The Impact of Generative AI Use on Weekly Working Hours in Management Consulting and the Roles of Trust, Peer Influence, and Fear of Deskilling as Determinants

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Abstract

Title: The Impact of Generative AI Use on Weekly Working Hours in Management Consulting and the Roles of Trust, Peer Influence, and Fear of Deskilling as Determinants

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The rapid advancement of generative artificial intelligence (AI) technologies such as ChatGPT has initiated substantial changes in management consulting, influencing how professionals approach knowledge-intensive tasks. This thesis examines the impact of generative AI adoption on consultants' weekly working hours and explores the roles of trust in AI, peer influence, and fear of deskilling as determinants of AI use.

Employing a quantitative, survey-based approach, the study utilizes data from 94 management consultants analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). Respondents provided insights into their experiences and perceptions of generative AI tools, assessing their levels of trust, peer influence, and concerns regarding skill erosion.

Results indicate that both trust in AI and peer influence significantly positively affect consultants' intentions to use generative AI. Notably, peer influence directly drives the actual use of generative AI tools, while trust primarily influences usage indirectly via intention. Contrary to expectations, the fear of deskilling does not significantly deter AI adoption. Importantly, the study reveals a negative correlation between generative AI use and weekly working hours, highlighting potential improvements in efficiency and work-life balance.

The findings underline the critical roles of organizational culture and peer dynamics in facilitating AI integration within consulting environments. Additionally, the negligible impact of deskilling fears suggests that generative AI may uniquely enhance, rather than diminish, professional capabilities. These insights offer valuable implications for consulting firms seeking to leverage AI effectively, emphasizing the importance of fostering trust and supportive peer networks to optimize productivity gains and enhance consultant well-being.

Keywords: AI, genAI, generative AI, Technology Adoption, Trust in AI, Peer Influence, Fear of Deskilling, Work-Life Balance, Consulting, Management Consulting

Resumo

Título: O impacto da utilização de IA generativa nas horas de trabalho semanais em consultoria de gestão e os papéis da confiança, da influência dos pares e do receio de desqualificação como determinantes

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O rápido avanço das tecnologias de inteligência artificial generativa (IA), como o ChatGPT, tem impulsionado mudanças significativas na consultoria de gestão, influenciando a abordagem dos profissionais a tarefas intensivas em conhecimento. Esta dissertação examina o impacto da adoção da IA generativa nas horas semanais de trabalho dos consultores e explora os papéis da confiança na IA, influência dos pares e receio de desqualificação como determinantes da utilização dessas tecnologias.

Utilizando uma abordagem quantitativa baseada em questionários, o estudo analisa dados de 94 consultores através do método Partial Least Squares Structural Equation Modeling (PLS-SEM). Os participantes forneceram informações sobre suas percepções relativas às ferramentas de IA generativa, avaliando níveis de confiança, influência percebida dos colegas e preocupações quanto à erosão de habilidades profissionais.

Os resultados mostram que tanto a confiança na IA quanto a influência dos pares têm impacto positivo e significativo na intenção de uso da IA generativa. Destaca-se que a influência dos pares conduz diretamente ao uso efetivo dessas ferramentas, enquanto a confiança influencia principalmente por meio da intenção. O receio de desqualificação não apresentou impacto significativo na adoção da IA. Além disso, o estudo revela uma correlação negativa entre o uso de IA generativa e as horas semanais trabalhadas, sugerindo melhorias na eficiência e equilíbrio entre vida profissional e pessoal.

Esses resultados destacam a importância da cultura organizacional e das dinâmicas interpessoais para facilitar a integração eficaz da IA na consultoria.

Palavras-chave: IA, genAI, IA generativa, Adoção de Tecnologia, Confiança na IA, Influência dos Pares, Medo de Deskilling, Equilíbrio Trabalho-Vida, Consultoria, Consultoria de Gestão

Table of Contents

List of Figures & Tables

List of Abbreviations

AI	Artificial Intelligence
MC	Management Consulting
PLS-SEM	Partial Least Squares Structural Equation Modeling
GPT	Generative Pre-Trained Transformer
NLP	Natural Language Processing
LLM	Large Language Model
IRI	Instructed Response Item
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait
CR	Composite Reliability
CMB	Common Method Bias
ISO	International Organization for Standardization
TIA	Trust in AI
PI	Peer Influence
FOD	Fear of Deskilling
IUA	Intent to Use AI
AUA	Actual Use of AI
WWH	Weekly Working Hours

1 Introduction

Chapter 1 introduces the thesis, outlining the research objectives, key questions, and overall structure. It provides context for the study, explains its relevance, and sets the stage for the following chapters.

1.1 Topic Overview

"AI will not replace managers, but managers who use AI will replace those who don't." This statement by Erik Brynjolfsson and Andrew McAfee (2017) captures the essence of the transformative impact AI is having on contemporary business environments, particularly within the management consulting (MC) industry. The rapid development and proliferation of generative AI signifies not merely an incremental technological advancement but rather a fundamental shift in how businesses operate, and professionals execute their tasks.

The introduction of ChatGPT by OpenAI in November 2022 marked a significant milestone, highlighting generative AI's potential to revolutionize how organizations and individuals perform knowledge-intensive tasks. Remarkably, ChatGPT achieved unprecedented adoption rates, surpassing one million users within just five days and reaching 100 million monthly active users in only two months, making it the fastest-growing consumer application in history (Vaghasiya, 2024). Unlike earlier technological innovations, generative AI does not merely automate routine tasks but profoundly enhances cognitive functions such as creativity, analysis, and strategic thinking (Feuerriegel et al., 2024; Noy & Zhang, 2023).

MC, characterized by intense workloads, complex problem-solving, strategic advisory, and high-value intellectual contributions (Kubr, 2002; Muhr & Kirkegaard, 2013), is uniquely positioned at the intersection of digital innovation and human expertise. As generative AI continues to transform the landscape of consulting activities, encompassing domains such as data analysis, client communication, and strategic planning, consultants are witnessing a marked evolution in their roles. This evolution entails a shift from manual, often repetitive tasks towards more strategic, higher-order responsibilities. Moreover, the integration of generative AI into workflows has been shown to result in productivity gains of up to 40%, as reported in a study by Dell'Acqua et al. (2023). This technological shift holds the potential to enhance efficiency and improve work-life balance, while simultaneously introducing new challenges. These include the necessity of maintaining human-centered trust in AI systems (Afroogh et al., 2024), managing the influence of social dynamics on adoption behaviors, and addressing concerns about potential deskilling effects and ethical implications. Consequently, understanding these dynamics becomes crucial to fully grasp the broader implications of AI adoption within consulting.

1.2 Relevance and Objective

Given the transformative impact of generative AI technologies on the MC industry, it is essential to understand the factors influencing their adoption and how this affects consultants' weekly working hours. Although substantial literature addresses the technical capabilities and general impacts of AI, there remains a notable gap concerning the psychosocial factors that influence individual adoption behaviors within professional environments, specifically in MC contexts. Thus, this research aims to fill the gap by examining how trust in AI, peer influence, and the fear of deskilling influence consultants' intention and actual use of generative AI tools, as well as the subsequent effects on their weekly working hours.

The study employs a quantitative, survey-based approach, using Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze data from management consultants. Specifically, it seeks to answer the following research questions:

RQ1: *How do trust in AI, peer influence, and fear of deskilling influence management consultants' adoption of generative AI tools?*

RQ2: *How does the adoption of generative AI affect management consultants' weekly working hours?*

Understanding these aspects provides valuable insights for managers and academics alike. For managers, this research highlights how generative AI can enhance efficiency and improve consultants' well-being by potentially reducing working hours. Academically, the study extends existing literature by exploring trust and peer influence specifically in the context of generative AI in consulting, while also addressing the under-investigated issue of fear of deskilling.

1.3 Structure

Following this introductory chapter, Chapter 2 presents a comprehensive literature review addressing essential theoretical concepts relevant to this thesis. It includes discussions on AI, specifically generative AI, its application within the MC industry, and critical determinants such as trust in AI, peer influence, and fear of deskilling. Additionally, it addresses the potential effects of generative AI on work-life balance, develops hypotheses, and introduces the conceptual framework guiding the study. Chapter 3 outlines the research methodology employed, detailing the survey-based quantitative approach and the use of PLS-SEM. In Chapter 4, the collected data is analyzed, and the hypotheses derived from the conceptual framework are tested. Chapter 5 discusses the implications of the study's findings, addresses its limitations, and proposes avenues for future research. Finally, Chapter 6 provides a summary of the key findings and concludes the thesis.

2 Literature Review

Chapter 2 provides an overview of the theoretical background and existing research relevant to the subject. It covers the essential aspects of AI, examines the management consulting industry, and investigates how generative AI adoption influences work-life balance within this field. Finally, hypotheses are formulated from the findings and linked together in a conceptual model.

2.1 Artificial Intelligence

2.1.1 Definition and Key Concepts of AI

AI is a broad discipline within computer science that focuses on creating machines capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, perception, and language understanding (Russell & Norvig, 2021). Computational advancements have reached a boundless frontier with AI, where autonomy, learning, and inscrutability are defining aspects (Berente et al., 2021). This frontier shifts continuously as technology progresses, causing what was once labeled AI to now fall under the broader category of computing. Autonomy describes the independent functionality of modern AI systems, visible in applications like autonomous vehicles. Learning captures AI’s capacity for self-improvement through data and accumulated experiences. Inscrutability, on the other hand, highlights the complexity of advanced AI systems, which often renders them difficult for non-experts or even humans in general to fully understand. (Berente et al., 2021)

The term "**generative AI**" is used to describe computer-aided technologies that can generate content that appears novel and meaningful, including text, images, and audio (McKinsey & Company, 2024). This is achieved through the use of training data, and the advent of such technologies is transforming the manner in which we work and communicate (Feuerriegel et al., 2024). W. M. Lim et al. (2023) define the term generative AI as follows: "*Generative AI can be defined as a technology that leverages deep learning models to generate human-like content (e.g., images, words) in response to complex and varied prompts (e.g., languages, instructions, questions).*". Generative AI has a multitude of potential applications, with the most prominent being natural language processing (NLP) and image generation. Contemporary NLP models are now predominantly based on large, pre-trained transformer models and can be classified as belonging to the field of generative AI (Min et al., 2023).

AI today is heavily rooted in Machine Learning (ML), which emphasizes improving performance through learning from data (Jordan & Mitchell, 2015). ML encompasses various methods, including supervised learning (using labeled data), unsupervised learning (handling unlabeled data), deep learning, and reinforcement learning. Supervised learning relies on predefined labels, such as classifying emails as spam or not, whereas unsupervised learning seeks patterns without labels. Reinforcement learning operates between these approaches (Jordan & Mitchell, 2015), as agents learn by trial and error, receiving rewards for correct actions (Sutton & Barto, 2018). Deep learning, distinguished by multilayer neural networks, has made significant advances in processing complex data types like images, video, and text (LeCun et al., 2015). Neural networks in deep learning consist of interconnected layers of neurons, where learning occurs through the adjustment of connection weights between these layers (Abdi et al., 1999).

Advanced AI models often integrate multiple ML techniques to enhance performance. For example, OpenAI's GPT is pre-trained through unsupervised learning (Radford et al., 2018) and subsequently refined with reinforcement learning (OpenAI, 2022). Reinforcement learning in GPT employs human feedback to train a reward model, which guides the model in generating appropriate outputs (OpenAI, 2024). Stephen Wolfram (2023) simplifies this by describing GPT as producing statistically plausible continuations of given text, based on its training data and methodology.

Language models like BERT and especially ChatGPT have become central in NLP (Devlin et al., 2019). GPT-based applications, such as ChatGPT, leverage vast datasets from the internet (OpenAI, 2024) and exhibit both impressive linguistic capabilities and extensive general knowledge retention (Petroni et al., 2019). These capabilities offer great potential for improving access to information, enhancing communication, and supporting decision-making across various domains. However, despite these advantages, these models also reflect and potentially amplify human biases, which poses challenges for fairness and inclusivity in AI applications (van Dis et al., 2023). For instance, GPT-2 has shown gender-based biases, associating males with terms like ‘captain’ or ‘president’ and females with adjectives such as ‘sassy’ or ‘diva’ (Liang et al., 2021). Addressing these biases is crucial to ensuring that generative AI fulfills its promise of being a positive force in society.

Despite these challenges, many researchers view generative AI as transformative, offering immense opportunities and risks (Floridi & Chiriatti, 2020; Sanderson, 2023; van Dis et al., 2023). Eloundou et al., (2024) propose that GPTs could function as General-Purpose Technologies due to their widespread economic influence and potential to complement innovations such as legal and coding assistants. It can be argued that General-Purpose Technologies, such as the steam engine, are pivotal for ongoing technical advancement and economic growth (Bresnahan & Trajtenberg, 1995).

2.1.2 Evolution and Trends in AI Development

The field of AI was first proposed in 1956 with the vision that machines would eventually be able to speak, form abstract concepts, solve problems that could previously only be solved by humans, and improve themselves. As early as 1950, Alan Turing proposed what is now known as the "Turing test" in a famous article. This test involves determining which of two chat partners is a human and which is a bot. (Collins et al., 2021)

In the initial phase of AI development that was commercially viable until the 1980s, expert and planning systems were created for clearly defined tasks utilizing manually input symbolic knowledge (e.g. if-then rules). The emphasis was placed on domains such as chess, mathematical proofs, and diagnostics, while natural language, vision, and robotics were investigated as standalone disciplines. The outcomes were constrained, resulting in the "AI winter" and the term "good old-fashioned AI (GofAI)". (Hecker et al., 2017)

From approximately 1990, a further novel approach emerged in the form of distributed AI, which can be traced back to the work of Marvin Minsky. This also formed the basis of what is known as agent technology, which can be used for simulation-based analysis in a number of different areas of investigation (Chaib-Draa et al., 1992). Significant advancements were also made in the field of robotics during the 1990s. One notable competition is the RoboCup, in which scientists and students from diverse geographical locations engage in a competitive setting, pitting their robot teams against each other in a soccer match (Mackworth, 1993). This phase also witnessed the development of complex algorithms in the field of artificial neural networks (Nilsson, 2014; Russell & Norvig, 2021). In 1997, IBM's Deep Blue generated considerable public interest when the computer narrowly defeated world chess champion Garry Kasparov. While this was celebrated as a triumph of the machine over man, critics highlighted that Deep Blue was not genuinely intelligent, but rather calculated all potential moves using pure computing power (Standford, 2012).

In recent years, there has been a notable advancement in the field of AI, particularly in the domain of ML. This development has been identified by experts such as Erik Brynjolfsson and Andrew McAfee (2017) from MIT as the most important general-purpose technology of our era. Building upon the foundations established by ML, with deep learning representing a pivotal subset (Sahoo et al., 2022), AI has advanced into increasingly sophisticated domains. The advent of deep learning, which enables the modeling of intricate patterns within data, has paved the way for generative AI, exemplified by transformative models like ChatGPT and DALL-E that showcase its full potential (W. M. Lim et al., 2023).

Trends in AI adoption indicate its increasing ubiquity across industries, driven by advancements in computational power, algorithmic techniques, and the availability of large datasets. The growth of generative AI exemplifies these trends, with projections indicating the potential for up to 30% of current working hours to be automated by 2030, resulting in productivity gains of 2–3% annually in regions like Europe (Hazan et al., 2024). This is further supported by the rapid adoption of AI in workplaces, with 75% of knowledge workers globally now actively using AI, primarily for boosting efficiency and creativity (Microsoft & LinkedIn, 2024). Despite this momentum, 59% of leaders are concerned about measuring AI-driven productivity gains, and 60% feel their organizations lack a coherent vision for integrating AI solutions (Microsoft & LinkedIn, 2024). Addressing this gap through targeted investments in AI training and strategic implementation will be essential for transforming individual productivity into scalable organizational outcomes. Considering the recent advancements in the field of generative AI, it is worth examining two key trends in relation to the subject matter of this thesis.

In recent years, there has been a notable increase in the use of multimodal AI, with researchers integrating data of varying types, including text, images, and speech, into their models to achieve optimal results (Jayagopal et al., 2022). In the initial stages of development, AI models such as ChatGPT, based on LLM technology, were limited to text-based processing and output (Meskó, 2023). However, these models have since evolved to become multimodal, enabling them to process and generate a more diverse range of inputs and outputs (Bang et al., 2023). For example, multimodal AI models exemplified by Vision-and-Language Models (VLMs) outperform single-modal systems by mimicking human-like processing of language and visuals (Y. Chen et al., 2024). In industries like consulting, such technologies allow for improved client engagement, from creating dynamic visualizations to personalizing insights across languages and cultural contexts, enhancing the impact of services.

Other than that, there is a trend toward individualized AI models tailored to the specific needs of businesses or teams reflects the growing maturity of AI solutions in addressing industry-specific challenges. Unlike generic, out-of-the-box AI tools, these custom solutions integrate domain-specific knowledge and workflows, enabling organizations to optimize processes, improve decision-making, and address unique operational demands (A. Taylor, 2024). For example, Siemens' Industrial Copilot demonstrates how generative AI can be adapted to industrial automation, easing workload challenges and addressing labor shortages (A. Taylor, 2024). Such advancements underscore the transformative potential of AI when aligned closely with organizational contexts and goals.

2.1.3 Impact of Generative AI on Task Automation and Efficiency

Generative AI is profoundly impacting task automation and efficiency in MC by enhancing productivity and optimizing workflows. Tools like ChatGPT have demonstrated the ability to reduce task completion time by up to 40% while improving output quality by 18%, particularly for mid-level tasks such as report writing, data analysis, and content creation (Noy & Zhang, 2023). By automating repetitive and time-consuming processes, generative AI allows consultants to focus their efforts on higher-order, strategic activities that require critical thinking and creativity, thereby significantly improving overall efficiency (Pan, 2024). For instance, in the field of supply chain management, the implementation of generative AI has been shown to enhance decision-making processes, facilitate process optimization, and improve operational efficiency, resulting in a notable increase in accuracy and resilience within the operational framework (Fosso Wamba et al., 2024; Jackson et al., 2024).

A recent study conducted by Dell'Acqua et al. (2023) with Boston Consulting Group (BCG) provides further empirical evidence for the positive effects of generative AI on knowledge work. In a randomized experiment involving 758 consultants, the study demonstrated that access to AI tools like GPT-4 significantly increased productivity and output quality. Consultants using AI completed 12.2% more tasks on average and were 25.1% faster, while producing results of 40% higher quality compared to a control group. Interestingly, the benefits were most pronounced for consultants with below-average initial performance, who saw a 43%

improvement, while top performers still experienced a notable 17% increase. However, the study also highlighted that AI's effectiveness depends on the nature of the task: while it excels at tasks within its "technological frontier," it can reduce performance when used for tasks beyond its current capabilities. (Dell'Acqua et al., 2023)

Generative AI facilitates the automation of labor-intensive tasks, allowing organizations to manage complex cognitive and knowledge-based activities with greater efficiency. While this automation can lead to job displacement and disruptions in the labor market, it also creates opportunities for role transformation and the development of new skills (Bankins et al., 2024; Lazaroiu et al., 2024). In MC, this transformation enables professionals to shift their focus from routine, manual processes to more complex and strategic work. Furthermore, in areas such as innovation management, generative AI supports critical early phases of the innovation process, including exploration and prototyping (Bilgram & Laarmann, 2023). By enabling faster iterations and reducing costs, it allows consultants to test and refine ideas more efficiently, enhancing both productivity and creative output.

2.2 Management Consulting Industry and Technological Change

2.2.1 Overview of the Management Consulting Sector

The MC industry plays a pivotal role in the global economy due to its expertise in problem-solving, client-centered approaches, and ability to adapt to a myriad of challenges across various sectors, including finance, healthcare, technology, and government (Kipping & Clark, 2012). Management Consulting can be defined as: "… an independent professional advisory service assisting managers and organizations to achieve organizational purposes and objectives by solving management and business problems, identifying and seizing new opportunities, enhancing learning and implementing changes" (Kubr, 2002). Consultants are highly valued for their exceptional communication skills, which allow them to convey complex ideas with clarity and precision, and for their immense expertise, which equips them to address intricate challenges and provide innovative, tailored solutions across diverse industries (Kipping & Clark, 2012).

Since the onset of the pandemic in 2020, the global market for MC has experienced a notable expansion. In 2020, the market had an value of USD 876 billion, subsequently surpassing the one trillion USD mark for the first time in 2022 (IBISWorld, 2024). In 2024 the total market value was 1020.39 billion USD (The Business Research Company, 2025). The surge in digitalization across the business landscape, precipitated by the pandemic, has manifested in notable shifts in lifestyle, work patterns, and business strategies (Amankwah-Amoah et al., 2021). MC firms play a pivotal role in driving this transformation by facilitating the diffusion of management and business model innovations across industries, offering critical guidance on the planning, integration, and implementation of novel digital models (Piumelli, 2019; Tavoletti et al., 2021). In addition to the digital transformation, the contemporary business environment is generally characterized by rapid and continuous change, which many organizations are unable to adapt to effectively and timely, especially in the absence of significant resources and expertise (Engwall & Kipping, 2002).

Nevertheless, despite sustained expansion, the consulting sector is confronted with several significant challenges. These challenges are shaped by the imperative to deliver effective outcomes and enhance the value of the diverse services provided to clients, particularly in the context of intensifying competition between major consulting firms. In order to maintain competitiveness in an inherently volatile market, data analysis and digitalization have emerged as pivotal strategies, prompting leading consultancies to offer digital transformation services (Bughin et al., 2017). Furthermore, the MC industry is facing challenges due to clients' demands for greater transparency. This is evidenced by the ISO 20700 standard, "Guidelines for Management Consultancy Services," which emphasize the need for increased transparency in the industry (ISO, 2017).

2.2.2 Impact of Technological Innovations on Consulting Practices

Technological advancements have led to significant shifts within the consulting industry, fundamentally altering its existing business models and service delivery methodologies. The advent of digital transformation has introduced new paradigms, including automation, AI, and remote collaboration. These new paradigms have both disrupted traditional consulting models and enhanced their functionality. In this context, digital transformation can be defined as a process whereby the introduction of digital technologies gives rise to disruptions that prompt strategic responses from companies seeking to alter their value creation pathways and surmount structural changes and organizational obstacles (Vial, 2019). In their analysis of the digital transformation, Verhoef et al. (2021) identify three principal phases: digitization, digitalization, and digital transformation. The process of **digitization** entails the conversion of analog information into a digital format, enabling computers to store, process, and transmit this information (Yoo et al., 2010). The concept of **digitalization** encompasses the transformative process through which information technology or digital tools are utilized to modify, enhance, or entirely reinvent existing business processes (Li et al., 2016). At last, the **digital transformation** is the predominant phase, signifying a comprehensive company transformation that gives rise to novel business models, either novel within the specific company or industry under consideration (Verhoef et al., 2021).

According to Weber (2021), digital transformation has been a significant driver of growth in the consulting industry, driven by clients' demands for advanced technologies to optimize business models. However, this growth also introduces challenges, as technological advancements outpace human capabilities, threatening established consulting paradigms and demanding a shift towards scalable, digital-focused operations (Weber, 2021). The pandemic notably accelerated these shifts, with the industry transitioning from in-person engagements to remote operations, as outlined by Levishchenko et al. (2022). This transition has expanded geographic and functional boundaries, facilitating broader access to consulting services and introducing efficiency gains through remote engagements. The pandemic-driven necessity for remote work also highlighted the potential for asynchronous, technology-mediated collaboration, marking a notable departure from the industry's traditional on-site operational norm (Levishchenko et al., 2022).

The growing use of AI and digital platforms not only enhances the work of consultants but has become integral to their methodology, stimulating innovation in problem-solving while necessitating the acquisition of new skills and mindsets within the workforce. This shift highlights a broader transformation in the consulting industry, where technology is not merely a tool but rather a fundamental element of service delivery, thereby influencing the industry's value proposition and operational strategies.

2.3 Generative AI in Management Consulting

2.3.1 Generative AI: Capabilities and Use Cases in Consulting

Generative AI introduces transformative capabilities that are reshaping traditional consulting practices. By enabling more accurate forecasting, breaking down complex processes into actionable insights, and tailoring solutions to client needs, it strengthens client-consultant relationships and drives value creation (Pattanayak, 2019). Furthermore, its integration allows consultants to anticipate emerging trends, ensuring their clients remain competitive in rapidly changing markets (Pattanayak, 2019).

Large language models (LLMs) like GPT are playing a pivotal role in democratizing innovation management. These tools enhance the early phases of the innovation cycle, such as idea generation, exploration, and digital prototyping, by accelerating iterations and reducing associated costs (Bilgram & Laarmann, 2023). They also streamline tasks like user journey mapping and knowledge management, making them invaluable for early-stage innovation efforts (Bilgram & Laarmann, 2023).

In software development, tools such as Bard, ChatGPT, and CoPilot are revolutionizing productivity. They assist with a range of activities, from writing and debugging code to bridging gaps across development stages (Ebert & Louridas, 2023). By improving efficiency and reducing development times, these AI-powered tools help streamline workflows and deliver faster results (Ebert & Louridas, 2023).

As its adoption grows, the future trajectory of generative AI in consulting hinges on its ethical integration into business processes. Prioritizing transparency, fairness, and accountability will be essential for maintaining trust and ensuring sustainable development (Sengar et al., 2024). These principles are not only key to mitigating risks but also to maximizing the long-term benefits of this transformative technology.

By enhancing strategic decision-making, streamlining innovation, and boosting productivity, generative AI is redefining the consulting industry. Its far-reaching applications underscore the need for responsible practices, enabling consultants to deliver customized solutions, accurate insights, and a competitive edge to their clients.

2.3.2 Drivers and Barriers of AI Adoption in Consulting

The adoption of AI within the consulting sector is shaped by a complex interplay of motivating factors and challenges. As a transformative technology, AI holds significant potential to revolutionize consulting practices, offering substantial economic and operational benefits (Makridakis, 2017). The automation of routine tasks and the enabling of data-driven decision-making through the use of AI enhances productivity and efficiency, which in turn results in a reduction of costs and an improvement of business outcomes (L. Chen et al., 2021; Cubric, 2020; Shang et al., 2023). These advantages create a compelling incentive for consulting firms to invest in AI technologies.

Support from top management plays a crucial role in acquiring new technologies (Hsu et al., 2018). Organizational readiness, driven by the commitment of top management, fosters an environment where innovation can thrive and ensures alignment between technological capabilities and strategic goals (Shang et al., 2023). External pressures further accelerate the integration of AI, as consulting firms face the need to remain competitive in a rapidly evolving Industry 4.0 landscape and adapt to the demands of a post-COVID-19 market (L. Chen et al., 2021; Shang et al., 2023). AI also holds promise for enhancing customer relationships, as it enables more effective relationship management, predictive analytics, and personalized solutions, ultimately improving client satisfaction and loyalty (L. Chen et al., 2021). Additionally, the continuous development of AI tools, characterized by increasing accessibility and user-friendliness, lowers barriers to entry, making adoption more feasible for organizations (Venkatesh, 2022).

Despite these drivers, numerous barriers impede the adoption of AI in consulting. Financial constraints often represent a significant obstacle, as the implementation and maintenance of AI systems can entail substantial costs (Shang et al., 2023). This challenge is particularly pronounced for smaller firms or organizations with limited resources. Compounding this issue is the widespread shortage of skilled employees (Shang et al., 2023). Expertise in data science, ML, and system integration is essential for successful AI implementation.

Technical challenges also present a considerable hurdle. Issues such as limited data availability, difficulties in reusing AI models, and the complexities of integrating new technologies with legacy systems can delay or derail adoption efforts (Cubric, 2020). Social and ethical concerns further complicate the process. Employees may resist AI due to fears about job security, while broader concerns about trust, transparency, and the ethical implications of AI create hesitancy among stakeholders (Booyse & Scheepers, 2023; Cubric, 2020). Finally, regulatory and environmental factors, including restrictive laws and the unpredictability of dynamic business contexts, often exacerbate these challenges, making the adoption process even more demanding (Booyse & Scheepers, 2023).

Balancing these drivers and barriers is essential for consulting firms seeking to leverage the transformative potential of AI. While the benefits of enhanced efficiency, stronger customer relationships, and competitive advantage are clear, overcoming the associated hurdles requires strategic planning and investment. By addressing financial and technical constraints, fostering employee skills through targeted training, and cultivating a culture of trust and innovation, consulting firms can navigate the complexities of AI adoption and unlock its full potential in a rapidly evolving business landscape.

2.3.3 Trust, Peer Influence, and Fear of Deskilling

The adoption of generative AI in the field of MC is influenced by a variety of factors, including trust in AI, peer influence, and the fear of deskilling. While trust and peer influence have received considerable scholarly attention, the phenomenon of fear of deskilling, particularly in the context of generative AI, remains under-explored. The investigation of these determinants underscores their significance and paves the way for the forthcoming survey, which aims to gather empirical evidence.

Trust in AI represents a driving factor when it comes to the acceptance of AI (Kelly et al., 2023), including generative AI systems like ChatGPT (Choudhury & Shamszare, 2023). According to Afroogh et al. (2024), "Trust in AI can be viewed as 'the willingness of people to accept AI and believe in the suggestions, decisions made by the system, share tasks, contribute information, and provide support to such technology'". This highlights that trust functions as both a regulator and a driver of AI adoption, shaping how readily individuals integrate AI systems into their workflows.

The intricate nature of AI systems, encompassing their capacity for learning and the possibility of opacity, renders the establishment of trust both imperative and arduous. As Afroogh et al. (2024) emphasize, factors such as accuracy, reliability, transparency, and explainability of decisions play a pivotal role in determining how trustworthy AI is perceived. In a similar vein, Glikson and Woolley (2020) emphasize that transparency, reliability, task characteristics, and immediacy behaviors collectively influence the establishment of cognitive trust in AI and the role of AI's anthropomorphism specifically for emotional trust.

Empirical studies also underscore that trust in AI is not monolithic but is shaped by cognitive and emotional factors. For instance, Choudhury and Shamszare's (2023) research indicates a direct correlation between user trust and intent to use, as well as actual use of ChatGPT. Conversely, distrust, frequently originating from AI's opaque nature, impedes adoption (Afroogh et al., 2024). This underscores the significance of system transparency and user education in fostering trust. However, overreliance or "blind trust" in AI can also lead to risks, particularly in high-stakes applications such as healthcare, where unchecked reliance might result in errors or ethical concerns (Choudhury & Shamszare, 2023). Subsequently, fostering balanced trust is crucial.

In the context of **peer influence**, it is worthwhile to examine how colleagues perceive their own position in relation to that of their peers. Social comparisons are motivated not only by evaluation but also by the aspiration for self-improvement (gaining knowledge from others and improving their abilities) and self-enhancement (maintaining or elevating self-esteem) (S. E. Taylor et al., 1995; Wood, 1989). Individuals compare themselves to others to assess their opinions and abilities, as outlined by Festinger's (1954) social comparison theory. Conversely, the observation of colleagues utilizing AI effectively can serve as a source of motivation and offer practical insights into enhancing one's own AI skills. As S. E. Taylor and Lobel (1989) have observed, this approach offers a combination of motivational benefits and practical learning opportunities for employees.

Peer influence plays a significant role in shaping technology adoption behaviors, particularly in organizational settings. Eckhardt et al. (2009) emphasize that social influence varies across different workplace referent groups, such as colleagues, superiors, and departmental peers. Their findings suggest that the social dynamics within a team or department significantly impact both the adoption and non-adoption of technologies. This aligns with the Theoretical Model of Artificially Intelligent Device Use Acceptance (AIDUA), which posits that social influence positively affects performance expectancy, thereby shaping individuals' perceptions of AI device capabilities and their subsequent acceptance decisions (Gursoy et al., 2019). Similarly, Chatterjee et al. (2021) highlight the moderating effect of peer influence on the relationship between perceived usefulness and behavioral intention in technology adoption. Their study, conducted within the context of vocational education, underscores that peer endorsement can enhance individuals' attitudes towards adopting new technologies, fostering a sense of shared motivation and acceptance. In the context of AI adoption, similar mechanisms are likely to apply. As Soodan et al. (2024) point out, peer networks characterized by high density and homophily accelerate the diffusion of innovations, including AI tools like chatbots. These network characteristics facilitate information sharing and create a reinforcing loop, where observing peers successfully adopting AI motivates others to do the same. Consequently, it can be inferred that in MC, peer influence is likely to act as a powerful driver of AI adoption, as employees observe and emulate successful use cases among their colleagues, fostering both confidence in and acceptance of the technology.

Despite the growing body of research on the effects of AI in organizational contexts, there remains a notable gap in the literature specifically addressing the **fear of deskilling** arising from the adoption of generative AI in MC. Historically, deskilling has been examined in the context of broader technological and organizational changes, where it is understood as a reduction in the level of skill required to perform specific tasks (Braverman, 1974). Studies on automation and AI have highlighted the potential for technology to diminish certain expert functions and erode professional autonomy (Frey & Osborne, 2017; Susskind & Susskind, 2018), which can trigger anxiety among employees about losing their craft or being replaced. This concern, in turn, may hinder the adoption of new technologies, as individuals perceive the risk of devaluation of their expertise (Davenport & Kirby, 2016).

Additional evidence underscores these anxieties. Mishra et al. (2019) highlight that automation often narrows workers' tasks, eroding their holistic understanding of processes and limiting skill development, which negatively impacts professional growth and well-being. Sinagra et al. (2021) similarly caution that over-reliance on AI in professional training, in the context of healthcare, can undermine self-confidence and autonomy, particularly for junior professionals, emphasizing the need for balanced AI integration to preserve human expertise.

While these analyses underscore the importance of deskilling fears in shaping attitudes toward automation, the unique capabilities of generative AI highlight the need for dedicated empirical research on how these fears manifest and influence AI adoption in MC.

2.3.4 Predictive Power of Intentions in Technology Adoption

Intentions consistently emerge as robust predictors of actual technology use within the literature on technology acceptance, influenced by psychological and contextual determinants (Venkatesh et al., 2012). The Unified Theory of Acceptance and Use of Technology (UTAUT) highlights how behavioural intentions, shaped by performance expectancy, effort expectancy, and social influence, significantly forecast actual usage behaviours (Venkatesh et al., 2012).

Further studies support these findings by emphasizing that intentions toward technology adoption are substantially influenced by both perceived practical utility and alignment with personal ethical values (Turja et al., 2020). Similarly, the Almere model underscores the importance of social and functional acceptance in shaping intentions related to assistive technologies (Heerink et al., 2010).

Additionally, Müller et al. (2019) demonstrate the critical mediating role of trust between intention and actual behaviour, highlighting the significance of personality-driven differences in shaping technology adoption.

In sum, intentions are central and effective predictors of actual technology adoption, shaped by functional, ethical, social, and personality-related factors, which are essential for understanding broader adoption processes.

2.3.5 Effects of Generative AI on Work-Life Balance

The consulting industry has historically been characterized by prolonged work hours and an intense, fast-paced work environment (Muhr & Kirkegaard, 2013). The question thus arises as to what constitutes work-life balance. The concept of work-life balance pertains to the management of the demands of both work and personal life, with the objective of minimizing conflict and maximizing satisfaction (Sirgy & Lee, 2018; Wong et al., 2023). It encompasses the balancing of paid work responsibilities with family and leisure activities (M. Lim & Misra, 2019). The aim is to achieve a state where individuals can maintain a satisfactory quality of life while pursuing career advancements (M. Lim & Misra, 2019). Work-life balance is influenced by various factors, including work demands, job autonomy, and supervisor support, which can either hinder or enhance the balance (Haar et al., 2019).

Generative AI has the potential to improve work-life balance in MC by enhancing productivity and reducing workloads. Tools like ChatGPT allow professionals to complete tasks faster while improving quality, reducing time spent on repetitive activities and freeing up hours for personal commitments (Noy & Zhang, 2023). Increased job autonomy enabled by AI fosters flexibility, allowing consultants to manage work schedules around personal needs (Cramarenco et al., 2023). However, the adoption of AI can also blur boundaries between work and personal life. Enhanced efficiency may lead to higher expectations, as employees are tasked with "doing more" in less time, potentially increasing workloads despite productivity gains (Kreacic et al., 2024). Additionally, concerns about deskilling and the pressure to continuously upskill can cause stress, undermining well-being and work-life balance (Cramarenco et al., 2023).

Positive work-life balance outcomes are most evident when generative AI is implemented with a "people-first" approach. Studies show that aligning the use of AI with employee well-being strategies, such as redesigning workflows to maximize joy and minimize effort, can reduce resistance and increase satisfaction (Lovich et al., 2024). For example, AI can reduce the amount of time spent on "low joy" tasks like data analysis, allowing advisors to engage in more fulfilling professional activities (Lovich et al., 2024). By fostering autonomy and skill development, AI can ultimately lead to a more balanced and satisfying professional life.

To ensure a positive impact, organizations must manage AI integration carefully, balance workloads, and provide reskilling opportunities. When implemented effectively, generative AI can alleviate pressure and contribute to a more sustainable work-life balance.

2.4 Formulation of Hypotheses and Conceptual Model

Building upon the preceding discussion of generative AI in MC, especially the roles of trust, peer influence, and fear of deskilling (Section 2.3.3) as well as the potential implications for work-life balance (Section 2.3.4), this chapter derives and presents the hypotheses that guide the empirical portion of this study. As highlighted, the constructs of trust, peer influence, and fear of deskilling emerge as critical psychosocial factors determining whether and how management consultants embrace new technologies. Further, the capacity of AI to redistribute work tasks and potentially reduce working hours underpins the rationale for exploring its influence on weekly working hours in consulting settings.

As previously mentioned in Chapter 2.3.3, the factors Trust in AI and Peer influence have been identified in numerous studies as having a positive effect on the intention to use AI or new technologies (Choudhury & Shamszare, 2023; Eckhardt et al., 2009). Consequently, Hypotheses H1a and H1b are clearly supported by these findings. However, the influence of fear of deskilling on the intention to use AI remains unclear, as no studies have yet demonstrated its direct impact. This aspect, therefore, warrants further examination and testing. A thorough examination of this factor in Chapter 2.3.3 reveals its potential to influence the intention to use AI negatively, thereby supporting the formulation of Hypothesis H1c:

H1a: *Trust in AI is positively associated with Intent to Use AI.*

H1b: *Peer Influence is positively associated with Intent to Use AI.*

H1c: *Fear of Deskilling is negatively associated with Intent to Use AI.*

Behavioral intention is a pivotal construct in technology acceptance models, as evidenced by its consistent ability to predict actual usage, a finding that has been validated by prior research (Heerink et al., 2010; Müller et al., 2019; Turja et al., 2020). Specifically, the Unified Theory of Acceptance and Use of Technology (UTAUT) posits that higher behavioral intention directly translates into increased actual use of technology (Venkatesh et al., 2012). Once consultants decide they intend to utilize AI tools for tasks such as data analysis or report generation, they are more likely to follow through:

H2: *The actual use of AI increases with users' intent to AI.*

Additionally, trust in AI, peer influence, and fear of deskilling have the capacity to exert a more direct influence on the actual implementation of AI. This phenomenon was previously demonstrated in the study conducted by Choudhury and Shamszare (2023), which investigated the impact of user trust on the adoption and use of ChatGPT. In a similar vein, Zhang et al. (2018) have established that the immediate peer network exerts a direct influence on the adoption of novel technologies. Consequently, it can be posited that the phenomenon of "fear of deskilling" may be analogous, thereby giving rise to the following hypothesis:

H3a: *Trust in AI is positively associated with Actual Use of AI.*

H3b: *Peer Influence is positively associated with Actual Use of AI.*

H3c: *Fear of Deskilling is negatively associated with Actual Use of AI.*

Furthermore, prior research on technology acceptance highlights that an individual's intention to adopt a new system can partially mediate the impact of underlying psychological and social factors on actual use. For instance, a study on technology acceptance for assistive social robots among older adults showed that people's intentions to use a robot played a mediating role in the relationship between trust and how often they used it (Heerink et al., 2010). Applied to the context of MC, this suggests that while strong trust in AI, supportive peer feedback, or the absence of deskilling concerns may foster positive attitudes, these factors must be channeled through an explicit intent to use AI for them to lead to actual usage. Conversely, if fear of deskilling undermines one's intention, even initially favorable perceptions may fail to generate meaningful adoption behaviors. To test this mediating mechanism, the following hypotheses are made:

H4a: *Intent to Use AI mediates the positive relationship between Trust in AI and Actual Use of AI.*

H4b: *Intent to Use AI mediates the positive relationship between Peer Influence and Actual Use of AI.*

H4c: *Intent to Use AI mediates the negative relationship between Fear of Deskilling and Actual Use of AI.*

Finally, given the overarching objective of this thesis, which is to explore the impact of generative AI adoption on weekly working hours, existing literature indicates that effective implementation of generative AI can result in a reduction of task completion time while concomitantly enhancing output quality (Dell'Acqua et al., 2023; Noy & Zhang, 2023). Studies have indicated that generative AI can mitigate "low-joy" or repetitive work (Lovich et al., 2024), thus allowing consultants to complete the same workload with fewer hours, if implemented thoughtfully. Accordingly, one may expect a direct, inverse relationship between the level of AI usage and weekly working hours:

H5: *Actual Use of AI is negatively associated with weekly working hours.*

In summary, the proposed model integrates trust, peer influence, and fear of deskilling as critical factors for the intention to use AI and the actual use of AI. The intention to use AI is posited to function as a potential mediator. Furthermore, it is anticipated that the actual use of AI will result in a reduction of weekly working hours by automating repetitive tasks and enhancing efficiency. The interplay and dependencies among these factors are illustrated in Figure 1 below.

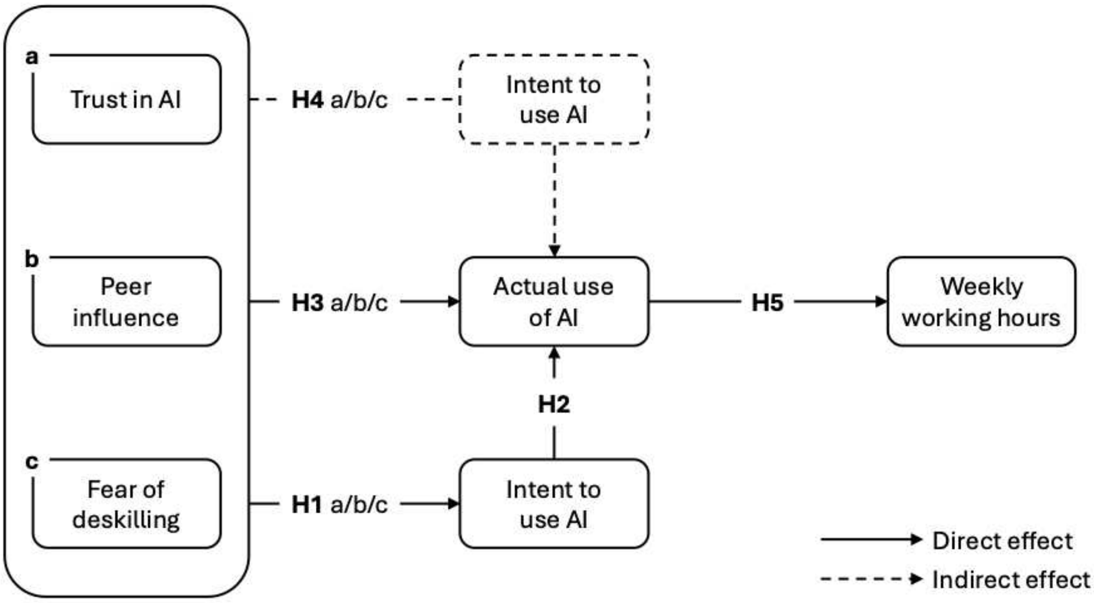

Figure 1: Conceptual Model

3 Methodology

Chapter 3 describes the methodological approach employed to address the research objectives. It outlines ethical considerations, research design, and detailed procedures for data collection. Furthermore, it explains participant recruitment and the analytical methods utilized to ensure rigorous and valid empirical results.

3.1 Ethical Considerations

This study follows strict ethical guidelines to ensure participant protection, confidentiality, and transparency. Participation is voluntary, with informed consent implied upon survey initiation. Respondents confirm their eligibility (18+ years old) and are explicitly informed of their right to withdraw at any time without their data being recorded. The survey is anonymous, with no personally identifiable information collected, and all responses are used solely for academic research purposes. To prevent response bias, the full research purpose is disclosed only after survey completion through a debriefing statement. These measures align with recognized ethical research standards, ensuring data integrity and participant autonomy (BSA, 2017).

3.2 Research Design

Empirical research aims to systematically generate knowledge by collecting and analyzing data (Creswell & Creswell, 2022). Broadly, empirical research can be classified into qualitative and quantitative approaches (Christofi et al., 2021). Qualitative research focuses on exploring complex social behaviors and underlying motivations, often using open-ended methods such as interviews or case studies (Denzin & Lincoln, 2017). It follows an inductive approach, seeking to develop theories rather than testing predefined hypotheses (Corbin & Strauss, 2014; Morgan & Smircich, 1980). In contrast, quantitative research emphasizes the measurement and statistical analysis of relationships between variables, typically using structured data collection methods such as surveys or experiments (Bryman et al., 2021; Smith, 1983). This approach is deductive in nature, aiming to test hypotheses and derive generalizable conclusions (Saunders et al., 2023).

The most appropriate methodological approach for this study is a quantitative, correlational, survey-based approach, as it enables systematic hypothesis testing, objective measurement, and statistical analysis (Creswell & Creswell, 2022). The study employs a structured survey conducted via Qualtrics to collect data on trust in AI, peer influence, and fear of deskilling as determinants of AI adoption and their subsequent impact on working hours. The collected data will be analyzed using PLS-SEM, allowing for the simultaneous examination of multiple relationships and the assessment of both direct and indirect effects (Hair et al., 2021).

3.3 Procedure

The study was conducted in English to ensure accessibility for an international audience of management consultants and professionals in related fields. The survey was administered via Qualtrics and designed to maintain neutrality, response validity, and data reliability throughout. It begins with a brief introduction, providing a general thematic context without revealing the precise research focus to minimize response bias. Participants are also provided with contact details for inquiries and must confirm that they are at least 18 years old before proceeding. If they do not meet this criterion, the survey automatically terminates, thereby aligning with the recognized ethical research standards mentioned before (BSA, 2017). Following this, a definition of Generative AI is presented to ensure a shared understanding among all respondents before they continue.

The initial section of the survey assesses trust in AI, using seven validated statements measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), adapted from Choudhury and Shamszare's (2023) study on the impact of user trust on the adoption and use of ChatGPT. Next, peer influence is measured using three statements, also rated on the same scale, sourced from Eckhardt's et al. (2009) study on the social influence of workplace referents on IT adoption and non-adoption. The subsequent section examines fear of deskilling, for which five custom-developed statements were used, as no existing validated measures were identified in prior research.

Following this, intent to use AI is measured using three statements, again derived from Choudhury and Shamszare (2023). To ensure participant attention and response quality, an Instructed response item (IRI) is embedded next in the survey, requiring respondents to explicitly select "Agree". Such IRIs have been shown to identify inattentive respondents effectively (Gummer et al., 2021), where failure would lead to the exclusion of their responses from the final dataset. The next section captures actual AI usage frequency, where participants indicate whether they use AI Never, Rarely, Occasionally, Frequently, or Every Day, following the scale used by Choudhury and Shamszare (2023).

Participants are then asked to report their weekly working hours in a numerical text field restricted to whole numbers between 0 and 168, ensuring validity of responses. The final section collects demographic information, including age, gender, country of origin, education level, employment status, primary industry, and years of experience in consulting or related fields.

The last two demographic questions are particularly important for ensuring the relevance of responses to the study.

At the conclusion, participants are given the option to leave additional comments before being debriefed on the true purpose of the study and thanked for their participation. To maximize data quality and completeness, all responses were mandatory, except for the optional comment field. Demographic questions were placed at the end to ensure that participants' cognitive attention remained focused on the core constructs earlier in the survey. The survey in its entirety is available in the appendix.

3.4 Participants

Participants were recruited primarily through personal networking and social media outreach. Direct invitations were sent to individuals with consulting experience, who were also encouraged to share the survey with colleagues in the field. Additionally, participation was promoted via LinkedIn, explicitly targeting professionals with consulting backgrounds. To ensure relevance and data quality, only individuals with consulting experience were invited, and incomplete responses were removed before analysis.

A total of 106 participants fully completed the survey, with 100% correctly answering the IRI, indicating sufficient attention to the survey. However, five respondents reported weekly working hours below 30, which, for the purposes of ensuring comparability with full-time employment standards, led to their exclusion. Additionally, two participants indicated zero years of consulting experience, which, given the study's focus, warranted their removal. Finally, another five participants were excluded from the evaluation because they did not primarily work in the consulting industry or a related field. These participants were excluded even though they had experience in the consulting industry. However, it was not ascertained when this experience occurred or whether generative AI had already had an impact there. This resulted in a final sample size of 94 valid responses.

The final 94 respondents comprised 67 males and 27 females, reflecting a gender distribution that is somewhat imbalanced. The mean age of participants was 27.59 years (SD = 4.76), with the youngest respondent being 23 years old and the oldest 58 years old. The educational background was predominantly postgraduate, with 65 participants holding a Master's degree, 24 a Bachelor's degree, three having completed some college without a degree, and one holding a PhD. Given the researcher's professional network being mostly in Germany, 65 participants

(69.1%) were German, followed by six Austrians, with the remaining respondents representing a diverse set of nationalities (full distribution available in the appendix).

Regarding employment status, the majority (70 participants) were employed full-time, while the remaining sample included 8 interns, 6 working students, 6 students, and 4 unemployed individuals. In terms of industry affiliation, 67 participants worked in MC, 18 in other consulting services, and 9 in strategy/advisory services.

Participants self-reported their years of consulting experience in 0.5-year increments, resulting in a mean tenure of 2.12 years (SD = 2.16). This distribution captures a mix of early-career and experienced consultants, providing a diverse perspective on AI adoption and weekly working hours in the industry. The sample composition and selection process ensure that the data reflect individuals relevant to the research question, providing meaningful insights into the relationship between AI adoption, trust, peer influence, fear of deskilling, and weekly working hours in consulting. An overview of the demographics of the participants can be found in Table 1.

Table 1: Demographics of the respondents (n=94)

Variable	**Category**	**Frequency / Statistics**
Gender	Female	27
	Male	67
Age	Mean	27.59
	Standard Deviation	4.76
	Maximum	58
	Minimum	23
Country of Origin	Germany	65
	Other	29
Level of Education	Some College	3
	Bachelor’s Degree	24
	Master’s Degree	65
	Ph.D. / Dr.	1
Current Employment Status	Employed (Full-Time)	70
	Unemployed	6
	Student	6
	Student-Worker	6
	Intern	8
Primary Industry	Management Consulting	67
	Other Consulting Services	18
	Strategy / Advisory Services	9
Years of Consulting-Experience	Mean	2.12
	Standard Deviation	2.16
	Maximum	10
	Minimum	0.5

3.5 Data Analysis

All data analysis is conducted using SmartPLS, a widely used software for PLS-SEM. PLS-SEM is particularly suited for studies examining complex relationships between latent constructs, as it allows for simultaneous estimation of measurement and structural models without imposing strict distributional assumptions (Hair et al., 2019). It is also well-suited for small to medium sample sizes and provides robust results when working with models containing multiple constructs and indicator variables (Hair et al., 2011). Consequently, the PLS-SEM method has emerged as a quasi-standard in marketing and management research for the analysis of cause-and-effect relationships between latent constructs (Hair et al., 2011).

To implement this method, a model with four latent variables and two manifest variables is developed. The four latent variables are "Trust in AI," "Peer Influence," "Fear of Deskilling," and "Intent to Use AI". Each of these latent variables is composed of statements evaluated in the respective section of the survey. Specifically, the "Trust in AI" variable comprises seven statements, the "Peer Influence" variable contains three statements, the "Fear of Deskilling" variable contains five statements, and the "Intent to Use AI" variable contains three statements. The two manifest variables, "Actual Use of AI" and "Weekly Working Hours," each consist of the corresponding single-term questions. All these variables were linked to each other using the previously established conceptual model shown in Figure 1.

To ensure the validity and reliability of the measurement model, convergent and discriminant validity are assessed. Reliability is evaluated based on three key criteria proposed by Hair et al. (2019): factor loadings (>0.708), Cronbach's α (>0.70), composite reliability (CR) (>0.70). To confirm convergent validity we look at the average variance extracted (AVE) which should be above the threshold of 0.50 (Hair et al., 2019). To assure discriminant validity the Heterotrait-Monotrait (HTMT) ratio is applied, ensuring that values remain below the 0.90 threshold (Ab Hamid et al., 2017). Finally, the Harman single-factor test will be assessed to determine whether common method bias (CMB) is an issue in this study.

Once the measurement model is validated, a bootstrapped PLS-SEM is used to test the structural model and hypotheses. PLS-SEM is particularly advantageous in exploratory research, as it enables the estimation of direct, indirect, and moderating effects within a theoretical framework while maintaining the flexibility to explore complex interdependencies between constructs

(Hair et al., 2019). The bootstrapping procedure, which involves resampling the data to generate robust standard errors and confidence intervals, enhances the statistical reliability of the estimated path coefficients. By leveraging this approach, the study derives empirical insights into the relationships between trust in AI, peer influence, fear of deskilling, AI adoption, and weekly working hours in MC, ensuring greater robustness and validity in the interpretation of results.

4 Results

Chapter 4 presents the empirical findings of this research. It covers reliability and validity assessments of the measurement model, addresses CMB, and systematically details the outcomes of hypothesis testing, providing a clear view of the relationships examined in the conceptual model.

4.1 Reliability and Validity

4.1.1 Reliability

As previously mentioned, the reliability of the latent variables and the overall measurement model is first assessed. Table 2 provides an overview of the four constructed latent variables and their respective indicator items, each of which was rated by participants on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The evaluation of reliability is conducted by examining the factor loadings, which, according to Hair et al. (2019), should exceed 0.708. The results indicate that all items meet this threshold. Furthermore, as presented in Table 2, both Cronbach's α and CR for all four latent variables exceed the 0.700 threshold stipulated by Hair et al. (2019), thereby substantiating the internal consistency and reliability of the measurement model. Consequently, the reliability of the measurement model is substantiated.

Table 2: Measurement items and their reliability

Latent Variables and their respective items	Factor loadings
Trust in AI (α: 0.912, CR: 0.930)	
1. Generative AI is competent in providing the information and guidance I need.	0.793
2. Generative AI is reliable in providing consistent and dependable information.	0.847
3. Generative AI is transparent.	0.877
4. Generative AI is trustworthy in the sense that it is dependable and credible.	0.865
5. Generative AI will not cause harm, manipulate its responses, or create negative consequences for me.	0.725
6. Generative AI will act with integrity and be honest with me.	0.802
7. Generative AI is secure and protects my privacy and confidential information.	0.740
Peer influence (α: 0.870, CR: 0.920)	
1. My peers think that I should use generative AI tools.	0.888
2. My peers recommend using generative AI tools.	0.913
3. My peers use generative AI tools frequently.	0.869
Fear of deskilling (α: 0.865, CR: 0.901)	
1. I fear that over-reliance on generative AI tools reduces my need to develop new skills.	0.796
2. I fear that frequent use of generative AI tools weakens my ability to think critically.	0.822
3. I fear that frequent use of generative AI tools weakens my ability solve problems independently.	0.744
4. I fear that the automation of tasks by generative AI tools limits my hands-on experience.	0.805
5. I fear that generative AI replaces tasks that help me develop expertise.	0.849
Intent to use AI (α: 0.894, CR: 0.934)	
1. I am willing to use generative AI tools for work related tasks / problems.	0.951
2. I am willing to take decisions based on the recommendations provided by generative AI tools.	0.878
3. I am willing to use generative AI tools in the future.	0.895

α represents value of Cronbach's α, and CR represents composite reliability.

4.1.2 Validity

After the confirmation of the reliability of the measurement model, the subsequent step is to examine and verify the convergent and discriminant validity. To that end, an examination of Table 3 is warranted. According to Ab Hamid et al. (2017), the HTMT ratios shown there must each be below the threshold value of 0.9. The ratios from Table 3 are all below this threshold, thus confirming the discriminant validity of the measurement model. To ascertain the convergent validity, the AVE values from Table 3 for the respective latent variables are examined, revealing that all values exceed the 0.5 threshold recommended by Hair et al. (2019), thereby substantiating the convergent validity.

Table 3: Discriminant validity analysis

	AUA	FOD	IUA	PI	TIA	WWH
AUA						
FOD	0.427					
IUA	0.885	0.493				
PI	0.788	0.347	0.876			
TIA	0.567	0.720	0.752	0.561		
WWH	0.361	0.515	0.486	0.449	0.521	
AVE	N/A	0.636	0.826	0.794	0.641	N/A

The matrix displays the HTMT ratios to evaluate the discriminant validity of the constructs, as well as the AVE for each latent variable to assess their convergent validity.

4.1.3 Common Method Bias

CMB can occur in self-reported survey research when variance is attributed to the measurement method rather than the constructs being examined, potentially inflating relationships between variables (Podsakoff et al., 2003). To assess whether CMB poses a threat to the validity of this study, Harman's single-factor test is conducted, a widely used diagnostic tool recommended by Podsakoff et al. (2003) for detecting such biases. An unrotated exploratory factor analysis (EFA) is performed, where all 18 indicators, rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), are forced to load onto a single latent factor. The analysis indicates that this factor accounts for 48.9% of the average variance explained. While this figure approaches the 50% threshold (Podsakoff et al., 2003), it remains within the acceptable range, suggesting that CMB is not a significant concern. Although this outcome is not optimal, it is adequate to conclude that CMB is unlikely to compromise the validity of the study's findings to a substantial extent.

4.2 Hypotheses Testing

To test the proposed hypotheses, a PLS-SEM analysis with bootstrapping using 1,000 subsamples is conducted, ensuring statistical robustness and reliable confidence intervals. Given that the hypothesized relationships are based on theoretical reasoning, one-tailed significance tests are applied, as this approach is appropriate when the direction of effects is well-established (Hair et al., 2019). The results, summarized in Table 4, provide insights into the direct and mediating effects within the model.

Table 4: Summary of hypothesis testing

Hypothesis	β	Bootstrap M (SD)	Remark
H1a: Trust in AI → Intent to use AI	0.384	0.382 (0.109)***	Supported
H1b: Peer Influence → Intent to use AI	0.550	0.550 (0.074)***	Supported
H1c: Fear of deskilling → Intent to use AI	-0.038	-0.040 (0.084)	Not supported
H2: Intent to use AI → Actual use of AI	0.698	0.700 (0.124)***	Supported
H3a: Trust in AI → Actual use of AI	-0.128	-0.120 (0.107)	Not supported
H3b: Peer Influence → Actual use of AI	0.234	0.227 (0.112)*	Supported
H3c: Fear of deskilling → Actual use of AI	-0.106	-0.102 (0.113)	Not supported
H4a: Trust in AI → Intent to use AI → Actual use of AI	0.268	0.264 (0.083)***	Supported
H4b: Peer Influence → Intent to use AI → Actual use of AI	0.383	0.386 (0.091)***	Supported
H4c: Fear of deskilling → Intent to use AI → Actual use of AI	-0.026	-0.030 (0.061)	Not supported
H5: Actual use of AI → Weekly working hours	-0.358	-0.360 (0.107)***	Supported

Standard error in parenthesis. ***$p \leq .001$, **$p \leq .01$, *$p \leq .05$, +$p \leq .10$

The findings indicate that trust in AI (H1a, β = 0.384, p ≤ .001) and peer influence (H1b, β = 0.550, p ≤ .001) significantly and positively influence the intent to use AI, thereby supporting these hypotheses. However, fear of deskilling (H1c, β = -0.038, p > .10) does not exhibit a significant relationship with intent to use AI, and thus, the analysis does not find support for this hypothesis.

Furthermore, intent to use AI (H2, β = 0.698, p ≤ .001) is found to be a strong predictor of actual AI use, supporting the hypothesis. When analyzing the direct effects on actual AI use, peer influence (H3b, β = 0.234, p ≤ .05) is found to have a significant positive effect, whereas trust in AI (H3a, β = -0.128, p > .10) and fear of deskilling (H3c, β = -0.106, p > .10) do not show significant relationships, and thus, the analysis does not find support for these hypotheses.

Regarding mediation effects, both trust in AI (H4a, β = 0.268, p ≤ .001) and peer influence (H4b, β = 0.383, p ≤ .001) significantly influence actual AI use through intent to use AI, supporting these mediation hypotheses. However, the indirect effect of fear of deskilling (H4c, β = -0.026, p > .10) is non-significant, and thus, the analysis does not find support for this hypothesis.

Finally, the relationship between actual AI use and weekly working hours (H5, $\beta = -0.358$, $p \leq .001$) is negative and significant, suggesting that increased AI adoption is associated with reduced working hours, thereby supporting the hypothesis.

Additionally, the bootstrap mean values, derived from 1,000 resamples, closely align with the estimated β coefficients, confirming the stability of the parameter estimates. The relatively low standard deviations further indicate that the estimated effects are consistent across resampling iterations, reinforcing the robustness of the results.

Figure 2 offers a visual representation of these relationships in SmartPLS, with the R-squared values displayed in the blue nodes, path coefficients and their *p*-values in parentheses on the connecting arrows between latent variables, and *t*-values on the paths from each latent variable to its indicators.

The R^2 values indicate the proportion of variance explained by the independent variables for each dependent variable. In this model, intent to use AI ($R^2 = 0.719$) and actual use of AI ($R^2 = 0.731$) exhibit strong explanatory power, suggesting that the predictors effectively account for a substantial portion of variance in these constructs. In contrast, weekly working hours ($R^2 = 0.128$) has a lower explained variance, indicating that while AI use significantly impacts working hours, additional factors may also play a role.

The *t*-values on the measurement paths from latent variables to their indicators assess the reliability of each item. In this model, all *t*-values exceed the 1.64 threshold, indicating that all indicators are significant at the 5% level under one-tailed testing (Hair et al., 2021). This provides additional evidence for convergent validity, as it confirms that each observed variable contributes meaningfully to its respective latent construct.

Taken together, these results provide strong empirical support for the role of trust in AI and peer influence in shaping AI adoption through intent, while fear of deskilling does not emerge as a decisive factor. Furthermore, the findings confirm that AI adoption has a measurable impact on reducing working hours, underlining its potential role in improving work-life balance in consulting professions.

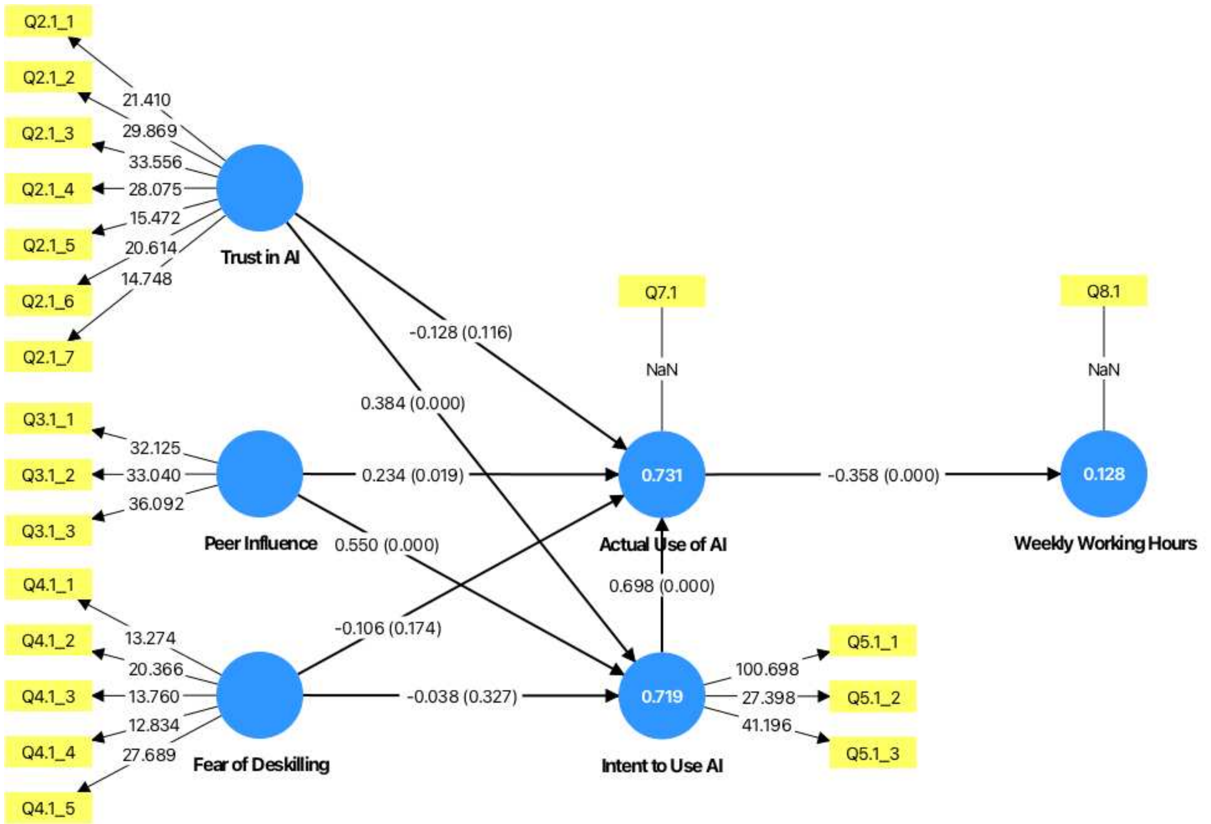

Figure 2: Structural Model Results (SmartPLS) displaying R² values (explained variance) in blue nodes, path coefficients with p-values in parentheses, and t-values along measurement paths.

5 Discussion

Chapter 5 interprets the study's findings, connecting them with existing literature and highlighting their significance. It thoroughly discusses theoretical and managerial implications derived from the results and transparently addresses limitations, offering clear directions and suggestions for future research.

5.1 Summary of Results

This study examines the impact of generative AI adoption on weekly working hours in management consulting, focusing on the roles of trust in AI, peer influence, and fear of deskilling as determinants of AI usage. Using PLS-SEM analysis with bootstrapping (1,000 resamples), the study evaluates both direct and indirect relationships between these factors and their influence on AI adoption and weekly working hours.

The findings indicate that trust in AI (H1a) and peer influence (H1b) significantly enhance the intent to use AI, confirming their importance in shaping AI adoption attitudes. However, fear of deskilling (H1c) does not exhibit a significant effect, suggesting that concerns about skill erosion do not strongly deter AI adoption. Furthermore, intent to use AI (H2) emerges as a strong predictor of actual AI use, reinforcing the idea that forming an adoption intention is crucial for behavioral implementation.

Regarding direct effects on actual AI usage, peer influence (H3b) has a significant positive impact, whereas trust in AI (H3a) and fear of deskilling (H3c) do not show significant direct effects. This implies that social influences play a more critical role in directly driving actual AI adoption than personal trust perceptions or concerns about skill obsolescence. Mediation analyses further confirm that intent to use AI mediates the effects of trust in AI (H4a) and peer influence (H4b) on actual AI use, while no significant mediation effect is observed for fear of deskilling (H4c).

Additionally, the study finds a negative and significant relationship between actual AI use and weekly working hours (H5), indicating that higher AI adoption is associated with reduced working time. This suggests that AI tools may contribute to improved efficiency and work-life balance by reducing the time spent on routine tasks.

Overall, these results provide strong empirical support for the role of trust in AI and peer influence in shaping AI adoption through intent, while fear of deskilling does not emerge as a decisive factor. The findings further highlight that AI adoption is linked to a measurable reduction in working hours, underscoring its potential impact on work-life balance in management consulting.

5.2 Connection to the Existing Literature

The findings of this study align with existing literature in several respects, while also highlighting notable divergences, thereby contributing nuanced insights to established research streams on technology acceptance, social influences in technology use, and the largely unexplored area of fear of deskilling.

In line with previous literature, the findings confirm the importance of peer influence as a significant predictor of both intention and actual use of generative AI tools. This aligns well with the work of Eckhardt et al. (2009) and Chatterjee et al. (2021), who emphasized that colleagues' recommendations and behaviors significantly affect individual decisions to adopt new technologies. The present study reinforces these conclusions specifically within the context of MC, an industry highly dependent on collaborative and social dynamics.

In the context of Trust in AI, the findings of this study largely corroborate those of Choudhury and Shamszare's (2023), confirming three out of their four key hypotheses: trust significantly predicted intent to use AI, intent to use AI significantly influenced actual use, and intent to use AI mediated the relationship between trust and actual usage. However, the direct relationship between trust in AI and actual use observed by Choudhury and Shamszare (2023) was not replicated in this study. This discrepancy might be attributed to contextual differences or specific methodological variations, such as sample characteristics or measures used. Specifically, Choudhury and Shamszare (2023) investigated ChatGPT usage in general contexts, whereas this study focused explicitly on management consultants, whose reliance on AI might be influenced by additional industry-specific factors.

Furthermore, regarding fear of deskilling, the results did not support the hypothesized negative effects on AI adoption, diverging from broader theoretical discussions presented by Mishra et al. (2019). This prompts further inquiry into the existence of a genuine fear of deskilling, a notion previously highlighted by Sinagra et al. (2021) in their concise article. This absence of empirical support may reflect the unique nature of generative AI, which could have distinct implications compared to traditional automation. Given the limited existing literature specifically examining fear of deskilling related to generative AI, these results contribute important empirical insights into an area previously dominated by theoretical assumptions.

Additionally, this study substantiates existing claims from Dell'Acqua et al. (2023) and Noy and Zhang (2023) regarding the benefits of generative AI adoption in terms of task efficiency. Specifically, the findings reinforce the hypothesis that higher actual use of generative AI is associated with a reduction in weekly working hours, supporting theoretical expectations about potential improvements in work-life balance within high-intensity professional contexts like MC.

Overall, the study enriches the existing literature on technology acceptance, emphasizing the critical role of peer influence, nuanced trust dynamics, and highlighting the need for deeper exploration of fear of deskilling. These insights contribute valuable perspectives to ongoing discussions around generative AI, particularly within literature addressing technology acceptance and biased decision-making processes.

5.3 Implications

The findings from this study make several significant contributions to both academic literature and managerial practice, particularly within the realm of technology adoption and its impact on work-life balance in MC.

5.3.1 Theoretical Implications

The theoretical contributions of this research build upon and extend existing literature, primarily by addressing conceptual gaps and clarifying previously unexplored or inadequately explored relationships.

First, the study contributes significantly to the theoretical discourse on the concept of fear of deskilling. While previous literature primarily introduced and defined the concept of deskilling as a potential concern associated with technological automation (Braverman, 1974; Mishra et al., 2019; Sinagra et al., 2021), empirical evidence specifically relating to its influence on generative AI adoption has been sparse. By formulating and empirically testing this previously largely theoretical notion, this study provides initial empirical insights that challenge the assumed negative relationship. The absence of significant findings in the hypothesized negative relationship between fear of deskilling and AI adoption suggests that, at least within the MC context, consultants might perceive generative AI differently from traditional automated technologies. Rather than seeing generative AI as a threat to their skillsets, professionals in this knowledge-intensive sector may view it as complementary to their existing competencies, an insight that provides a new theoretical angle warranting deeper investigation.

Second, this research enriches our understanding of the determinants influencing generative AI adoption by empirically testing and validating critical factors such as trust in AI and peer influence. Confirming prior research (Chatterjee et al., 2021; Choudhury & Shamszare, 2023; Eckhardt et al., 2009) the study reinforces the importance of trust and social dynamics as foundational components in shaping the intention to adopt innovative technologies. The study notably highlights the robust mediating role of behavioral intent between psychological drivers—trust and peer influence—and the actual use of generative AI, thus affirming key assumptions of the Unified Theory of Acceptance and Use of Technology (UTAUT).

Finally, the empirically confirmed relationship between actual AI use and reduced working hours advances theoretical discussions regarding AI-driven efficiency. By empirically quantifying the effect of generative AI on task efficiency and working hours, this research substantiates existing theoretical predictions regarding productivity enhancements through AI (Dell'Acqua et al., 2023; Noy & Zhang, 2023). These results suggest that generative AI's practical implications extend beyond theoretical efficiency gains, having measurable impacts on professional workloads and work-life dynamics.

In sum, the theoretical implications of this research primarily reside in the nuanced exploration of the fear of deskilling, clarification of trust dynamics within technology adoption models, and the empirical validation of generative AI's impact on efficiency and work-life balance, thereby extending and refining the theoretical landscape of AI adoption in professional contexts.

5.3.2 Managerial Implications

This research provides critical insights and practical guidance for MC firms aiming to successfully integrate generative AI into their operations.

Firstly, the significant role of peer influence in shaping intentions and actual usage of generative AI highlights the need for consulting firms to foster environments that capitalize on social dynamics. Managers should actively establish structured internal communication systems and leverage both formal and informal knowledge-sharing mechanisms—such as work teams, technology-based platforms, and social networks—to facilitate the effective exchange of expertise and best practices in generative AI adoption (Yeboah, 2023). As highlighted by Eckhardt et al. (2009), organizational practices that encourage positive peer interactions and shared experiences significantly enhance the acceptance and integration of new technologies.

Secondly, given the crucial role of trust identified in this study, top management holds a critical responsibility in establishing and maintaining a trustworthy perception of generative AI technologies. Managers should implement transparent communication strategies and predeployment tactics like 'twinning' and 'experimenting' to enhance AI trustworthiness and social acceptance (Hasija & Esper, 2022). Additionally, upskilling initiatives signal workforce stability and support successful AI integration (Hasija & Esper, 2022). As argued by Hsu et al. (2018), effective adoption and utilization of new technologies fundamentally rely on strong support and clear communication from top management, which significantly shapes employees' perceptions and acceptance.

Additionally, managers should note that fear of deskilling was not found to be a significant barrier in this context, suggesting that consultants perceive generative AI as complementary rather than substitutive of their skills. Managerial efforts should thus focus on highlighting AI's potential for enhancing existing competencies, rather than emphasizing fears about skill obsolescence. Providing targeted professional development initiatives and emphasizing the role of AI tools in enriching strategic and analytical capabilities can effectively align employee perceptions with organizational goals (McKinsey & Company, 2023).

Moreover, the empirically confirmed benefit of generative AI in reducing weekly working hours provides MC firms with a strategic lever to improve employee well-being, reduce burnout, and foster a healthier work environment. By leveraging generative AI tools to systematically decrease routine workloads, firms can enhance employee satisfaction, thereby positively influencing retention rates and overall workplace morale. The implementation of work-life balance practices has been demonstrated to exert a positive influence on organizational performance by fostering social exchange processes, reducing costs, boosting productivity, and minimizing turnover (Beauregard & Henry, 2009).

Finally, consulting firms should adopt a balanced approach in integrating generative AI. This involves careful attention by top management to both technological implementation and the human and cultural dimensions of AI integration, aligning adoption strategies with sustainable organizational practices. By addressing these combined strategic, technical, and human factors, MC firms can establish a healthier, more productive, and ultimately improved competitive workplace environment.

5.4 Limitations and Future Studies

While the current study provides valuable insights into generative AI adoption within the MC industry, several limitations should be acknowledged, which also present opportunities for future research.

Firstly, the method of sample recruitment primarily through personal networks and social media outreach, along with a geographically concentrated participant group predominantly from Germany, potentially limits the generalizability of the findings. Additionally, the relatively uneven gender distribution in the sample—with notably more male participants—may influence results, as gender dynamics can play a role in technology adoption perceptions. Future research could benefit from more balanced gender representation and diversified geographical sampling, ideally incorporating participants from multiple countries and organizational contexts to validate findings across broader demographic segments.

Secondly, the sample size, although sufficient for the employed analytical methods (PLS-SEM), is relatively modest (n = 94). A larger sample would increase statistical power and allow for more nuanced subgroup analyses, potentially uncovering differences in AI adoption behaviors across various demographic or professional subgroups. Future research should aim for larger samples to enable more robust generalizations and detailed subgroup explorations.

Furthermore, this study exclusively assesed weekly working hours, as it is particularly relevant and easily measurable within the consulting sector. However, balance is inherently a multidimensional construct involving various aspects such as emotional well-being, satisfaction with personal time, family engagement, and overall job satisfaction, beyond merely hours worked. Future studies might include additional dimensions of work-life balance to provide a more holistic understanding of generative AI's impact on consultants' overall well-being and personal satisfaction.

Regarding measurement limitations, although validated scales were utilized for trust in AI and peer influence, the measure developed for fear of deskilling, due to the absence of existing validated instruments, might have limitations. While this research offers an initial empirical exploration, future research could further refine and validate this newly developed measurement instrument across different contexts and technologies.

The quantitative survey-based approach used here, while effective in exploring broad trends and relationships, does not fully capture the complexities and nuanced perceptions individuals might have towards AI, especially concerning fears related to deskilling. Future research could benefit from qualitative approaches such as interviews or case studies to delve deeper into consultants' subjective experiences and perceptions, providing richer insights into why deskilling fears might differ from traditional expectations.

Additionally, the study's correlational nature, while suitable for exploratory research, restricts definitive conclusions regarding causality. Future research using experimental or longitudinal designs could more clearly establish causal relationships, particularly examining how interventions related to trust-building or peer influence could directly affect AI adoption and actual use.

Lastly, several determinants of AI adoption discussed in the earlier literature review, specifically in Section 2.3.2 "Drivers and Barriers of AI Adoption in Consulting," such as financial constraints, availability of skilled employees, organizational readiness, technological infrastructure, and ethical concerns, were not explicitly examined in this study. Future research should aim to incorporate these additional factors explicitly into empirical models, which could further enhance the explanatory power and practical relevance of findings related to AI adoption.

In summary, while acknowledging its limitations, this study lays valuable groundwork for further research, particularly through encouraging comprehensive, diverse, and contextually nuanced explorations of generative AI's adoption and its broader implications within MC.

6 Conclusion

This research explores the use of generative AI within the management consulting sector, and its potential to reduce consultants' weekly working hours.

Addressing Research Question 1 (RQ1), the findings suggest that trust in AI and peer influence play critical roles in shaping consultants' adoption behaviors, primarily by influencing their intention to use generative AI tools. Trust in AI was found to significantly enhance intent, which in turn drove actual adoption, while peer influence further reinforced adoption decisions through social validation mechanisms. However, contrary to theoretical expectations, fear of deskilling did not emerge as a significant barrier, suggesting that generative AI may be perceived more as a complement to existing skill sets rather than a direct threat to professional expertise in consulting contexts.

In response to Research Question 2 (RQ2), the findings indicate that higher adoption of generative AI is associated with a reduction in weekly working hours, providing initial evidence of its efficiency-enhancing potential. By automating repetitive routine and time-intensive tasks, generative AI appears to enable consultants to allocate more time to strategic and high-value activities, potentially improving productivity and reducing overall work stress. The results suggest that generative AI adoption could contribute to broader well-being improvements by alleviating workload pressures and fostering a more sustainable professional environment, especially in the consulting sector.

Collectively, these insights provide valuable theoretical considerations and practical recommendations for consulting firms aiming to effectively integrate generative AI into their organizational practices.

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Appendix

Full Survey:

Q0.1

Informed Consent Form

Welcome and thank you for considering participating in this survey on Artificial Intelligence. I, *Tim Thurn* am conducting this survey as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of *Professor Ana Filipa Martinho de Almeida*.
The study consists of answering questions about work practices and Technological Adoption. It will take approximately less than 5 minutes to complete.
The purpose is to gain insight into how professionals interact with new technologies and perceive changes in their work environment. Your participation will contribute to research on work dynamics and technological adoption in modern workplaces.

Please answer as honestly as possible. All answers will be kept strictly confidentially and are anonymous. This means that it will not be possible to link your responses to your identity. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in an aggregated form, never about any individual response.
By clicking the button below, you acknowledge that your participation in the study is voluntary, you are 18 years of age, and that you are aware that you may choose to terminate your participation in the study at any time and for any reason. If you have any questions about this study, please email *Tim Thurn* (*s-tthurn@ucp.pt*).

Thank you!

○ I consent, begin the study (1)

○ I do not consent, I do not wish to participate (2)

Introduction to Generative AI
Before proceeding, here is a brief explanation of generative AI to ensure a common understanding: Generative AI is a branch of artificial intelligence that creates new content, such as text, images, and audio, rather than just analyzing or processing existing data. Unlike traditional AI, which focuses on recognizing patterns and making decisions, generative AI can produce human-like responses, generate realistic images, and assist with creative tasks. Well-known tools include ChatGPT for text, DALL·E for images, and GitHub Copilot for code. These technologies are increasingly shaping how we work, communicate, and innovate across various industries. Now, please continue with the survey.

Q2.1 Using a scale of 1 (Strongly Disagree) to 5 (Strongly Agree), please rate the following statements for yourself:

	1 (Strongly Disagree) (1)	2 (Disagree) (2)	3 (Neutral) (3)	4 (Agree) (4)	5 (Strongly Agree) (5)
Generative AI is competent in providing the information and guidance I need. (1)	○	○	○	○	○
Generative AI is reliable in providing consistent and dependable information. (2)	○	○	○	○	○
Generative AI is transparent. (3)	○	○	○	○	○
Generative AI is trustworthy in the sense that it is dependable and credible. (4)	○	○	○	○	○
Generative AI will not cause harm, manipulate its responses, or create negative consequences for me. (5)	○	○	○	○	○
Generative AI will act with integrity and be honest with me. (6)	○	○	○	○	○
Generative AI is secure and protects my privacy and confidential information. (7)	○	○	○	○	○

Q3.1 Using a scale of 1 (Strongly Disagree) to 5 (Strongly Agree), please rate the following statements for yourself:

	1 (Strongly Disagree) (1)	2 (Disagree) (2)	3 (Neutral) (3)	4 (Agree) (4)	5 (Strongly Agree) (5)
My peers think that I should use generative AI tools. (1)	○	○	○	○	○
My peers recommend using generative AI tools. (2)	○	○	○	○	○
My peers use generative AI tools frequently. (3)	○	○	○	○	○

Q4.1 Using a scale of 1 (Strongly Disagree) to 5 (Strongly Agree), please rate the following statements for yourself:

	1 (Strongly Disagree) (1)	2 (Disagree) (2)	3 (Neutral) (3)	4 (Agree) (4)	5 (Strongly Agree) (5)
I fear that over-reliance on generative AI tools reduces my need to develop new skills. (1)	○	○	○	○	○
I fear that frequent use of generative AI tools weakens my ability to think critically. (2)	○	○	○	○	○
I fear that frequent use of generative AI tools weakens my ability solve problems independently. (3)	○	○	○	○	○
I fear that the automation of tasks by generative AI tools limits my hands-on experience. (4)	○	○	○	○	○
I fear that generative AI replaces tasks that help me develop expertise. (5)	○	○	○	○	○

Q5.1 Using a scale of 1 (Strongly Disagree) to 5 (Strongly Agree), please rate the following statements for yourself:

	1 (Strongly Disagree) (1)	2 (Disagree) (2)	3 (Neutral) (3)	4 (Agree) (4)	5 (Strongly Agree) (5)
I am willing to use generative AI tools for work related tasks / problems. (1)	○	○	○	○	○
I am willing to take decisions based on the recommendations provided by generative AI tools. (2)	○	○	○	○	○
I am willing to use generative AI tools in the future. (3)	○	○	○	○	○

Q6.1 To make sure you read the questions carefully, please select "Agree".

○ Strongly disagree (0)

○ Disagree (0)

○ Neutral (0)

○ Agree (1)

○ Strongly agree (0)

Q7.1 How frequently do you use generative AI?

○ Never (1)

○ Rarely / Less than once per week (2)

○ Occasionally / 1–2 times per week (3)

○ Frequently / 3–4 times per week (4)

○ Every Day (5)

Q8.1 On average, how many hours do you work per week in general? *If applicable, and you are not currently working full-time in management consulting or a related field, please refer to the period when you last held a full-time position in this industry.*

____

Text The final step in this process is to respond to the following set of demographic questions.

Q1.1 How old are you?

____

Q1.2 Which gender do you identify as?

- ○ Male (1)
- ○ Female (2)
- ○ Other (3)
- ○ Prefer not to say (4)

Q1.3 Where are you from?

▼ Afghanistan (1) ... Zimbabwe (195)

Q1.4 What is your highest level of education?

- Less than high school (1)
- High school degree (2)
- Some college (3)
- Bachelor’s degree (4)
- Master’s degree (5)
- Ph.D. / Dr. (6)
- Other (please specify) (7) ____

Q1.5 What is your current employment status?

- Employed (full-time) (1)
- Unemployed (2)
- Retired (3)
- Student (4)
- Student-Worker (5)
- Intern (6)
- Other (please specify) (7) ____

Q1.6 Which industry do you primarily work in?

- Management Consulting (1)
- Other Consulting Services (2)
- Strategy / Advisory Services (3)
- Other (please specify) (4) ____

Q1.7 How many years of experience do you have in management consulting or a related field? *If you have more than 10 years of experience, please just select "10".*

	0 1 1 2 2 3 3 4 4 5 5 6 6 7 7 8 8 9 9 10
Years of experience ()	

Q9.1 Do you have any comments you would like to share with the researcher? If so, please write them in the box below. Otherwise, just leave it blank.

List of Countries of Respondents:

Country	Percentage	Frequency
Australia	1%	1
Austria	6%	6
Brazil	1%	1
Cameroon	1%	1
Denmark	1%	1
France	1%	1
Germany	69%	65
Hungary	2%	2
Italy	1%	1
Luxembourg	1%	1
Netherlands	1%	1
Norway	3%	3
Spain	1%	1
Sweden	2%	2
Switzerland	3%	3
Turkey	2%	2
Ukraine	1%	1
United States of America	1%	1

Correlational Matrix of Variables:

	AUA	FOD	IUA	PI	TIA	WWH
AUA	1.000	-0.432	0.838	0.741	0.569	-0.358
FOD	-0.432	1.000	-0.472	-0.338	-0.643	0.501
IUA	0.838	-0.472	1.000	0.777	0.715	-0.459
PI	0.741	-0.338	0.777	1.000	0.557	-0.419
TIA	0.569	-0.643	0.715	0.557	1.000	-0.510
WWH	-0.358	0.501	-0.459	-0.419	-0.510	1.000