interview design, and data analysis.

4.2.2.1 Interview Sample

The interview sample for this study was selected to cover a diverse range of perspectives, drawing from multiple interviewees representing various organizations. To achieve this, a priori-purposive sampling technique was employed, wherein interview subjects were chosen based on predetermined criteria established in the initial stages of the research to ensure their relevance to the study's focus area (Bell et al., 2019). For this study, criteria included (i) full-time employment at the organization; (ii) a minimum of 6 months at the organization; (iii) a role as a management consultant; and (iv) a diverse range of organizations. The first two criteria ensured that all interview subjects had enough experience in their role and organization to have attained a good understanding of their tasks, workflows, and processes, especially those related to AI. The third criterion was implemented to target management consultants as interview subjects, ensuring that the participants represented this particular professional domain, rather than any other similar consulting roles. This selection criterion was essential to align the research focus with the intended exploration of the management consulting field. Lastly, incorporating management consulting firms of various sizes: small, medium, and large: provides a range of perspectives. This allowed the authors to gather a more nuanced perspective beyond a single organization and provide insights that hold relevance on a broader level, within the confines of qualitative research.

Unlike the predetermined criteria mentioned above, the number of interviews to be conducted was not set in advance. Instead, the authors employed theoretical saturation as a guiding principle. This approach ensured that interviews were conducted until reaching a point of saturation, where additional interviews ceased to yield significant new insights, thus ensuring the value-added nature of each interview and avoiding diminishing returns (Bell et al., 2019). Following the 17th interview, it became apparent that the point of saturation was close, as only a few new insights emerged. After the 19th interview, little new insights were generated, and the data only confirmed themes that were already present. As such, the authors concluded that saturation had been reached. To fully explore the empirical setting and prevent that theoretical saturation was falsely assumed, 2 more interviews were held to ensure all themes had been exhausted (Crouch & McKenzie, 2006).

In total, the main study included 21 interviews with management consultants from 12 companies. Figure 7 shows the distribution of different firms among the interview subjects. Interviewees were primarily identified through the author's network, as well as through outreaches on LinkedIn to appropriate candidates. For a more exhaustive list of the interview sample, see Appendix 1. Consultants with "Senior" in their job titles are labeled as such due to their managerial responsibilities, which differentiate them from junior consultants. Firms H, J, and K are most common in the sample, as 3–4 interviews were conducted with employees of these firms. The authors conducted further interviews within the same firms as good personal contacts had been established there, and the initial interviews yielded intriguing findings. This motivated further exploration of those insights by conducting additional interviews within the same organizations. However, although certain firms are more occurring than others, it did not affect the quality of the sample as interviewees within the same firm often had diverse experiences and perceptions.

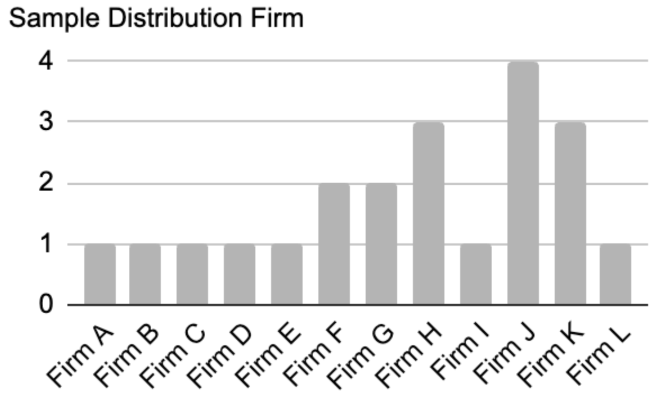

Figure 7. Main Study Sample Distribution of Firms

The authors sought to gather a varied sample by conducting interviews with management consultants from firms of varying sizes. Nevertheless, it's crucial to acknowledge the potential bias in the results, as those interviewed may be more inclined to participate if they have a strong interest and familiarity with GenAI, leading to a favorable attitude towards it and potentially skewing the study's findings. However, as will be shown in the empiric section, no such bias was indicated in the sample, as the interviewees shared experiences and perspectives of both positive and negative nature towards GenAI.

4.2.2.2 Interview Design

Interviews were conducted using a semi-structured approach, with interviewees being asked a variety of open-ended questions that were slightly altered based on the answers being provided. This methodology aimed to enhance the likelihood of obtaining authentic perspectives from the sample participants (Bell et al., 2019). The length of the interviews varied from 27 to 55 minutes. The variation in terms of length is explained by subjects' varying knowledge and usage of GenAI and the fact that management consultants have limited time to lend to activities outside of their work. The interviews started similarly with simple questions to make the subject feel at ease (Dilley, 2000). As the conversation progressed, more open-ended questions were introduced and follow-up questions were asked to adapt the interview based on the interviewee's responses. At the end of each interview, to guarantee that all information and insights were included, the participants were given the chance to share any additional insights that had yet to be brought up during the interview (Bell et al., 2019). In several interviews, this approach captured interesting insights that otherwise would have been overlooked.

To accommodate the busy schedules of management consultants, all participants were offered to do the interviews either digitally or physically. Not surprisingly, all subjects opted for the more time-efficient digital interview option. As such, all interviews were conducted digitally through Microsoft Teams. The interviews were recorded and automatically transcribed after the participant had given consent and been informed that transcripts would be treated with confidentiality to align with ethical data collection (Bell et al., 2019). In addition, considering the intricate nature of the topic, interviewees were assured that their names and organizations would be anonymized. Although physical interviews are always preferred as being in the same room makes it easier to interpret body language, facial expression, and other non-verbal cues (Bell et al., 2019), they are only marginally advantageous compared to video interviews (Irani, 2019).

Lastly, to ensure that all participants could express themselves without any language constraints, all interviewees were asked if they preferred to interview in either English or Swedish. As a result, 3 interviews were held in English, and 18 were held in Swedish. Although conducting research in two languages may present translation challenges, particularly when incorporating quotations, the authors prioritized obtaining a genuine understanding of participants' perspectives on GenAI adoption. Thus, it was imperative to minimize the risk of miscommunication (Felderman & Hielb, 2020).

4.2.2.3 Data Analysis

The analysis began with transcript refinement, a crucial step where each author reviewed and corrected the recordings to ensure accuracy in language and meaning, thereby maintaining data integrity for further analysis. After refining the transcripts, the authors independently coded the data, using an open-coding approach (Corbin & Strauss, 1998). The coding software ATLAS.TI was used to expedite the coding process. The software simplified the identification and organization of codes within the dataset, as well as streamlined the retrieval of quotes when building the empirical results. It also enabled easy visualization of the codes and a quick overview of the most frequently mentioned codes. When the individual coding phase was completed, the authors had a thorough discussion to solve all discrepancies and remove duplicates, to finally reach a consensus of what codes should be included (Bell et al., 2019).

Once a comprehensive understanding of the open codes was reached, Gioia et al. (2012) data analysis methodology was applied, which is tailored for abductive reasoning, to organize and interpret data systematically. Firstly, the open codes provided the base of the analysis, where 1st order concepts were identified. The focus was on capturing what interviewees said faithfully and growing the code database. Examples of first-order themes are formulation tasks and learning a new domain. Secondly, 2nd order themes were constructed, categorizing the 1st-order concepts into a more manageable number and analyzing what is interesting in regards to the research questions. Examples of 2nd order themes are productivity and cognitive expansion. The final step involved synthesizing these findings into aggregate dimensions, providing a structure for presenting our empirical results. A visual representation of how we progressed from 1st order concepts to aggregate dimensions can be seen in figure 8 below.

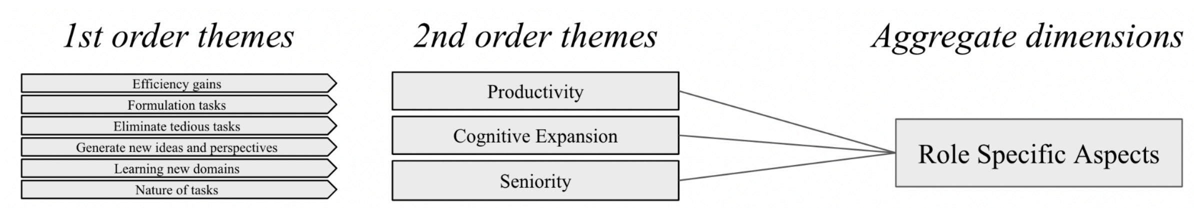

Figure 8. Visual representation of Gioia et al. (2012) analysis

4.3 Quality and Trustworthiness of Study

4.3.1 Quality of Research

In academic research, reliability and validity serve as common metrics for assessing research quality, though they are predominantly associated with quantitative research methods (Bell et al., 2019). Gauging the quality of qualitative research, such as this thesis, poses a distinct challenge. However, Guba and Lincoln (1994) propose that its quality can be evaluated through an examination of its trustworthiness. The concept of trustworthiness consists of four criteria, each stemming from its equivalent criteria in quantitative research (Bell et al., 2019). As such, the criteria to assess qualitative research are *credibility*, *transferability*, *dependability*, and *conformability*.

4.3.2 Trustworthiness

The criteria of credibility revolve around the exploration of diverse viewpoints to comprehend social reality. This underscores the importance of ensuring that research conclusions are credible, which depends on the plausibility of the account among various possible explanations (Bell et al., 2019). To ensure the credibility of this thesis, the authors leveraged the technique of member validation which suggests sharing the research with the sample group to ensure that the findings are aligned with the perspectives of the interviewees.

Given that qualitative research typically focuses on a limited group, its findings tend to be context-specific. Therefore, transferability is crucial to determine whether the research findings remain applicable in different contexts and at various points in time (Lincoln & Guba, 1985). Geertz (1973) advises qualitative researchers to create a “thick description”, meaning a detailed description of the context being studied so that others can make judgments regarding the transferability of the study in question. Hence, the authors of this thesis have provided a detailed review of the sample in section 4.2.2.1.

The third aspect, dependability, centers around keeping complete records of the research process in an accessible manner to demonstrate that the research is trustworthy (Bell et al., 2019). As such, the authors have included rich descriptions of the methodology in this chapter and included relevant appendices. The fourth and last criterion is conformability, which concerns findings and insights derived from data rather than theoretical inclinations or personal values (Bell et al., 2019). To uphold conformability, both authors were present for all interviews except two; however, as those interviews were recorded, the absent authors could review the material later to prevent distortion. Moreover, biased interpretations were mitigated as both authors independently analyzed the data before engaging in joint processing of the data (Timmermans & Tavory, 2012).

5. Empirics

This section presents the results of interviews conducted with management consultants. The findings are structured based on the Gioia methodology, and selected quotes are incorporated to exemplify, shed light on specific topics, and provide background to the findings.

The empirical result showed that all interviewees had used GenAI at some point as management consultants. However, the extent of their usage and perception of GenAI varied among individuals. Moreover, various themes could be extracted regarding their decisions to adopt GenAI (see figure 9).

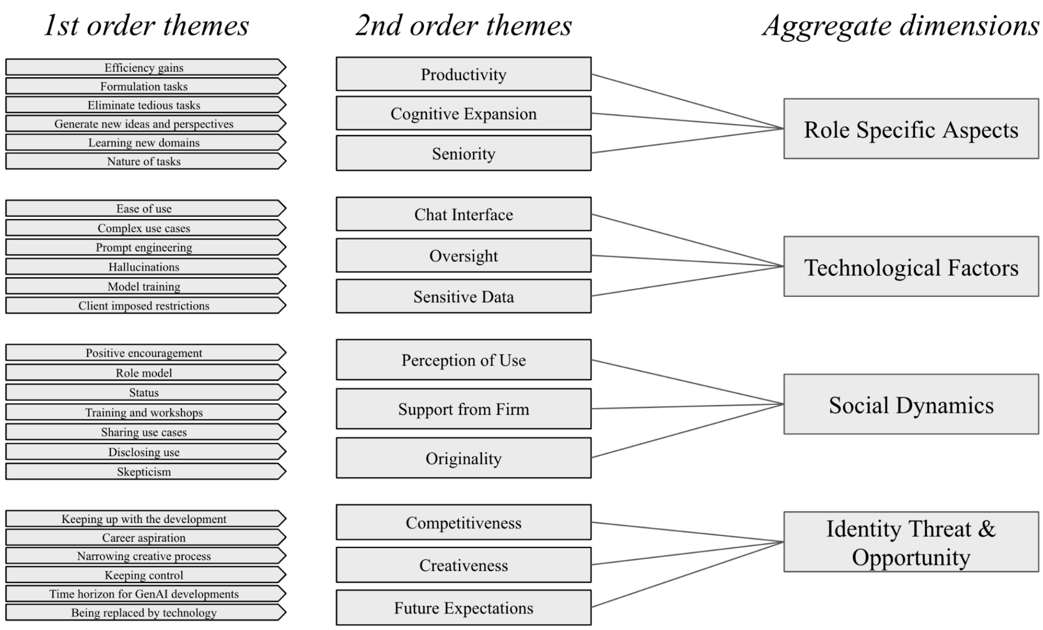

Figure 9. Gioia empirical structure

5.1 Role-specific Aspects

The study identified three role-specific aspects impacting the interviewees' adoption of GenAI: *Productivity gains, Cognitive Expansion,* and *Seniority.* The participants highlighted GenAI's capability to help them to become more productive in simple communication tasks. GenAI could also aid management consultants in brainstorming ideas or learning new domains. However, seniority limited the applicability of the technology.

5.1.1 Productivity

The most common benefit of using GenAI was productivity gains, allowing consultants to effectively approach their tasks. Many stated that the decision to adopt the technology was guided by its ability to improve language, summarize insights, and ultimately facilitate communication with a professional tone.

"I use it [ChatGPT] practically every day (...) If I'm writing emails, I use it quite a bit just to make the formulation simpler and better. We also have an internal tool, our own GPT tool. I use that in all situations where I need to formulate text" - Participant 6

"I would say it's to save time. And also, to make better formulations." - Participant 12

Consultants are often pressed for time, so many emphasized that saving time on formulating communication allowed them to focus more on higher-value activities, such as tackling complex problems or building strong client relationships.

"GenAI helps us summarize key insights from transcripts (...) This normally takes a lot of time and it doesn't add a lot of value for me to do it on my own." - Participant 11

Given the fast nature of the management consulting industry, the interviewees constantly seek to maximize their time. As such, GenAI tools were leveraged daily for these repetitive and "simple" use cases across all interviewees, but the extent varied.

5.1.2 Cognitive Expansion

In addition to increased productivity, the interviewees were also prone to use GenAI, given its ability to aid them in performing cognitive tasks. Most interviewees indicated that GenAI supports them by offering guidance, suggesting new perspectives, and generating ideas, thereby enhancing the quality of their overall output.

"The main area of use is as a sounding board for me in the assignment I'm currently in (...) GenAI becomes a good tool to broaden the horizons." - Participant 4

Several interviewees used GenAI as a tool to get input on ideas and alleviate the cognitive effort required to perform their jobs. Others use it to gain a general understanding of entirely new subjects or industries. This capability is particularly valuable because consultants frequently switch between projects and industries.

"A use case for me could be, okay, so I have this problem and I've never approached it before. What different aspects should I consider when solving this problem?" - Participant 1

"It creates a direction in one's work. If you talk about starting a market analysis, for example, and you ask [ChatGPT] about the major trends within this industry it list this and that. Then you get a first draft, something to work from." - Participant 15

Previously, the interviewees would share their thoughts with peers or managers to gain new perspectives, a role that is now increasingly fulfilled by GenAI. Although colleagues continue to be an essential aspect of one's work, having GenAI available always enables them to work more efficiently and gives increased confidence to tackle novel tasks.

5.1.3 Seniority

The junior consultants we interviewed stated that GenAI's current capabilities align well with their tasks, which often revolve around producing material. These tasks are substantially different from those of more senior employees, whose responsibilities revolve around managing and selling consulting projects and building long-term relationships with clients.

“If you look at our juniors, the younger they are, it's just more and more a standard tool. It's just a part that exists, a tab that's always open.” - Participant 18, Senior

“I would say that it's relatively widespread. Many use it to some extent at junior or junior mid-levels. But it is less widespread the higher up it goes in the hierarchy. I can understand that; it becomes less useful.” - Participant 19

The interviews indicated a significant difference in GenAI usage between junior and senior employees which is explained by the technological capabilities of GenAI. Junior employees have more incentives to adopt GenAI as it enhances their work, whereas senior employees are less likely to benefit from using it.

“When it comes to language, that's something I'm constantly working with [as a junior consultant]. I collect information, make it more understandable, apply it to what we do, and present it. So, in that sense, it [ChatGPT] is always relevant to use” - Participant 15

The empirical data indicates that GenAI's usefulness is determined not only by the technology's capabilities but also by the consultant's role and responsibilities in seeking to utilize it. Different levels of seniority within the organization play a significant role in determining GenAI's extent of applicability.

5.2 Technological Factors

The study identified three technological aspects impacting the interviewees' adoption of GenAI: *Chat interface, Oversight, and Sensitive data*. The participants highlighted GenAI's chat interface as providing an easy user experience. However, being provided factually false answers and training on the input were stated to be limiting factors for using the technology.

5.2.1 Chat Interface

Many interviewees cited the user experience of GenAI tools as a critical factor in their adoption. They found these tools easy to get started with, which encouraged initial use. However, while GenAI tools are accessible and user-friendly for simple tasks, fully realizing their value is more challenging and demands more significant effort from the user.

“It's a low threshold because it's a chat where I can ask any question and get an answer in the direction I want. But if I'm really going to benefit from it, it requires that I'm clear in my formulation. I need to include important parameters and context.” - Participant 4

“I think since it's [ChatGPT] a chatbot, I think that all humans can chat, especially via text. But I think there's a difference between just using it and getting the outcomes or valuable output that you want” - Participant 1

This finding reveals a paradox in the participants' usage of GenAI tools. While the tools are easy to start using, mastering them is significantly harder, requiring an understanding of prompt engineering. This results in a divide among users, where some overcome the challenges and become advanced users, while others remain limited to basic use cases.

5.2.2 Oversight

Although GenAI creates a lot of value for consultants, the interviewees also recognized the limitations of the technology. LLMs can hallucinate, presenting the user with incorrect or false information, which influenced several interviewees to use GenAI tools to a lesser extent. This indicates that while GenAI can create productivity gains, it can also create extra work as it requires the user to constantly review the output.

"So it gives a picture and various alternatives or ways one can structure it. But I wouldn't blindly trust it.” - Participant 5

“It still happens quite often, if we take ChatGPT as an example, that the material does not correspond with reality.” - Participant 7

While a few interviewees stated that they could manage this flaw by revising their prompts, others considered it to be time-consuming, ultimately opting for more manual processes

“Sometimes I feel that it's just as fast to simply write the text myself. It might take a bit longer to put the text together, but it turns out exactly how you want it right away. Rather than having to rewrite it.” - Participant 9

“If it doesn't help me in one or two tries, then I do it myself without AI. So, AI doesn’t get many chances. - Participant 7

Considering the importance of accuracy for management consultants delivering to clients, critically reviewing the output was seen as obligatory when using GenAI. Every consultant stressed that they need to be able to take full responsibility for the content delivered.

5.2.3 Sensitive Data

Interviewees expressed concerns about handling sensitive client data when using GenAI, which imposed significant limitations on their usage of the technology. As the most popular GenAI models, such as ChatGPT, train themselves on the input data they receive; clients are concerned that their proprietary data and information could leak. Therefore, clients can demand that management consultants refrain from usingenAI when working with their data.

“I would like to use it more definitely because it saves a lot of time. But again, then it's about a question to which point I can use the information [client data] I work with” - Participant 3

“The biggest barrier for me personally right now is the clients I work with. Most of them don't want ChatGPT to be used from a security perspective. They are afraid that data might leak in some way.” - Participant 13

In other instances, interviewees had no client-imposed limitations that affected their usage. Instead, their own concerns prevented them from using GenAI, as the effort required to remove sensitive data from a prompt was seen as too demanding and, at times, made the prompt insufficient.

“Everything that I post is anonymized. I actually, to be honest, don't use it for confidential client information. So if I'm working with a company, then I rather do the Googling versus ChatGPT.”
- Participant 11

Even with tools that do not train on input data, such as the ChatGPT Enterprise version or a company's own GenAI chatbot, consultants were still hesitant to use client data. When questioned about this hesitation, several interviewees preferred to avoid any risks when uncertain, even when the tools should be safe to use.

5.3 Social Dynamics

The interviews showed that social dynamics impacted the individual decision to adopt GenAI, and three categories were identified: *Perception of Use, Support from Firm, and Originality.* How well-supported the technology is by the firm, as well as how colleagues and superiors perceive the use of the technology, influenced interviewees. Although the use of the technology was optional at all firms, social dimensions complicate the extent to which the decision is truly voluntary. Managers ' skepticism of using GenAI also had an impact.

5.3.1 Perception of Use

Several interviewees highlighted the positive perception and benefits of using GenAI within their firm, influencing their decision to adopt the technology. As mentioned earlier, management consulting is a fast-paced and highly competitive industry. Given that GenAI can offer value in both aspects, it forms a foundation for its adoption.

"If you manage to complete a task faster and better with AI, it's just praise." - Participant 8

"We've had some development discussions, and then I've received feedback about being efficient in ChatGPT and such. So, I would definitely say that using it is a positive thing." - Participant 14

While GenAI is still in its early stages, it is increasingly perceived as an essential tool everyone should know how to use. Some participants stated that a new norm had emerged, where there is an expectation of some level of proficiency in GenAI.

"If you said a year ago that you never used ChatGPT, people probably wouldn't have cared. Today you couldn't say that. Within the role, there are certain expectations that you can use some tools, like Powerpoint and Excel. And ChatGPT is increasingly seen as such a tool." - Participant 21

"We who use AI find it very strange those who don't use it." - Participant 18, Senior

Being at the forefront of GenAI development is associated with higher status within the firm and the potential to be a role model for others. Once again, referring to the nature of the management consulting industry where so much is about career progression, GenAI offers a way to signal your progressiveness to others. Some interviewees were involved in AI initiatives at their respective firms, influencing decisions about company-wide implementation.

"I probably acted a bit as a role model because I think I helped four or five people to improve their prompting technique. Just like super simple examples. (...) And I also instruct them." - Participant 1

Most interviewees described GenAI as something cool and exciting that is entering the management consulting industry.

"It's cool to use AI. (...) Some are at the forefront, leading the way and exploring all the possibilities. They're like evangelists for AI, and it's cool in a way to stay at the top of new technology."
- Participant 4

"I believe that it is status-enhancing to have a person who truly masters ChatGPT and uses it wisely.
- Participant 21

Several interviewees expressed a desire to gain further knowledge and proficiency in using GenAI tools, aspiring to attribute themselves to the people pioneering the technology in their respective firms.

5.3.2 Support from Firm

Another factor influencing consultants' adoption of GenAI tools was the level of support and education provided by their firms. Some firms prioritized upskilling their employees in GenAI usage, organizing workshops and presentations to showcase various use cases. Meanwhile, other firms adopted a more passive approach, only encouraging usage without offering substantial support.

“We have workshops at least once a month, and every other week we run through updates on what's happening in the AI world right now. There we get to have an hour's lunch lecture where we go through what the new trends are, what the new features are, and how we can use them. - Participant 13

People at the company who use Gen AI get to go up on stage and tell how they solved this thing. So it becomes some sort of testimonial and show: 'I can do that too,' and then usage increases." - Participant 4

The level of support to begin learning about GenAI tools varied among firms. Some had detailed development plans in place, while others had no plans at all.

“Soon it will probably be part of the training for new employees, to have an education in how to use GenAI." - Participant 6

“This week they had four workshops on how to use it, but they are not mandatory. (....) So they really try to get us to use it more, which is good” - Participant 3

Adoption was more common in firms with a strong supportive culture that actively encouraged upskilling in GenAI. Conversely, in firms where individuals received less educational support, this remained a barrier.

“No training, unfortunately, so I have not learned that much about how to use it. But there have been some inspirational lunches talking about the potential of GenAI. " - Participant 21

“There was a very basic AI session just before I started. But was it sufficient for people to fully adopt it [ChatGPT]? No, I don't think so. I mostly relied on my own curiosity to become good at using it” - Participant 1

Personal interest in GenAI continued to be a key factor for learning among individuals in firms with limited support and educational resources.

5.3.3 Originality

One barrier several consultants described was maintaining a balance between benefitting from GenAI and being perceived as producing original work. Numerous interviewees emphasized the importance of ensuring that while GenAI may aid in tasks, the final output must always reflect your own effort and expertise. Submitting work that appears to be AI-generated could be perceived negatively, potentially suggesting a lack of personal contribution.

"There definitely exists some skepticism. I actually heard that quite early in my career. When I used it, there was a more senior colleague who said, 'This is AI-generated, isn't it?' In that case, it actually wasn't. - Participant 13

"There is a risk that it [disclosing GenAI use] may be perceived as if one has not done the work by yourself and therefore you cannot be credited with the achievement. So much in a company like this [Management Consultancy] is tied to promotion, so what one can attribute to oneself, one tries to do." - Participant 5

Empirics indicated a minority expressed concern about disclosing their use of GenAI to superiors, fearing skepticism of their contribution and effort level, potentially impacting adoption decisions.

"Overall, it's seen as positive, but I've been a bit unsure about how much I should disclose regarding the tasks I've completed using AI, because people are still skeptical" - Participant 20

"Most people didn't want to show that they had ChatGPT up on their computer. They hid it behind some other tabs. (...) you have these senior partners who hate every new technology. So if someone used it, they weren't like, oh, I'm impressed by this, rather they were more skeptical of your work. - Participant 1

Some junior management consultants faced skepticism from senior consultants, which created a barrier to fully using GenAI in their daily work. Empirical findings demonstrate that social dynamics significantly influence individuals' decisions to adopt GenAI technology.

5.4 Identity Threat and Opportunity

Participants believe GenAI tools have a much broader impact compared to previous tools, with the potential to significantly enhance and disrupt multiple aspects of the consulting profession. GenAI presents both identity threats and opportunities for consultants, influencing adoption decisions and redefining what it means to be a consultant. Three key categories emerged from the empirical data: *Competitiveness, Creativeness, and Future Expectations*. Interviewees discussed the importance of staying updated, remaining competitive, and balancing augmentation in creative processes. Although GenAI's full potential has yet to be realized, its anticipated profound future impact is already influencing individuals' adoption choices as they aim to position themselves for their future careers strategically.

5.4.1 Competitiveness

A key driver for adopting GenAI was the need to stay competitive. Management consultants operate in one of the most competitive work environments you can be in, both in getting an entry-level position and rising the ranks inside a company. Many of the most prestigious consultancies operate on an "up or out" principle, where consultants must either get promoted to partner or leave the company.

"In a few years, it will be expected that I can use AI to be able to do my work within reasonable time frames and with good quality." - Participant 6

"It won't be a question of whether we should start using AI or not, but rather how should we start using AI? It will become increasingly clear that individuals with AI capabilities will perform much better, faster, and more efficiently than those without." - Participant 12, Senior

Most participants saw the productivity and quality gains of using GenAI to increase their competitiveness within the firm. In most firms, GenAI was still in the early stages of being introduced and being among the first to learn and use it could offer an advantage over peers who are slower to embrace it.

“I believe that if a management consultant does not learn to use generative AI, they will be replaced by other consultants who can use it." - Participant 19, Senior

In addition, some participants recognized the career opportunity of being experts in GenAI and being able to compete with more experienced consultants on this specific topic.

“It’s a great opportunity for many juniors. I can’t really compete with a partner who has worked in telecom for 30 years, he knows everything by heart. But I probably know more about AI than most partners. In that way, I can really use it to my advantage to become a bit of an expert and give value.” - Participant 20

Some junior management consultants saw it as a way to seize the opportunity and be recognized as internal leaders in AI, which positively impacts their competitiveness.

5.4.2 Creativeness

While many consultants have emphasized the importance of learning and utilizing GenAI, some have also pointed out potential downsides. They've noted that relying too heavily on GenAI can limit creativity by locking users into certain options, narrowing down the creative process. This can result in a more generic output and not challenging yourself creatively.

“If ChatGPT says there are these ten options, and you then dig deeper to maybe three, then you kind of narrow down the options and get something very general. Instead of starting from a clean slate and maybe thinking more from your own point of view. I believe in diversity of thought.” - Participant 21

“It can often happen that you get five options, and then you start thinking only about those five, and your brain gets stuck on them. You can't find a sixth thing beyond them. But perhaps there could have been better things you could have thought of yourself. But then your mind is a bit locked.” - Participant 13

As management consultants are paid for their cognitive abilities and to generate novel solutions to complex problems, it is problematic if GenAI negatively affects their creativity. Hence, a few participants were concerned about the potential long-term effects of incorporating GenAI in creative processes. Others raised concerns from a macro perspective, suggesting that widespread adoption of GenAI could diminish the value of hiring management consultants, resulting in less uniqueness in solutions across the industry.

“Because ChatGPT creates a generic response rather than a unique one, there's a risk of giving the answer that everyone will give, not thinking innovatively. That's one of the key points - to not rely too much on AI because we still need to deliver a unique product, not same as competitors.”
- Participant 14

Therefore, for management consultants, there exists a delicate balance between being empowered by GenAI and potentially being held back because of it. Navigating these contradictory outcomes in their use of GenAI tools becomes increasingly complex, as there are many positive outcomes from using it, like increased competitiveness and reputation within the firm. Moreover, some explained the effect of not having ChatGPT available, potentially hurting long-term capabilities.

"When ChatGPT was down or can’t get the answer I want. Then I feel more constrained now than I did a month ago. (...) the answer to everything is just asking ChatGPT and then double-checking it on the internet. But if I have to go find it on the internet myself now, it feels much harder”
- Participant 16, Senior

While this was an uncommon opinion among management consultants, it highlighted the potential of getting worse at the ordinary knowledge work skill of retrieving information.

5.4.3 Future Expectations

As stated above, many of the interviewees believed and expected that GenAI would become an integral part of the management consulting profession. However, the time horizon projected for GenAI to penetrate the industry varied from the near future to several decades ahead.

“Give it another year or so, and I don't think one will be able to do my job nearly without GenAI. Consulting is fundamentally about communication (...) And you become a better communicator if you use GenAI. So, as I see it, one must keep up with the development.” - Participant 6

“I believe that in 20 years, we will look back on now and think how crazy it was that we, people, worked on doing this a few years ago. In the same way that we now think it's crazy that people were standing on assembly lines, hammering once a minute, or once a second, which robots do now." - Participant 16, Senior

While it's undeniable that participants believe that GenAI will become an integral part of the management consulting profession, very few interviewees expressed actual concerns about being replaced by the technology. Referring to the social nature of consulting and the ability to work with clients, GenAI was perceived primarily as an augmenting tool rather than a potential replacement for human expertise.

“Generally, consulting is surprisingly a lot about the client and just being a reasonable person. (...) So, it is quite a social profession in that way. I believe, unless we develop AI very far in the future that is essentially equivalent to humans, it will probably never be able to be replaced in that way." - Participant 17

“There are a lot of people-oriented elements within consulting. When talking about organizational changes or getting buy-in from clients on various strategy proposals, psychology and being a decent person, someone to believe in, plays a big role. That is very hard to replace” - Participant 15

The different perceptions among management consultants regarding the timeframe they believe GenAI will become a fundamental aspect of the industry likely influence their sense of urgency in adopting and learning about it.

6. Analysis and Discussion

In this section, we analyze our empirical findings with the extended Technology Acceptance Model (TAM2) as a lens to provide a deeper understanding of individual adoption decisions. Moreover, we compare and contrast our findings with prior literature to enhance our understanding of GenAI adoption in knowledge work. Lastly, we discuss our additional contribution discovered outside the existing model, providing a foundation for future research.

Using the TAM2 model as a framework, our empirical evidence was examined to better explain our findings. We found that social dynamics could be broadly associated with the social influence processes described in the model. Furthermore, role-specific aspects and technological factors could be linked to the cognitive influence processes outlined in TAM2. Identity threat and opportunity represent an additional contribution that influenced management consultants but is not described in the TAM2 model (see figure 10).

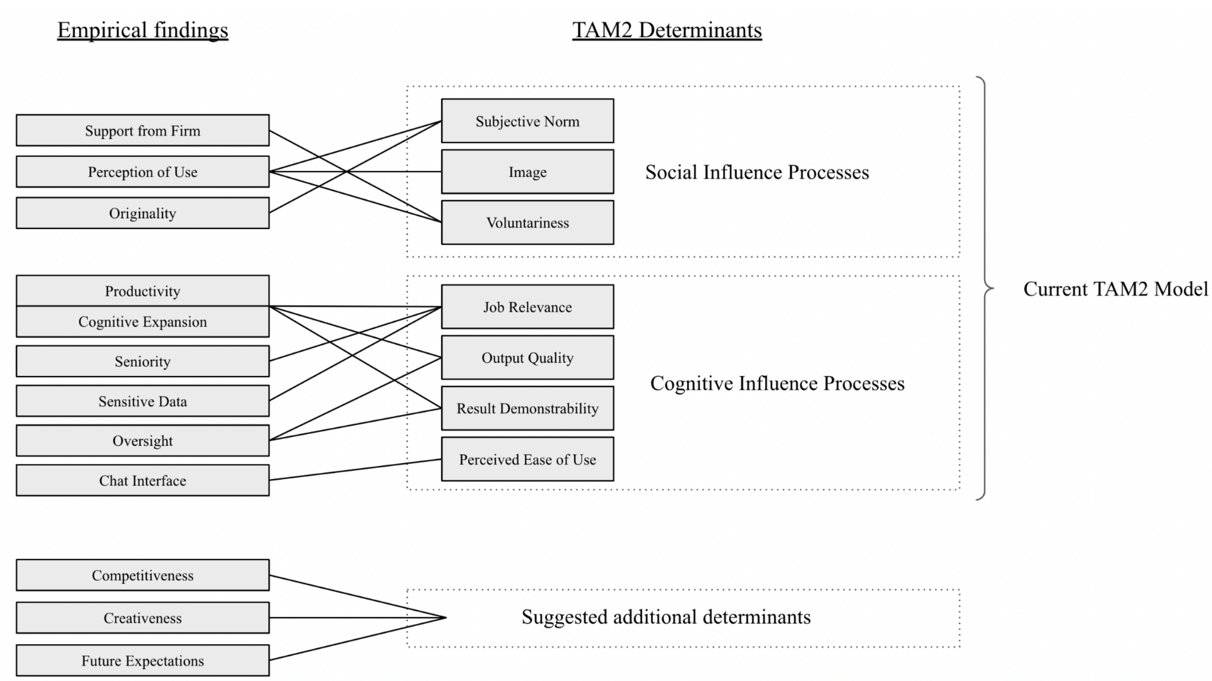

Figure 10. The empirical findings connected to the determinants of TAM2.

6.1 Social Influence Processes

Social influence processes include subjective norm, voluntariness, and image. We found that *social dynamics* were linked to these processes.

6.1.1 Subjective Norm

Subjective norm entails an individual's belief that important people around you think you should perform a specific behavior. Our empirical findings regarding *Perception of Use and Originality* align with this notion, demonstrating that management consultants are influenced by their peers and superiors.

Management consultants described the *perception of using* GenAI as overwhelmingly positive, receiving positive feedback and praise from colleagues and superiors. While quickly learning new technologies is a standard expectation in management consulting, the extensive applicability of GenAI in the profession is what sets it apart. Consultants frequently discuss new GenAI developments and their potential impact on their work. As influential members of your social group emphasize the importance of GenAI in consulting, you naturally feel compelled to learn more about it and recognize the importance of adopting it.

However, a significant concern affecting adoption is the *originality* of work content, a novel finding in the GenAI knowledge work literature. When managers express skepticism about the originality of work produced using GenAI, it creates insecurity around disclosing its use. Consultants worry that excessive reliance on GenAI might undermine perceptions of their contributions and expertise. This skepticism from senior managers leads to the cautious use of GenAI, where consultants might underreport or minimize their use of AI tools to avoid negative implications. This represents a novel barrier to technology adoption, as GenAI is the first technology capable of closely mimicking human knowledge work (Ritala et al., 2023). While it is apparent *originality* influenced adoption among management consultants, it remains uncertain how subjective norms will evolve as GenAI output quality improves. Will managers become more skeptical of the inputs, negatively impacting subjective norms? Or will they get used to GenAI tools and embrace their use in the workplace? Additionally, can superiors actually distinguish between human and GenAI output, given their current difficulties in doing so? Further research is needed to understand how managers perceive the originality of work content when using GenAI. This is discussed further in section 7.5.

6.1.2 Voluntariness

Voluntariness is the extent to which one perceives the adoption decision as non-mandatory. Our empirical findings of *support from the firm* and *perception of use* align with this notion.

Based on the empirical results in *support from firm*, all of the 21 interviewees could decide whether to use GenAI or not. TAM2 theory states that in mandatory settings subjective norm has a significant effect on the intention to use a technology, but not in voluntary settings. In management consulting, subjective norms appear to greatly impact management consultants even in this voluntary setting, going against TAM2 results of compliance effects. One reason could be that social dynamics complicate the extent to which this decision is voluntary, given its potential impact on status and career progression. Management consultants operate within a highly competitive industry, facing competition not only in securing entry into firms but also in climbing up the career ladder within them. When there is high *support from the firm* towards GenAI, offering workshops and even incorporating it into performance evaluations, many employees feel compelled to adopt it. Russo‘s (2024) study confirms that a supportive organizational culture that encourages and invests in new technology impacts adoption decisions. This is connected to TAM2's notion of internalization (also referred to as expert power), where if peers or superiors suggest that a technology is useful, a person is more likely to start to believe that it is useful, affecting intentions to use it. Moreover, some expressed that *perception of use* affects the voluntariness of the decision. GenAI is increasingly perceived as a mandatory tool, even if not explicitly stated as such. As some participants argued, knowing how to use GenAI will soon become as essential as being proficient in Microsoft PowerPoint, making it less voluntary to learn today.

6.1.3 Image

Image is the degree to which the use of an innovation is perceived to enhance one's status in one's social system. Our empirical findings of *perception of use* align with this notion.

Empirical findings show that GenAI's *perception of use* benefits management consultants as it improves their status and career progression. Several of our interviewees expressed that they are role models and steer the company in this direction. While this can be seen as a selfless act to enhance company proficiency, it can also be seen from a TAM2 perspective, where the individual tries to enhance one's status. This influence on adoption is reflected in Russo's (2024) study on software engineers, which suggests that demonstrating the use of cutting-edge technology to solve problems and meet client needs can enhance reputation. Considering that management consulting is less technical in nature, it is interesting that this finding also appears in our empirical evidence. This highlights the disruptive power of GenAI within knowledge work, as even professions that aren't inherently technical see it as a tool to gain status. Furthermore, several of our interviews were part of initiatives at the company promoting GenAI, what TAM2 refers to as coalition forming. The more the company focuses on integrating GenAI, the more powerful the advocates and the coalition become inside the company. Connecting to subjective norm and voluntariness, if important members of your social group are advocating for AI use, then performing this will elevate your status within this group. In other words, there is an incentive to be a part of leading this high-status transformation at the company, so then you need to learn and use this new GenAI technology.

6.2 Cognitive Instrumental Processes

Cognitive instrumental processes include job relevance, output quality, result demonstrability, and perceived ease of use. We found that all *Role-specific aspects* and *technological factors* were linked to these processes.

6.2.1 Job Relevance

Job relevance involves a cognitive judgment where potential users assess the technology based on its applicability to one’s job. As such, job relevance is a function of the significance of the tasks that the technology can support, ultimately impacting the perceived usefulness of the technology. Our empirical findings link job relevance with *Productivity, Cognitive Expansion, Seniority,* and *Sensitive data*.

Productivity improvements are essential for management consultants, whose demanding schedules incentivize maximizing work output in minimal time. As a significant part of being a management consultant involves routine communication - whether with colleagues, superiors, or clients - GenAI's text generation capabilities can significantly streamline their work. This aligns with findings from other areas of knowledge work, as reflected in Woodruff et al.'s (2023) study of lawyers, business communicators, and advertisers. In these "simpler" tasks, GenAI can augment humans in creating communication by increasing accuracy and efficiency, freeing up more time for more value-adding activities.

Furthermore, GenAI works as a tool for *cognitive expansion,* broadening consultants' perspectives and helping them learn new subjects or industries. Ritala et al. (2023) note that GenAI is particularly beneficial at the novice stage of learning a new domain, making the process simpler and quicker. Management consultants are the epitome of knowledge workers as they constantly switch between projects, always needing to learn new skills and industry knowledge. This characteristic is common across knowledge work, which tends to be more general in nature. The ability of GenAI to offer guidance and enhance efficiency across a broad range of knowledge work areas and domains distinguishes it from earlier specialized machine learning technologies, increasing its job relevance.

Our empirical findings suggest that *seniority* influences job relevance. Senior management consultant´s responsibilities are centered around business development and long-term relationships, which is less applicable to GenAI. This observation is consistent with Brynjolfsson et al. (2023) study, which suggests that novice and lower-skilled workers benefit more from GenAI, a departure from earlier technology adoption research that showed computer technology primarily complements higher-skilled workers. This difference may stem from GenAI's broad and general use cases compared to previous AI technologies' narrower and more specialized applications. The focus of GenAI on improving and brainstorming content is particularly suited to junior roles in knowledge work. While our study focuses on management consultants, the insight seems applicable across various domains of knowledge work (Brynjolfsson et al., 2023; Woodruff et al., 2023; Mohan, 2024;

Ritala et al., 2023). Further research is therefore needed on how seniority plays a role in the job relevance of GenAI for knowledge workers.

Lastly, a limiting factor for job relevance is the concerns of *sensitive data* from clients, which restricts the use of the technology. Therefore, while certain technological aspects of GenAI hold high job relevance, other factors, particularly those related to sensitive data, carry more weight and ultimately decide how much it can be used. Ritala et al. (2023) reflect this sentiment, noting that client data needs to be removed before using GenAI tools. However, this requirement is expected to be eliminated in future versions of enterprise software. Interestingly, our empirical evidence shows that even when the company permitted sensitive information in GenAI applications, some consultants were still hesitant to use it and chose to omit sensitive data regardless. This hesitancy could stem from working in a highly reputationally sensitive industry, causing consultants to be risk-averse. Furthermore, there is still uncertainty about the technology's limitations and persistence in the narrative that GenAI, in general, is unsafe as it trains on data input. While this was the case during the release of ChatGPT in 2022, enterprise versions now exist. It seems that the persistence of uncertainty in using sensitive data in GenAI tools remains a barrier.

6.2.2 Output Quality

Output quality relates to how well a technology performs the tasks seen as relevant to the job of the user. The empirics revealed that output quality was related to *Productivity gains, Cognitive Expansion,* and *oversight*.

GenAI was cited to bring significant *performance gains* and increase *cognitive expansion.* Many interviewees relied on GenAI for its consistent speed and superior performance compared to manual processes. Given that GenAI is trained on a massive amount of text, it performs well in rephrasing and drafting, which is a common use case among participants. Several interviews also expressed achieving an overall higher quality output when working in tandem with GenAI and getting a broader perspective on a new subject quicker than they usually would.

However, GenAI also requires significant *oversight* to ensure its output quality. As GenAI is built on the LLM technology, which has inherent limitations of generating inaccurate information known as hallucinations, this negatively impacts output quality. This limitation created a hesitancy for some to adopt GenAI for complex tasks, emphasizing the time spent on manual *oversight* and review to ensure accuracy. Clearly, GenAI still requires augmentation by knowledge worker's expertise and judgment, as observed by Russo (2024) and Woodruff et al. (2023). Moreover, management consultants face challenges in determining when and how much to use GenAI across different tasks, a dilemma Dell'Acqua et al. (2023) describes as "navigating the jagged frontier". In Dell'Acqua et al. (2023) experimental test with made-up business cases, consultants relied too much on GenAI and were likely to make mistakes on tasks outside the frontier. Our empirical findings suggest that in real-world, high-stakes client scenarios, consultants tend to exercise increased caution and emphasize oversight. Some even revert to manual processes when necessary. Overall, mastering the skill of knowing when to rely on and when to refrain from using GenAI is becoming essential for knowledge workers.

6.2.3 Result Demonstrability

Result demonstrability is the extent to which a user can attribute gains in their performance to the use of the technology. This relates to our empirical findings of *Productivity, Cognitive Expansion,* and *oversight.*

The results were mixed, where many interviewees explained that in simpler tasks, it's easy to see the productivity boost or quality improvement, while in complex tasks, the need for oversight blurs how well GenAI actually gains the user. Some even reverted to manual processes as they felt that GenAI would not make them more effective in a certain task. Clearly, consultant's challenge with "navigating the jagged frontier" (Dell'Acqua et al., 2023) makes it harder to attribute gains of the system to their own performance. Tasks outside the frontier are especially hard to judge if you save time using GenAI compared to manual processes. GenAI, therefore, presents a scenario where the ease of attributing gain from GenAI is relative to the complexity of the task.

6.2.4 Perceived Ease of Use

The perceived ease of use of technology suggests that the less effort required to use it, the more it can enhance job performance. This concept was related to the *chat interface,* as many consultants noted that getting started with GenAI was straightforward due to its conversational interface. This echoes Ritala's (2023) and Russo's (2024) research, showing that the intuitive chat interface significantly contributes to the technology's ease of use for knowledge workers. While the chat interface offers an accessible entry point, it requires greater effort to master the skill of writing the proper prompts and providing the necessary context, truly realizing its full value. This dynamic suggests that the perceived ease of use of GenAI is not binary, but instead relative depending on the task complexity. In other words, prompt engineering remains a barrier for many consultants. It also indicates a divide among the participants; those who have overcome the challenge and those only using it for simple use cases.

6.3. Additional Contributions

In this section, we present our additional empirical findings outside of TAM2 regarding adopting GenAI in management consulting. This is aimed at laying the groundwork for future research. We found that *identity threat and opportunity* were outside the scope of TAM2. Therefore, *competitiveness, creativity, and future expectations* need further elaboration.

6.3.1 Competitiveness

The empirical results highlight that staying competitive as a management consultant when GenAI becomes increasingly capable, is a driver of learning and adopting the technology. *Competitiveness* is distinct from other TAM2 determinants as even when the technology is only partially relevant and output quality is mixed based on the task, the quick development of the technology creates a need to adopt it now. The pressure to rise within the ranks or risk being sidelined due to the 'up or out' policy serves as an influence on adoption. This finding is in line with Woodruff et al. (2023), who found that knowledge workers across various sectors are compelled to learn about GenAI to safeguard their relevance and future career prospects amid uncertainties about the future and intense workplace pressures. Furthermore, the urgency to adapt is not only about staying relevant but also about seizing opportunities. Younger or less experienced consultants view GenAI as a strategic tool that enables them to compete against more seasoned colleagues, highlighting a shift where technical proficiency with new technologies can offset years of experience. The perceived competitive edge is influencing younger consultants to enthusiastically embrace GenAI, positioning themselves favorably within the competitive consulting landscape.

6.3.2 Creativeness

In management consulting, one of the main services clients pay for is the creativity and problem-solving abilities of the consultants. It is, therefore, interesting that several consultants expressed concern about GenAI constraining the creative thinking process by locking them into a "simplistic" chain of thought or a narrow set of options. They experienced that it limited their creativity, influencing their willingness to use GenAI. *Creativeness* is inherently different from Job relevance and Output quality, as it relates to how using a system impacts the user's own skills, rather than how relevant the system's capabilities are to the user. In other words, this does not imply that the GenAI answer was inherently irrelevant or of poor quality. Instead, it suggests that using the system can confine the consultant to a narrow frame of thought, inhibiting their ability to deliver the highest quality answer possible. This notion contradicts Mohan's (2024) framework of possible augmentation/automation tasks, where "searching for possible solutions" is regarded as one of the critical aspects that GenAI could fully automate. Our empirical evidence suggests that consultants hesitated to give up full autonomy when searching for possible solutions, which presents a new perspective in the augmentation vs. automation discussion. While previous scholars have emphasized the technical capabilities of GenAI as a limitation in more cognitive tasks (Pettersen, 2019; von Richthofen et al., 2022.), it might be less about the technical challenge and more about individuals wanting to maintain creative control. GenAI can already effectively suggest possible solutions, but consultants might not want to give up control in this part of their job, even as GenAI becomes increasingly sophisticated. In the study by Cemaloglu et al. (2019), which explored the impact of artificial intelligence on consultants, it was found that while they were willing to accept some loss of control in execution tasks, they were unwilling to allow AI to take control of thinking tasks. Our study of GenAI seems to support the notion that consultants will want to keep control of the creative process while still using GenAI as a tool in many creative tasks. Further research in the domain of technology adoption is needed in this area, which will be discussed in section 7.5.

6.3.3 Future Expectations

Future expectations of GenAI could explain why some consultants have already embraced the technology while others have yet to. While all interviewees believed that GenAI would impact the industry, they had different timelines for such an impact, ranging from a year to several decades before any noticeable change would occur. This clarifies why several interviewees have yet to make significant efforts to learn about GenAI despite recognizing its transformative potential in the industry. Furthermore, participants had diverse beliefs regarding the potential implications of GenAI on the management consulting profession. Many acknowledge that GenAI excels in communication tasks and is rapidly improving, which is vital in consulting. This progress is seen as a compelling reason to adopt it now. Despite this advantage, most consultants believe that GenAI cannot replace the essential human elements required to build trust and form client connections. As the interviewees explained, organizational change heavily relies on securing client buy-in for strategic proposals, a process that is inherently human. Samokhvalov (2024) extends this notion, noting that although standard frameworks exist, communication and human interaction remain at the core of organizational change. Until GenAI can deeply understand human dynamics and the complexities of organizational change, it is unlikely to be applicable to more complex decision-making and senior-level execution tasks in management consulting, thus remaining a barrier to its full-scale adoption. How future expectations impact adoption decisions is a subject that needs future research.

6.4 Proposed Additional Contribution

Analyzing our empirical findings in relation to the extended Technology Acceptance Model (TAM2), we observe that many of our empirical findings can be explained by the model. Although GenAI is a very new technology, TAM2 qualitatively aligns well with individual consultants' empirically observed adoption decisions. However, TAM2 does not account for the identity threats and opportunities that GenAI adoption presents. Replacing tasks such as creativity and decision-making with machines is a highly psychological process that extends beyond previous adoptions of simpler and narrower systems. Therefore, our additional contribution focuses on incorporating identity into this new model.

This thesis defines identity as “individuals' subjective interpretations of who they are, based on their socio‑demographic characteristics, roles, personal attributes, and group memberships” (Caza et al., 2018). Our empirical analysis reveals both threats and opportunities to individual identities. Competitiveness represents both, where consultants strive to safeguard their relevance and career prospects while also viewing it as an opportunity to position themselves favorably for the future. Regarding creativity, consultants are reluctant to give up control over creative processes, fearing the long-term impact on their abilities. Finally, regarding future expectations, we observe diverse beliefs about the effects of technology on adoption decisions. Some consultants believe they will be replaced if they do not learn to adapt, while others argue that GenAI will never be capable of performing the social aspects of their job. The degree of impact and the direction that identity has on adoption decisions remain uncertain. Nevertheless, we believe that identity could influence consultants' adoption decisions, highlighting the need for further research at the intersection of adoption and identity theory. Based on this argumentation, we propose the addition of a new determinant, identity, defined as: “the degree to which a person believes a technology will impact their identity”. The new model is presented in Figure 11.

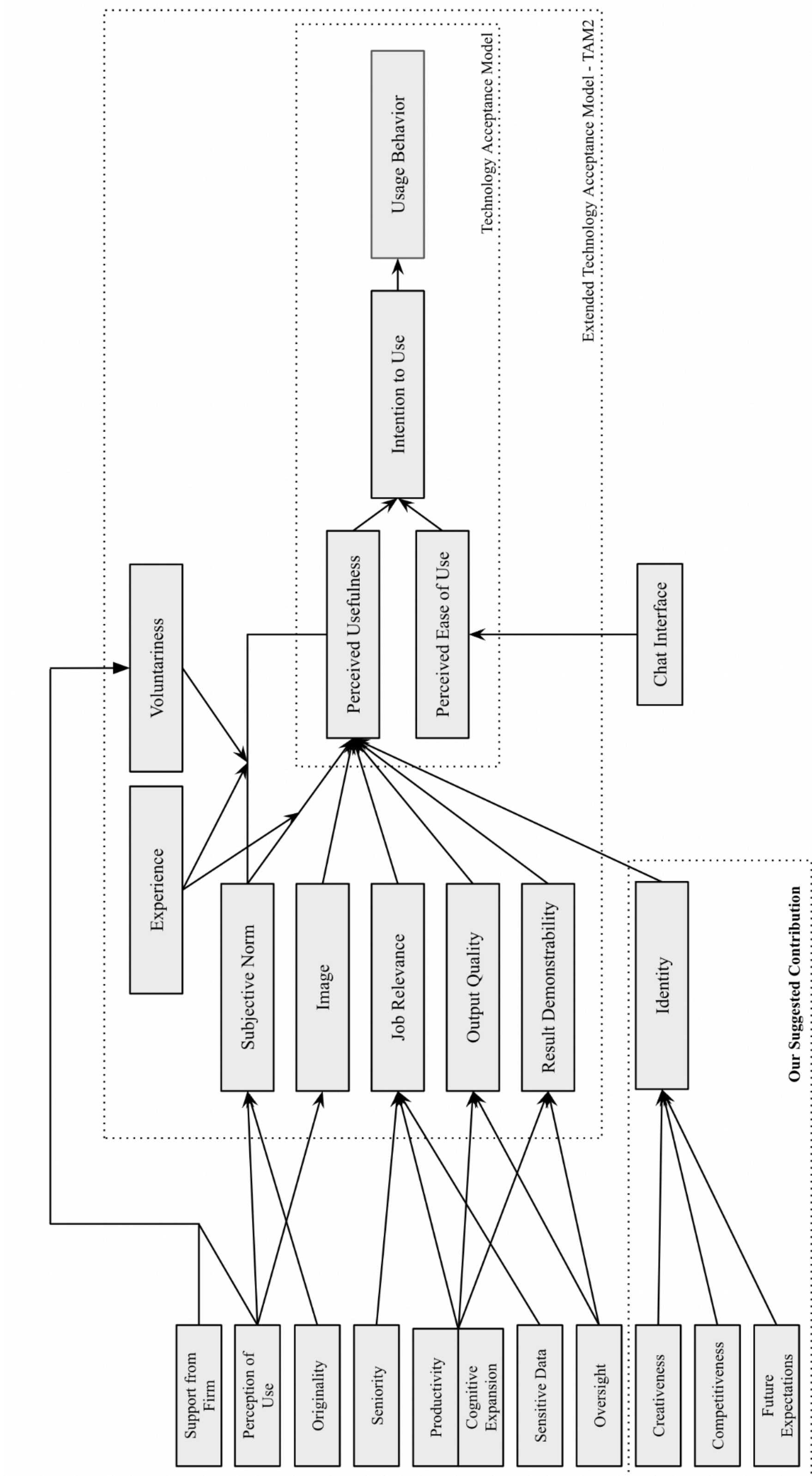

Figure 11. A proposed additional contribution to TAM2.

7. Conclusion

In this section, we first answer our research question. Then follows a discussion of the theoretical and practical implications. Lastly, we discuss the limitations of our study as well as present possible directions for future research.

7.1 What Influences Management Consultants' Adoption of Generative AI?

The purpose of this study was to provide the reader with a comprehensive understanding of the decision-making process of management consultants regarding the adoption of GenAI. Our study found that role specific aspects, technological factors, social dynamics, and identity threat and opportunity influence the adoption of GenAI by management consultants.

The role-specific aspects of *productivity, cognitive expansion, and seniority* influence the decision to adopt. The productivity gains and cognitive expansion that GenAI provides make it highly relevant for the use cases that management consultants encounter daily, including numerous communication and creative tasks. Seniority lowers the relevance of GenAI, as their job roles are more targeted towards building relationships and business development.

The technological aspects of the *chat interface, oversight,* and *sensitive data* also have an influence. The ease of use of the chat interface has made it accessible to all knowledge workers, providing a fast way to adopt the technology. However, it remains challenging to accomplish more complex tasks that require extensive context and prompting. Oversight remains crucial to ensure the quality of the output, as GenAI tends to provide false facts. Lastly, sensitive client data remains a barrier to full-scale adoption. These empirical findings seem to have broad support in the limited previous research on GenAI adoption within knowledge work.

Social dynamics dynamics of *perception of use, support from the firm*, and *originality* seem to influence adoption decisions. Perception of use shows that management consultants are influenced by peers and superiors when adopting the technology, making it less of a voluntary decision. Support from the firm also creates an environment where staying up to date with the latest GenAI technology is status-enhancing.

Identity threat and opportunity introduce a new area outside the framework of TAM2, suggesting that there is room for additional research within the realm of technology adoption theory. We found that *competitiveness, creativeness,* and *future expectations* have an impact. Competitiveness drives consultants to adopt GenAI today, as they want to stay relevant and see the potential to get ahead despite its limitations. Creativity limits adoption for some consultants who wish to remain in control of decision-making and avoid being confined to a narrow chain of thought. Lastly, future expectations of the transformative potential of the technology seem to impact adoption.

7.2 Theoretical Implications

The theoretical contribution of this thesis lies in the exploratory qualitative approach chosen to address the research questions, diverging from the predominantly quantitative focus of adoption theory literature. In doing so, we contribute to existing research in two ways. First, by suggesting additional contributions outside the scope of the TAM2 model, enabling an increased understanding of GenAI technology adoption. While our contribution holds no statistical significance, which also wasn't the purpose of this thesis, we instead provide a starting ground for further research to validate these findings. Secondly, we provide support for the notion that a qualitative approach of TAM2 indeed allows for theory building, as argued by Vogelsang et al. (2013). Through in-depth interviews, we discovered insights on a deeper level than possible through quantitative methods. Considering the complexity of GenAI and the intricacy of our suggested additional determinants, the value of the qualitative approach is demonstrated as those may not have been captured by quantitative methods. Lastly, while it is not the initial aim of this study, we ventured into the intersection between technology adoption and identity theory. Although going into the theoretical complexities of this intersection is beyond the scope of this thesis, it suggests that there is a theoretical domain that should be further investigated.

7.3 Practical Implications

This study provides valuable insights for management consulting firms by shedding light on consultants' perceptions and adoption processes of GenAI. When integrating GenAI in workflows, understanding the influences on GenAI adoption outlined in this thesis will be crucial to ensure its success. Some primary barriers to using GenAI included a lack of proficiency in prompting and concerns about potential social or career repercussions from superiors. Therefore, arguably, the most critical aspect for managers to be aware of is the need for thorough training that goes beyond the simple use cases, as well as educating employees when and when not GenAI is the most effective tool to use. Moreover, to ensure that no misconceptions or uncertainty remain regarding GenAI, companies should complement software investments with clear guidelines on appropriate use and safety standards. Doing so can help build a culture where the technology is accepted when used correctly and help mitigate the barriers. Furthermore, it also establishes a foundation for not only educating employees but also for educating and convincing clients of the benefits of GenAI.

Other practical concerns for managers include the potential impact that GenAI has on consultants' creativity and how they should position themselves in the long term to maintain their competitiveness. As highlighted by consultants in this study, addressing the issues related to creativity and the ability to generate novel ideas is a complex task that goes beyond managerial responsibilities. Solving such challenges needs to be addressed at a fundamental level by technology companies designing and providing Large Language Models (LLMs). However, leaders must know these dilemmas when formulating their AI strategies. Establishing such strategies and outlining long-term AI policies can also help alleviate consultants' anxieties about their future roles and help them navigate an environment where GenAI will be increasingly more present.

While the aim of this thesis is not to present any strategies for the successful implementation of GenAI, it lays the groundwork for understanding the adoption process among management consultants. Most importantly, it sheds light on the complex process of introducing a technology that has the potential to reshape the workflow for many professionals fundamentally. This thesis has investigated the field of management consulting, but the findings are intended to be a first step to understanding the adoption process of GenAI in the broader realm of knowledge work. While unsure to what extent, the authors are confident that many of the practical implications presented hold relevance in other facets of knowledge work and can provide valuable insights.

7.4 Limitations

This study has certain limitations that need to be addressed, many of which are inherent to qualitative research. Firstly, the small sample size allowed for an in-depth exploration of management consultants' adoption processes. However, the findings presented are not generalizable across the industry. This limitation is further amplified by the fact that we only interviewed management consultants based in Sweden. Although many participants worked for large global firms, being based in Sweden could have implications for the general attitude towards new technologies due to cultural differences between regions. Moreover, using the TAM2 model in qualitative research can be questioned, as the model was originally tested and validated in quantitative research. While our reliance on Vogelsang et al. (2013) method supports this approach and aligns with our study's aim, our link between empirical evidence and theory is based solely on our interpretation of the data. This approach opens the research to potential interpretative faults and confirmation biases despite our best efforts to limit it. If this study had not been constrained by the time limitations of the authors and the interviewees, a mixed-method approach similar to Russo (2024) would have been preferred. An inductive exploration followed by a questionnaire-based statistical validation would have been optimal to determine if our empirical results could have been generalized.

Secondly, given the popularity surrounding GenAI, participants may have felt compelled to speak about their perceptions in a way that portrays the technology in a favorable light rather than expressing their true thoughts. Our findings, where individuals can gain social status by assimilating new technologies, shed light on this potential limitation. Our approach of trusting the interviewees to be truthful in their answers without challenging their assertions may have contributed to this limitation.

Lastly, while the decision to focus solely on management consultants enabled a more nuanced understanding of their specific adoption decisions, its generalizability across other knowledge work remains uncertain and needs further investigation to gain validity.

7.5 Future Research

As GenAI is being rapidly adopted in knowledge work, there is an increasing need to thoroughly understand how this new technology is used and impacts workers. While there are many avenues for future research to explore, the most important is to more deeply investigate knowledge workers' perceptions and adoption, rather than speculate about potential implications based on secondary data. This study serves as an example of how novel contributions can be made by interviewing management consultants and investigating the complexities of adoption processes. While this study presents several directions for future research, we want to highlight two areas due to their implications for knowledge workers.

Firstly, future studies should examine how managers perceive the *originality* of work content and its effect on job relevance as GenAI continues to improve and better mimic human performance. Will managers accept that most of the work is done by GenAI, with consultants only performing quality checks? What impact will there be on adoption if managers choose not to embrace GenAI? This dynamic is intriguing because GenAI differs from previous technologies that are traditionally purchased and rolled out on a company level. In the case of GenAI, employees can obtain the technology themselves without any authorization from managers.

Secondly, our study indicates that consultants prefer to retain control over creativity while recognizing the benefits of using GenAI for various creative tasks. Future research should explore the balance of control between humans and GenAI in creative decision-making in real work contexts. Our empirical evidence, supported by Cemaloglu et al. (2019), suggests that consultants hesitate to give up their freedom to ideate. Meanwhile, Mohan (2024) argues that AI could play a significant role in creative processes. Understanding how technology shapes creativity and how this influences adoption remains to be determined in the GenAI era.

8. References

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9. Appendices

Appendix 1: List of interviewees

Interviews					
Participant	**Seniority**	**Firm**	**Interview format**	**Length (Min)**	**Date**
Participant 1	Junior	Firm A	Microsoft Teams	45	12/2/2024
Participant 2	Junior	Firm B	Microsoft Teams	38	15/02/2024
Participant 3	Junior	Firm C	Microsoft Teams	27	16/02/2024
Participant 4	Junior	Firm D	Microsoft Teams	29	16/02/2024
Participant 5	Junior	Firm E	Microsoft Teams	28	21/02/2024
Participant 6	Junior	Firm F	Microsoft Teams	34	23/02/2024
Participant 7	Junior	Firm G	Microsoft Teams	32	26/02/2024
Participant 8	Junior	Firm F	Microsoft Teams	30	26/02/2024
Participant 9	Junior	Firm H	Microsoft Teams	32	26/02/2024
Participant 10	Junior	Firm H	Microsoft Teams	30	28/02/2024
Participant 11	Junior	Firm I	Microsoft Teams	34	05/03/2024
Participant 12	Senior	Firm J	Microsoft Teams	29	08/03/2024
Participant 13	Junior	Firm J	Microsoft Teams	35	11/03/2024
Participant 14	Junior	Firm J	Microsoft Teams	30	14/03/2024
Participant 15	Junior	Firm K	Microsoft Teams	34	06/03/2024
Participant 16	Senior	Firm K	Microsoft Teams	37	06/03/2024
Participant 17	Junior	Firm G	Microsoft Teams	27	08/03/2024
Participant 18	Senior	Firm J	Microsoft Teams	35	08/03/2024
Participant 19	Senior	Firm K	Microsoft Teams	31	11/03/2024
Participant 20	Junior	Firm H	Microsoft Teams	24	21/03/2024
Participant 21	Junior	Firm L	Microsoft Teams	55	15/03/2024

Appendix 2: Interview Guide (Pilot study)

- Ask about recording, clarifying GDPR and consent form

- What is your role and day-to-day tasks? (broad question)
- Do you use generative AI (like chat GPT) in your daily work?
- Why did you start using it?
- What barriers do you experience when using GenAI in your work? Give examples
- IF USE: Do you inspire others to use GenAI? If so, how do you do that?
- Do other people at your workplace use GenAI?
- Would you say people you look up to influence you to use the system?
- Does your company push/inspire you to use the system?
- What would be the consequences of you not using the system?
- What impact do you anticipate the use of generative AI will have on how you and your work are perceived within the consulting industry?
- Do you believe that leveraging such technology enhances an individual's status within the consulting profession or social circles?
- How relevant would you say the system is based on your job tasks and requirements?
- What significance will this system have for your professional role? (1-5 years)
- How do you assess the quality of the results that this system provides?
- How tangible do you perceive the results of using this system to be?
- To what extent do you believe the outcomes achieved through this system are observable by others in your professional setting?
- How easily can the results obtained from using this system be communicated to your colleagues or stakeholders?
- What are your expectations regarding the level of effort needed to use this system effectively?
- How much do you trust the systems in your workflow?
- Is GenAI provided to you by your employer?
- Do you ever have problems using/accessing the system?
- Are you concerned about privacy and security?
- Does GenAI help you be more creative at work?

Appendix 3: Interview Guide (Main study)

- Ask about recording, clarifying GDPR and consent form

Questions always asked:

- Shortly, what is your role and day-to-day tasks? (broad opening question)
- Do you use any Generative AI tool (Chat GPT or equivalent) in your daily work?
    - What application and tasks?
- What was your motivation for starting using it?
- How relevant would you say the system is based on your role and daily tasks?
- How does the system perform when carrying out your specific job tasks?
- How do you assess the quality of the results?
- Do you experience any barriers to using the system in your work?
    - Give examples and describe them.
- Do other people at your workplace use GenAI?
- Do you believe GenAI impacts your status at work? If so, explain why!
- IF USE: Have you ever inspired others to use GenAI? If so, how do you do that?
- How do you find the difficulty of using the system compared to other systems?
- Can you see the effect of using the system? What are these effects?

Themes that often were further explored based on interviewees' answers:

- Employee resistance and skepticism towards new technology.
- Writer's block, brainstorming and creativity
- Augmentation vs Automation potential.
- Are you afraid of being replaced?
    - Do the tasks being replaced offer personal satisfaction to you?
- Are novice workers benefitting more than experienced ones?
- Gaining vs losing knowledge with the use of GenAI
- Productivity vs oversight. Are people really getting more productive?

Appendix 4: AI disclosure

In writing this thesis, we used the Generative AI tools Grammarly and ChatGPT to enhance grammar and formulations. These GenAI tools were used to detect and correct spelling errors, improving the readability of the text. The use of these tools not only elevated the quality of the thesis but also provided insights into how our interview subjects use generative AI to enhance their communication.

Given its limitations, such as hallucination, generative AI was not used for fact-based searches or in the creation of new ideas. This mitigated the risk of providing false statements. We also did not use Generative AI with any text relating to empirical data to ensure data confidentiality. Through the use of these tools, we learned that they can significantly boost the quality of a thesis. However, it is important to understand their limitations and always be responsible for the final output.