Artificial Intelligence and the Future of Consulting – An Exploratory Study

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Abstract

Title: Artificial Intelligence and the Future of Consulting – An Exploratory Study
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This thesis examines how artificial intelligence transforms the consulting industry. It addresses a research gap given consultancies' guiding role in digital transformations, while their own AI adaptation remains underexamined. This study is based on semi-structured expert interviews and analysis through the Gioia methodology. Based on 18 consultants across seniority levels from six leading firms, findings indicate an industry-wide AI adoption arms race that transforms the traditional business model of consultancies. AI tools integrate seamlessly into daily workflows of consultants, enhancing their individual productivity despite regulatory and technical constraints. Rising client expectations evolve project scopes from knowledge transfer to ecosystem orchestration, challenge traditional project staffing to become hybrid human-AI teams and incentivize the exploration of new revenue models. These insights indicate an emerging *efficiency trap* that threatens future learning opportunities for the junior workforce, thereby risking long-term capabilities of consultancies. Theoretically, the study highlights the importance of effective human-AI governance, offering implications for future research and strategic positioning for consultancies today.

Keywords: Artificial intelligence, Consulting industry, Business model innovation, New value creation, Human-AI collaboration

Resumo

Título: Inteligência Artificial e o Futuro da Consultoria – Um Estudo Exploratório

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Esta tese examina como a inteligência artificial transforma a indústria de consultoria. O estudo aborda uma lacuna de investigação dado o papel orientador das consultorias em transformações digitais, enquanto a sua própria adaptação à IA permanece pouco estudada. Este estudo baseia-se em entrevistas semiestruturadas com especialistas e análise pela metodologia Gioia. Com base em entrevistas a 18 consultores de diferentes níveis hierárquicos de seis firmas líderes, os resultados indicam uma corrida à adoção de IA em toda a indústria, que transforma o modelo de negócios tradicional das consultorias. Ferramentas de IA integram-se perfeitamente nos fluxos de trabalho diários dos consultores, elevando a sua produtividade individual apesar de restrições regulatórias e técnicas. Expectativas crescentes dos clientes evoluem o âmbito de projetos de transferência de conhecimento para orquestração de ecossistemas, desafiam equipas tradicionais a tornarem-se híbridas humano-IA e incentivam a exploração de novos modelos de receitas. Essas percepções revelam uma *armadilha de eficiência* emergente que ameaça oportunidades futuras de aprendizagem para a força de trabalho mais nova, arriscando assim as capacidades de longo prazo das consultorias. Teoricamente, o estudo destaca a importância da governança eficaz humano-IA, oferecendo implicações para pesquisas futuras e posicionamento estratégico para as empresas de as consultoria hoje.

Palavras-chave: Inteligência artificial, Indústria de consultoria, Inovação de modelos de negócio, Criação de valor, Colaboração humano-IA

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List of Abbreviations

AI	Artificial Intelligence
GenAI	Generative Artificial Intelligence
Agentic AI	Agentic Artificial Intelligence
RQ	Research Question
TOE	Technology-Organization-Environment
TAM	Technology Acceptance Model

1. Introduction

While artificial intelligence has already enhanced efficiency, automated processes, and predicted market dynamics for a period of time (Leone et al., 2021), the release of ChatGPT in November 2022 marked a pivotal moment in the technology's development. Artificial intelligence became accessible to the general public, reaching more than one million users within its first five days (Altman, 2022). Until then, this was not only unprecedented but also marked the beginning of generative AI rapidly establishing itself as a standard tool to support users in their tasks (Feuerriegel et al., 2024; Nisa et al., 2025). This growing relevance is also reflected at the macroeconomic level as AI adoption has accelerated significantly. Most organizations worldwide now integrate AI into their operations with an estimated annual economic impact of up to US$22.9 trillion by 2040 (McKinsey Global Institute, 2024; Stanford University, 2025).

The consulting industry has always played a foundational role in guiding organizations through digital and technological change (Sarvary, 1999; Swanson, 2010). Although consulting firms primarily generate value through knowledge transfer rather than physical outputs, the industry contributes approximately 0.3% to global GDP (Baligh et al., 1996; National Consulting Index, 2025; Sarvary, 1999). This also reflects the industry's substantial economic and societal relevance and might contribute to why 50% of business graduates aspire to become consultants (Graduate Management Admission Council, 2025). Given this widely acknowledged central role of the industry, it is alarming that the implications of AI for consultancies' own practices, structures, and value creation remain insufficiently explored. The Chief AI Officer of Deloitte highlights the perceived magnitude and urgency of recent AI developments for the consulting industry: "Given the rapid advancements of AI technology, the consulting industry is experiencing a fundamental shift" (Keltsch, 2025). To understand how artificial intelligence is affecting the consulting industry, this thesis implements two research questions (RQ):

RQ1: *How does artificial intelligence reshape the day-to-day work of consultants?*

RQ2: *How is artificial intelligence affecting the business model of consultancies?*

Given the limited state of academic research in this area, the study adopts an exploratory perspective to examine macro-level shifts. The thesis explores shifts in consultants' daily work, evolving client expectations, and emerging pressures on traditional consulting business models. By doing so, the thesis aims to contribute to a deeper understanding of the transformation currently unfolding within the consulting industry and to derive implications for consultancies.

After this introduction, chapter two examines existing literature on artificial intelligence and the foundations of consulting to create a general understanding for the thesis. While chapter three presents the methodological approach, chapters four and five report and discuss the empirical findings. Chapter six concludes the study by synthesizing the key insights.

2. Literature Review

2.1. Definition of Artificial Intelligence

Understanding how artificial intelligence (AI) transforms the consulting industry requires first understanding what AI itself is. Alan Turing, often regarded as one of the founding figures of AI, shifted the debate away from the abstract question of whether machines can think to a more practical one: whether a machine's behaviour could be indistinguishable from that of a human being (Saygin et al., 2000). In his paper *Computing Machinery and Intelligence* (Turing, 1950), Turing proposed what later became known as the Turing Test. Instead of defining "intelligence" explicitly, he argues that if a machine could convincingly imitate human conversation, it could be considered intelligent. He operationalized the concept, emphasizing measurable performance and observable behaviour over philosophical speculation (Turing, 1950). Like Turing's operational view of intelligence, Newell (1980) argued that intelligent behaviour arises from a system's ability to structurally manipulate symbols. He proposed a physical symbol system, where a physical device that can combine, transform, and interpret symbolic representations provides the sufficient means for general intelligent action. According to his view, intelligence is not an abstract quality, but the consequence of symbolic processes realized through physical mechanisms.

The term *artificial intelligence* was formally introduced by John McCarthy and his colleagues in their 1955 Dartmouth Proposal. They defined AI as the study of making machines "use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves" (McCarthy et al., 1955). This definition emphasized not only the replication of human reasoning but also the potential for self-improvement, an idea that has since become central to modern AI systems capable of learning and adapting through data (Saygin et al., 2000). Modern discussions of AI continue to oscillate between human-centric imitation and machine-centric optimization. On one hand, explainability and interpretability aim to make AI systems intelligible to its users (Boge & Mosig, 2025). On the other, advances in machine learning emphasize autonomous optimization and performance, often at the expense of transparency (Abbate, 2023; Pantsar, 2023).

As AI continues to evolve, a particularly transformative subset known as generative artificial intelligence (GenAI) has emerged as central to discussions of optimization across industries (Raisch & Krakowski, 2021; Vial et al., 2023; Liu et al., 2025; Leone et al., 2021; Matthews et al., 2025). GenAI is defined as computational techniques capable of producing novel content from training data when requested by a user. These systems are typically built on large-scale machine learning architectures that learn complex data structures and generate new, meaningful outputs with greater efficiency than traditional methods (Bordas et al., 2024; Feuerriegel et al., 2024). Building on these generative capabilities, agentic artificial intelligence (agentic AI) represents the next level in AI systems by enabling decision-making and action-taking mechanism (Nisa et al., 2025). Agentic AI comprises systems designed to act autonomously, capable of perceiving their environment, reasoning, and taking actions to achieve specific goals without constant human intervention (Gnewuch et al., 2024; Adam et al., 2025). Fundamentally, GenAI can only create an output after it was requested by a human counterpart (Feuerriegel et al., 2024), whereas agentic AI systems exhibit a degree of autonomy that enables them to make independent decisions and dynamically adapt to changing environments (Nisa et al., 2025). It is important to highlight that AI agents pursue long-term goals independently with minimal or no human oversight (Nisa et al., 2025). Therefore, the system can identify challenges that are too complex for the system itself to handle and will delegate these tasks autonomously to a human counterpart (Gnewuch et al., 2024).

Drawing from these foundational and contemporary perspectives, this thesis adopts a functional understanding of artificial intelligence to provide greater analytical clarity. Unlike philosophical definitions that engage with abstract questions of machines and intelligence, a functional understanding focusses on real outcomes and observable behaviours (Proudfoot, 2020; Turing, 1950; Yang et al., 2024). Similarly, technical definitions centre on the explanation of architectural mechanisms and system processes, while a functional approach reflects the reality that most employees of organizations use AI systems regardless of their technical understanding (Hassija et al., 2024; Yang et al., 2024). With this view, AI is a system that processes and learns from data to perform tasks that typically require human cognition, such as reasoning, decision-making, and creating (Nisa et al., 2025). In contrast to traditional algorithms, AI systems often operate with limited transparency regarding their internal mechanisms, a feature commonly referred to as the *black box problem* (Hassija et al., 2024). Despite this intransparency, the outputs of AI models have tangible and far-reaching real-world consequences, as most organizations worldwide already use AI for their operations (Stanford University, 2025).

2.2. Impact of Artificial Intelligence across Industries

As AI technologies mature, their influence has expanded far beyond the realm of computer science into many sectors of the global economy (Raisch & Krakowski, 2021; Vial et al., 2023; Liu et al., 2025; Leone et al., 2021; Matthews et al., 2025). While adoption patterns differ among industries, the literature highlights recurring themes regarding how AI positively affects industries and what challenges arise with the new technology.

2.3.1. Key Benefits of AI Adoption

According to the literature, there are three key benefits from AI adoption.

First, studies consistently highlight AI's contribution to efficiency and process optimization. In manufacturing, AI-enabled predictive maintenance, process automation, and real-time decision-making reduce unplanned downtime and improve product quality (Leone et al., 2021; Zeba et al., 2021). In other sectors, such as the financial services, machine-learning models are leveraged to enhance the speed and accuracy of credit scoring, risk assessment, and algorithmic trading. Banks and insurances can increase responsiveness to market development and improve profitability through AI-driven solutions (Costello et al., 2020; Cheng et al., 2025). Similarly, for the public sector, research shows that predictive analytics can streamline administrative routines and improve the timeliness and targeting of service delivery (Sousa et al., 2019; Sun & Medaglia, 2019). For example, timeliness is achieved by identifying at-risk youth early on through smart algorithms, enabling government agencies to intervene preventively (Sousa et al., 2019). Targeting is enhanced through AI-driven risk stratification that allocates limited public resources to those that need it the most (Sun & Medaglia, 2019).

Second, AI improves the quality of decisions and the creation of knowledge by processing large volumes of data beyond human cognitive capacity (Bertomeu et al., 2025; Costello et al., 2020; Leone et al., 2021; Vial et al., 2023). Empirical work in financial and healthcare contexts show that AI supports the detection of hidden patterns, the modelling of complex relationships, and the generation of evidence-based recommendations (Bertomeu et al., 2025; Costello et al., 2020). For example, decisions like credit or investment allocation in the financial sector are made more accurate through the utilization of AI (Costello et al., 2020). Within the healthcare context, this can be exemplified by hospitals reducing readmission rates through understanding complex medical patient data, allowing doctors to intervene preventively before patient health declines (Leone et al., 2021). Another result of the processing power of AI seems to be that AI facilitates knowledge transfer between firms and their stakeholders. By fusing data from customers and partners into shared analytics platforms, companies can transform raw data into actionable insights (Leone et al., 2021; Vial et al., 2023). Beyond this possessing technological capability however, scholars indicate that competitive advantage requires firms to deploy AI strategically within their distinctive context (Kemp, 2024; Teece et al., 1997). Kemp (2024) formally introduced this concept as "situated AI", where the firm deploys an AI grounded in

the firm's unique experiences. Additionally, the AI is bounded to protect proprietary assets and will adapt according to the strategic environment and interdependencies of the company (Kemp, 2024). Professional service firms are exploiting this approach, as they increasingly deploy AI solutions for their customers to forecast market trends, optimize resource allocation, or simulate different scenarios for long-term strategic decisions (Vial et al., 2023).
Finally, scholars highlight AI's role in innovation and new value creation. AI's generative and adaptive capabilities can enable the development of new products, services, and business models (Sousa et al., 2019; Vial, 2019; Zeba et al., 2021). Across industrial settings, intelligent and production systems link digital simulations with physical assets to support the development of new products and to gain value from improved processes (Zeba et al., 2021). Financial institutions specifically, leverage AI to design personalized financial products and data-driven investment solutions for individual risk-profiles and behavioural patterns (Vial, 2019; Cheng et al., 2025). Additionally, AI applications like chatbots are used to create new touchpoints for customers and improve customer engagement (Sousa et al., 2019; Sun & Medaglia, 2019). These new solutions are especially beneficial for the public sector, where personalized communication and citizen requests can leverage solutions such as chatbots, develop policy designs, or test alternative policy scenarios (Sousa et al., 2019; Sun & Medaglia, 2019).

2.3.2. Key Challenges of AI Adoption

On the challenge side, the literature points to three issues that frequently limit the utilization of AI.
One key issue is data quality, integration, and readiness. Incomplete unstructured data, legacy infrastructures, and disconnected systems undermine the reliability of predictive maintenance and automation solutions in the manufacturing context (Heimberger et al., 2025; Zeba et al., 2021). Data quality also heavily effects the financial services, where credit scoring and investment analytics have shown to be distorted based upon low quality or biased data. These faulty data sets have implications on both customer fairness and investment performances (Cheng et al., 2025; Costello et al., 2020). One of the main challenges for the public sector lies within their legacy systems (Campion et al., 2020). Several studies indicate that public institutions have outdated IT architecture and manage data in siloes. Fundamentally changing the IT infrastructure would require investments that lie outside their resources, preventing the large-scale deployment of AI (Campion et al., 2020; Sousa et al., 2019; Sun & Medaglia, 2019).
Another drawback lies within the *black-box* nature of today's generation of AI as researchers identify explainability and regulatory accountability as key concerns (Bertomeu et al., 2025).

The black-box character of many AI models limits managerial understanding of the recommendation, which complicates regulatory scrutiny and raises ethical questions (Bertomeu et al., 2025; Costello et al., 2020; Currie et al., 2025; Heimberger et al., 2025). In finance, outputs from models that can't be adequately justified to clients or auditors reduce investor confidence and present severe compliance risk (Costello et al., 2020; Cheng et al., 2025). Opaque AI models that are trained on historical data reflect past discriminatory lending practices, such as redlining or biased approvals, leading to unjustified denial rates for minorities (Cheng et al., 2025). Unexplainable decisions of AI solutions limit the capability of users to verify outputs or to understand the underlying reasoning (Sousa et al., 2019; Sun & Medaglia, 2019). This limited transparency heightens user resistance and not only fosters distrust, but also a psychological reaction in which individuals become motivated to restore control (Puntoni et al., 2020). As a result, accountability chains from developers to users are blurred, complicating liability for errors or biases (Costello et al., 2020; Leone et al., 2021). Responding to these concerns, regulatory initiatives such as the EU AI Act call for traceability, robustness, and fairness, pushing organizations to design explainable models with formal governance structures (EU AI Act, 2024). However, the *pacing-problem* describes the phenomenon that AI innovation is outpacing the regulatory capacity. To counter this phenomenon, harmonised governance mechanisms are required that are anticipative rather than reactive to emerging risks (Currie et al., 2025). These measures underscore AI's profound economic and societal implications (Currie et al., 2025; EU AI Act, 2024).

Lastly, the academic literature stresses the importance of organizational capabilities and talent for capturing AI's potential. Studies indicate that many firms lack employees who can interpret, validate, and appropriately challenge AI outputs (Campion et al., 2020; Choudhary et al., 2025; Heimberger et al., 2025; Liu et al., 2025; Teece et al., 1997). This creates a gap between algorithmic recommendations and managerial decision-making (Heimberger et al., 2025). For instance, manufacturing companies often face difficulties in embedding AI insights into established operational routines, whereas financial institutions and professional service firms must develop hybrid decision processes that integrate human judgment with algorithmic suggestions (Costello et al., 2020; Vial, 2019; Zeba et al., 2021). Public organizations similarly encounter cultural resistance and skill shortages when introducing AI-enabled systems (Campion et al., 2020; Sousa et al., 2019; Sun & Medaglia, 2019). Organizational AI-driven transformation is therefore dependent on organizational openness to new technology, AI-literate talent who collaborate cross-functional, and adaptive leadership as critical enablers of responsible and sustained AI-driven transformation (Nyberg et al., 2025; Pigni et al., 2016; Zhang et al., 2024).

2.3.3. Emerging Opportunities across Industries

The literature indicates shared opportunities across industries. During the rise of new technology, companies with superior technological capabilities have shown to become market-leaders as it allows them to influence the future trajectory of the technological development (Zhang et. al., 2024). The diffusion of AI enables the emergence of hybrid intelligence systems, in which human capabilities are augmented through machine collaboration (Raisch & Krakowski, 2021). However, this hybrid system fundamentally depends on organizational openness. Leadership must commit to transformation, cross-functional collaboration, and a culture that values experimentation alongside accountability (Raisch & Krakowski, 2021; Zhang et al., 2024). Rather than viewing AI as purely automating existing processes, progressive organizations recognize that AI handles computational complexity while humans provide judgment, ethical reasoning, and contextual understanding (Raisch & Krakowski, 2021; Vial et al., 2023). This complementary pairing is particularly potent as organizations move toward GenAI and agentic AI (Zhang et al., 2024). Organizations that cultivate openness towards AI position themselves to capture AI's transformative potential while mitigating its risks. They realize AI regulation as foundational to responsible innovation instead of a compliance burden. In this sense, organizational openness is less a technical capability and more a strategic stance (Currie et al., 2025; Heimberger et al., 2025; Kyriakopoulos et al., 2025; Yang et al., 2024). As AI continues to evolve, its transformative power lies not only in automating processes but in reshaping how industries generate value (Berg et al., 2023).

2.3. Consulting Industry and its Evolution

2.3.1. Emergence of the Consulting Profession

The consulting industry emerged as a response to the increasing organizational complexity during the twentieth century. Firms started to face managerial challenges of coordination and specialization due to the rapid industrialization. These challenges exceeded internal expertise and created a demand for external advisors, who could apply structured, analytical, and managerial approaches to organizational problems (Weinshall, 1982). Early consulting practices were deeply influenced by the scientific management principles developed by Frederick Taylor (Weinshall, 1982). His methods for process optimization and performance measurement laid the foundation for management consulting as a systematic discipline (Taylor, 1911; Weinshall, 1982). By the mid-twentieth century, consulting had developed into a recognized professional service industry, with consultants serving as intermediaries between management science and business practice (Mosley, 1970). It adopted distinctive economic characteristics typical for such industries, with time-based revenue models that reflect its labour-intensive, human-capital-driven nature through fees tied to billable hours, consultant seniority, and project scope (Ng, 2008; Sarvary, 1999). The growing complexity of corporations made consulting a vital instrument for strategic and operational decision-making. Consultants increasingly supported top executives in addressing managerial and organizational design challenges that required external objectivity and specialized knowledge (Mosley, 1970; Weinshall, 1982). The industry reached a new phase of professionalization and internationalization after World War II. U.S. consulting firms followed their multinational corporate clients abroad, transferring managerial expertise and reinforcing the globalization of management practices (Gaedeke, 1973). This expansion positioned consulting firms as key intermediaries in the global diffusion of management knowledge and technologies, a role that continues to define the industry today (Sarvary, 1999).

2.3.2. Shift towards Participative Consulting

While early consulting emphasized an outsider's diagnostic expertise, scholars soon highlighted the importance of a collaborative approach (Taylor, 1911; Katcher, 1972; Weinshall, 1982). The participative consulting model argued that effective change only occurs when consultants enable organizations to define their own problems and solutions. Rather than top-down prescriptions, measurements such as task forces and joint problem-solving are more suitable to achieve long-lasting transformation (Katcher, 1972). Adding to this change, consulting was reconceptualized as both problem definition and problem solving to prevent consultants falling into the *Type III error* of solving the wrong problem due to disciplinary biases (Kilmann & Mitroff, 1979). The type III error occurs when practitioners focus their resources on solving a well-formulated problem instead of questioning whether they are addressing the right problem in the first place (Mitroff & Featheringham, 1974). Within the consulting context, clients may present a surface-level problem that masks the underlying organizational issue, leading consultants to invest their efforts on solving the symptom instead of the root cause. Consulting became understood as an interactive and learning-based process, rather than a one-sided transmission of expertise (Kilmann & Mitroff, 1979). Research has also underscored that shift. As project success are determined by mutual commitment, trust, and alignment of objectives, project outcomes have significantly improved when consultants actively listen and involve their clients in the decision-making process (Corgnet & González, 2014; Gable, 1996).

These studies collectively indicate that consulting evolved from an expert-driven to a co-creative activity. Knowledge is jointly constructed through interaction and dialogue with a structure that reinforces mutual accountability and co-production of value (Corgnet & González, 2014; Gable, 1996; Katcher, 1972; Killmann & Mitroff, 1979; Roels et al., 2010).

2.3.3. Consulting as Driver of Organizational Change

A foundational principle in knowledge-based theories states that organizations fundamentally exist to coordinate and integrate the specialized knowledge of individuals (Grant, 1996). As consultancies matured, this principle became institutionalized, with knowledge management emerging as a defining capability of competitive advantage (Sarvary, 1999). Consultancies with the ability to transform individual client experiences into reusable intellectual capital were distinguishing themselves from their competitors (Grant, 1996; Sarvary, 1999). Consultants became agents who synthesize fragmented knowledge into coherent, implementable designs that transformed organizational structures and capabilities (Baligh et al., 1996). Recognizing that technology constitutes a primary driver for wealth creation and organizational value, consulting firms developed capabilities to help clients exploit technological assets (Baligh et al., 1996; Teece et al., 1997). Consultants' exposure to multiple industries and organizational contexts gives them unique insight into the potential of emerging tools and best practices, making them among the first professional groups to experiment with new technologies (Roels et al., 2010; Sarvary, 1999). Transferring internal knowledge effectively enables consulting firms to replicate and scale expertise, making knowledge management systems central to both service quality and profitability (Sarvary, 1999). By synthesizing and applying acquired knowledge in new contexts, consultancies facilitated clients' innovation adoption, diffusion, and eventual institutionalization of technology (Swanson, 2010). Through repeated engagements and knowledge transfer across industries, consultancies bring innovations from early adopters to broader organizational populations, while being constantly exposed to the most profitable technologies themselves (Kogut & Zander, 1992; Roels et al., 2010; Sarvary, 1999; Swanson, 2010).

2.4. Technology Adoption Theories

This subsection integrates four theories to develop a general understanding of technology adoption. The theory progresses from social diffusion to organizational and individual usage patterns.

According to the *Diffusion of Innovations* theory, technology spreads through populations and organizations through an innovation-decision process: awareness, persuasion, decision, implementation, and confirmation (Rogers, 1983). This process depends on five core attributes that explain most of the adoption rate variation. Relative advantage represents the users' perceived superiority of the innovation compared to existing alternatives, while compatibility reflects alignment with the users' values. Equally important is the complexity users associate with understanding and using the innovation. Closely related to difficulty of understanding is the trialability, the degree to which the innovation can be tested. Finally, observability represents the extent to which an innovation's benefit and result are visible to others, reinforcing social proof (Rogers, 1983). Mass media typically raises awareness while peer networks and opinion leaders drive persuasion, creating S-shaped diffusion curves across interconnected actors (Rogers, 1983). However, this macro perspective treats organizations as undifferentiated nodes, thereby leaving unexplained why individual firms diverge in adoption timing and extent (Wejnert, 2002).

The *Dynamic Capabilities Theory* addresses this firm-level gap by explaining why certain companies leverage innovations better than others. According to the Dynamic Capabilities Theory, firms must not only understand and integrate innovations, but also reconfigure internal and external competences to response to rapidly changing environments (Teece et al., 1997). Three foundational processes seem to be required for this ability. First, "iterative sensing" describes the ability to continuously spot opportunities on an organizational level. Second, "seizing" represents the ability to mobilize resources to capitalize on these opportunities and finally, "transforming" denotes how well a company can redesign established routines to institutionalize change (Teece et al., 1997). This theory emphasizes that companies who have institutionalized change, have a source of enduring advantage (Teece et al., 1997). Nevertheless, organizations must still face concrete contextual constraints at a given point in time that influence the adoption of innovations (Teece et al., 1997; Tornatzky & Fleischer, 1990; Tornatzky & Klein, 1982).

The *Technology-Organization-Environment* (TOE) framework provides this operational lens. It specifies how technological context (tool maturity and infrastructure), organizational context (resources, structure, and culture) and environmental context (partnerships, competition, and regulation) interplay and influence the innovation adoption rate of organizations (Tornatzky & Fleischer, 1990; Tornatzky & Klein, 1982). Scholars support relative advantage, compatibility, and complexity as consistent predictors across sectors for organizational adoption of innovation but highlight that IT-specific measures refine adoption performance, work practice alignment, and ease of understanding (Moore & Benbasat, 1991; Tornatzky & Klein, 1982). Thus, TOE anticipates adoption variation to be explained by internal organizational capabilities and external pressures but also understands that formal procurement processes of innovation alone do not guarantee employee acceptance (Davis, 1989; Tornatzky & Klein, 1982; Moore & Benbasat, 1991).

This individual acceptance on employee level is explained by the *Technology Acceptance Model* (TAM), which identifies the perceived usefulness and perceived ease of use as fundamental and distinct predictors (Davis, 1989). Whether an employee intends and benefits from organizational innovations is fundamentally dependent whether the employee believes it would enhance their performance without having to invest excessive efforts to handle the innovation itself (Davis, 1989; Moore & Benbasat, 1991).

Building on these four foundational perspectives, more recent work demonstrates how each theory applies in contemporary, technology-driven contexts characterized by advanced digital transformation. For diffusion of innovations, current models move beyond adoption S-curves by integrating other aspects like barriers to adoption, nonlinear dynamics, word-of-mouth effects, and policy interventions (Guidolin & Manfredi, 2023). Rather than a logarithmic adoption growth rate, these studies indicate that technologies with a societal impact spread through complex "critical diffusions". Beneficial innovations like renewable energy often require deliberate policy support to overcome critical adoption thresholds, before achieving market saturation (Guidolin & Manfredi, 2023). Recent dynamic capabilities literature provides insights into how the theory applies in practice (Han et al., 2026). While Teece et al. (1997) showed dynamic capabilities enable firms to adopt innovative technologies, analysis of 30,725 Chinese firm-years (2011–2021) reveals a bidirectional relationship: AI adoption also strengthens firms' absorptive, adaptive, and innovative capabilities. These enhanced capabilities then drive increased risk-taking behaviour and productivity, indicating how innovative technology creates a self-reinforcing capability cycle (Han et al., 2026). TOE-based research has been extended and applied in the online retailing adoption context. A sample of 325 Vietnamese firms indicate three new factors to the original framework, adding "entrepreneurial" and "technological orientation" to the organizational factor, and "perceived trend" to the environmental factor (Nguyen et al., 2022). These extensions further support that technological factors, organizational factors, and environmental factors jointly drive digital transformations in organizations (Nguyen et al., 2022; Tornatzky & Fleischer, 1990; Tornatzky & Klein, 1982). Finally, extensions of the TAM in the field of innovative Web 2.0 storytelling technologies further supports perceived usefulness and perceived ease of use as core predictors of technology among older adults. A sample of 112 retired Greek indicated that age-related factors can shape ease-of-use perceptions for new applications. Specifically, an individual's subjective sense of remaining lifetime positively influences perceptions of ease of use, even as chronological age and loneliness show no significant effects (Alexandrakis et al., 2020).

Despite the theoretical clarity on how companies could adopt innovative technologies like AI, and the wealth of literature highlighting the practical impact of artificial intelligence on organizations across industries, there remains a notable lack of research specifically focusing on how the consulting industry is effected by AI (Raisch & Krakowski, 2021; Vial et al., 2023; Liu et al., 2025; Leone et al., 2021; Matthews et al., 2025). This research gap is particularly paradoxical, because the consulting industry inherently has characteristics that are prone to adopting innovations such as AI. The industry is knowledge-intensive, innovation-driven, and strategically positioned to leverage emerging technologies (Corgnet & González, 2014; Sarvary, 1999; Swanson, 2010; Weinshall, 1982). Yet empirical insights into how AI is reshaping consultant roles and the business model of consultancies remain limited, showing a clear need for exploratory research.

3. Methodology

This thesis adopts a qualitative research design to explore the effect of artificial intelligence on the consulting industry. This methodology was chosen as it is especially suitable for studying a phenomenon that is emerging and has not yet been sufficiently theorized (Lincoln & Guba, 1985). Therefore, this method is used to understand meanings, experiences, and processes instead of measuring variables numerically (Bogner et al., 2009; Corbin & Strauss, 2015). This thesis combines two closely linked components of qualititative research. First, 18 semi-structured expert interviews were conducted with consultants across seniority levels and six leading consulting firms to capture first-hand practical insights. Second, a systematic data analysis using the Gioia methodology was performed after each interview to extract conceptual structures and to adapt the questionnaire continuously (Gioia et al., 2012).

Qualitative research offers several key benefits for this study. It enables rich, practical insights of how AI is experienced in the consulting industry, revealing details quantitative surveys might miss (Bogner et al., 2009; Lincoln & Guba, 1985). The approach captures various insights across individuals, roles, and organizational contexts, and supports the discovery of unanticipated themes, thereby facilitating theory development from practical insights that can be studied in future research (Corbin & Strauss, 2015).

On the other side, qualitative research also presents some challenges that must be considered. Findings from a sample of 18 experts can't be statistically generalized to the entire consulting industry (Lincoln & Guba, 1985). Results depend on researcher interpretation during coding and theme development, requiring transparency and reflexivity to establish credibility. Furthermore, data collection and analysis are time-intensive, limiting sample breadth compared to large-scale surveys (Corbin & Strauss, 2015). Nevertheless, these trade-offs are accepted to prioritize depth over quantity in exploring the under-researched phenomenon of how AI transforms the consulting industry.

3.1. Sample and Procedure

Due to the limited availability of literature in this matter, expert interviews were chosen in the first step of this thesis. Expert interviews are conversations with individuals who possess specialized knowledge in a particular domain. Questioning them enables researchers to understand complex phenomena through first-hand experiences and contextual insights that would be difficult to obtain otherwise (Bogner et al., 2009). Experts were defined as consultants who use and are immediately affected by AI initiatives in their companies. Semi-structured expert interviews allow the researcher to comprehend how AI transforms the consultants project work, client interaction, and consulting companies while leaving room for unanticipated themes to emerge (Bogner et al., 2009). Two sets of criteria guided participant selection. Following the purposive sampling strategy, the core criteria targeted individuals with specific characteristics relevant to the research questions (Patton, 2015). Participants were required to have at least one year of full-time experience as consultants in a leading consultancy. Additionally, they must have had direct client exposure and experience working on strategic projects. To ensure a diversity of perspectives, differentiating criteria were also applied in participants selection. The sample was designed to include a mix of seniority levels, from consultants to partners, to obtain views on AI from operational, managerial, and leadership perspectives. Furthermore, the sample included leading consultancies of different sizes and specializations to reflect variation in organizational structures, client portfolios, and project types. Participants were identified through a combination of personal and professional networks. Initial contacts were identified through convenience sampling, leveraging accessible networks within the researcher's academic and professional environment (Patton, 2015). These networks included academic contacts at leading universities and business schools, prior colleagues from the researcher's professional career in consultancies, and connections established through the professional networking platform LinkedIn. Following the initial recruitment, snowball sampling was then used, whereby interviewed experts recommended further eligible participants (Goodman, 1961). This approach yielded consultants with profound first-hand experience across industries who both use AI tools and are affected by AI-enabled changes in their daily work. Additionally, several interviewees held responsibilities for firm-wide AI adoption and integration, offering a macro-level perspective on how consultancies strategically view AI. The final sample comprised four consultants and eight senior consultants with one to three years of experience, three managers with more than four years of experience, two directors with more than 15 years of experience, and one senior director with more than 19 years of experience.

3.2. Data Collection

Data were collected through 18 semi-structured expert interviews, of which 17 interviews were held in German and one in English. All interviews were conducted through Microsoft Teams, which was also used to record and transcribe the interviews to enable in-depth analysis. Interviews lasted between 30 and 45 minutes. After the purpose of the study was explained, participants began to introduce themselves and describe their professional background. The interview guide was structured around three main topics. The first topic examined the context and degree of AI adoption, exploring how AI currently affects the daily work of the expert, which tools are employed, and the perceived benefits and drawbacks of these technologies. The second topic investigated AI's impact on client interaction, focusing on how clients have responded to AI implementation and the resulting changes in project conditions and expected deliverables. The third topic addressed talent and skills in the age of AI, exploring how AI influences recruitment strategies, which competencies are gaining importance, and how consultancies approach training and upskilling their workforce. The interview concluded with an opportunity for participants to reflect on their responses and provide additional comments they wished to contribute.

3.3. Data Analysis

Data were analysed using the Gioia methodology, a systematic approach that emphasizes rigorous, transparent links between raw data and emergent concepts. This analysis consists of three sequential phases (Gioia et al., 2012). The first-order coding (informant-centric) involved reading the interview transcripts iteratively. Direct citations or coded segments of the transcripts were used to produce a large number of detailed first-order concepts (Gioia et al., 2012). This step captures individual experiences, such as "AI transformation hits professional service firms first. This is the biggest business transformation since the company was founded." (INT_016), "I often use Copilot as a sparring partner to question ideas or to check whether something has been overlooked"(INT_004), or "Partners and seniors drive AI adoption; If the partners are behind it, it gives us confidence and the permission to use AI."(INT_006).

In the second stage, first-order concepts are compared and grouped to build more abstract second-order themes (researcher centric). The researcher interprets the data to develop second-order themes that go beyond individual quotations and capture recurring patterns across interviews (Gioia et al., 2012). For example, the statement "I often use Copilot as a sparring partner […]" was analysed together with other first order concept, such as "I see Copilot as a partner with whom you discuss, structure and fill white spots in your own thinking.", "I created a reliable solution and effort indication in 30 minutes with Copilot, which would previously have taken two to three hours with 10 to 12 architects", and "If I don't know an Excel formula, I describe the problem and get a solution from the AI." These examples all show consultants leveraging AI to gain information they would otherwise only get from colleagues with specific skillsets. Based on this pattern, these first order concepts were interpreted to the second order theme *AI enables direct access to specialized partners*. Other similar second order themes were *Everyday integration of AI, AI-driven efficiency gains,* and *Quality improvement through AI.*

In the final phase, the Gioia method requires an aggregated dimensions of second-order themes that represent the highest-level of concepts of the data (Gioia et al., 2012). Continuing the same example, the above second order themes all describe how AI has influenced the consultants' work on a regular basis, creating the aggregated dimension *AI as daily catalyst of a consultants' output*. The final stage of the Gioia method can often serve as the basis for developing hypothesis and data collection for future theory (Gioia et al., 2012).

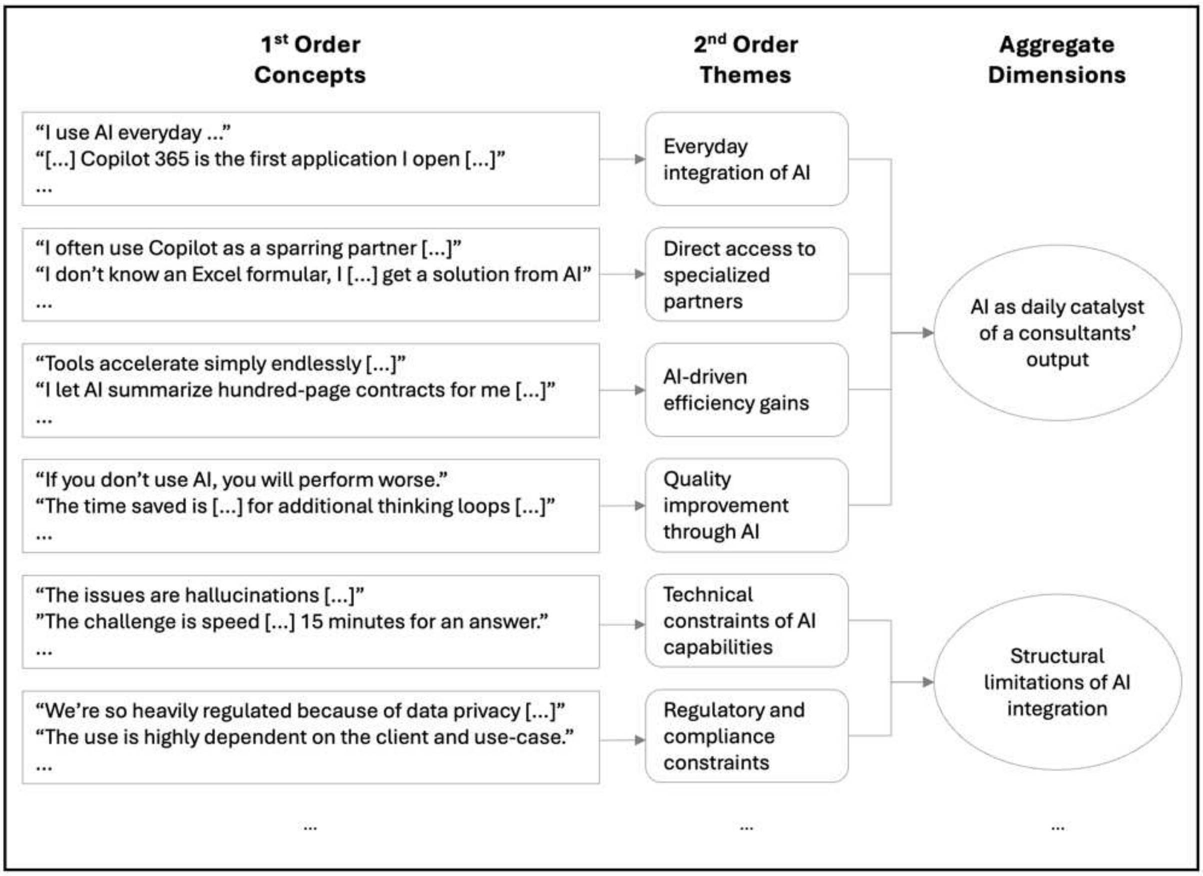

Figure 1: Data analysis based on Gioia et al. (2012) method

4. Results

This section presents findings from 18 semi-structured expert interviews analysed using Gioia methodology. Four key themes emerged regarding how AI is transforming the consulting industry: market dynamics, performance benefits, integration challenges, and success factors.

Table 1: Thematic analysis of the expert interviews based on Gioia et al., 2012

1st Order Concepts	2nd Order Themes	Aggregated Dimensions
"In the next 1-2 years, competence in AI will decide who gets projects and who doesn't." (INT_003)	AI Competence as existential competitive necessity	1. Persistent consultant function with evolving competency requirements
"The industry is faced with the question of which internal processes will be automated with employees and which with AI agents." (INT_003)		
"Global CIO says [to me], "In the age of agentic AI, I don't know if you'll still be around in five years. I can't sign a five-year contract."" (INT_016)		
"AI transformation hits professional service firms first – this is the biggest business transformation since the company was founded." (INT_016)		
"Gained time does not lead to less work: Arms Race, competitors use the same AI tools, more offers are managed in parallel." (INT_018)		
"The daily work routine has not changed fundamentally; classic consulting – understanding challenges, applying solutions – remains." (INT_007)	Core consultant function endures	
"Consulting remains a people business ... Customer relationships will remain face to face." (INT_002)		
"Communication skills remain very important, because you have to get information from the customer and ultimately reflect complex topics in an understandable way." (INT_015)		
"The classic role of business administration is becoming more irrelevant, technical backgrounds (maths, physics, engineering) are becoming more important." (INT_002)	Hiring shifts towards technical expertise	
"Profiles for new hires are now more IT-heavy; HR tends to suggest more people with an IT background." (INT_005)		
"We are specifically hiring people who have AI skills – not only technically, but also theoretically, who can understand and explain the topic." (INT_014)		
"I wouldn't hire anyone who hasn't been using AI privately for a long time; it's not about being a data scientist, it's about using the tools." (INT_016)		
"In the past, people would have asked: Have you already worked with PowerPoint, Excel, Word? Today, the equivalent is AI." (INT_016)		
"Customers will find it difficult to accept projects if you can't prove AI expertise; Expertise or access to experts becomes a prerequisite." (INT_017)		
"Everything I write goes through agents who know my style, my history and my target group and optimize it live." (INT_016)	Everyday Integration of AI	2. AI as daily catalyst of a consultants' output.
"I use AI every day... especially for paraphrasing, prescribing text and researching things." (INT_001)		
"When I boot up my laptop in the morning, Copilot 365 is the first application I open, and it stays open until I shut down in the evening." (INT_014)		
"If I don't know an Excel formula, I describe the problem and get a solution from the AI." (INT_002)	AI enables direct access to specialised partners	
"I often use Copilot as a sparring partner to question ideas or to check whether something has been overlooked." (INT_004)		

"I see Copilot as a partner with whom you discuss, structure and fill white spots in your own thinking." (INT_011)		
"I created a reliable solution and effort indication in 30 minutes with Copilot, which would previously have taken 2-3 hours with 10-12 architects." (INT_012)		
"I use an AI tool to schedule meetings to find the best time; this is embedded in the communication environment." (INT_003)	AI-driven efficiency gains	
"I automate many different, rather monotonous/time-consuming tasks that require little brainpower, but a lot of time." (INT_006)		
"I let the AI summarize hundred-page contracts for me instead of reading them in their entirety." (INT_002)		
"Tools accelerate 'simply endlessly'; personal productivity gain as an absolute game changer." (INT_012)		
Imagine that you exist as an AI-Digital Twin in the organization; while you work with colleagues, the Twins solve other tasks. (INT_016)		
"If you don't use AI, you will perform worse." (INT_013)	Quality improvement through AI	
"AI helps with structuring, simple data checks, emails, rephrasing; it polishes one's own skills." (INT_006)		
"The time saved is not used for free time, but for additional thinking loops and quality improvement." (INT_009)		
"In projects, there is an error rate of about 20%; AI can help reduce these errors – especially with large amounts of data." (INT_007)		
"We don't use AI to design complete solutions, but to present loose ideas coherently and formulate them better." (INT_005)		
"At junior level, you will need significantly fewer people in 2+ years to save costs" (INT_017)	Fewer demand for junior consultants	3. Overreliance on error-prone systems harms workforce and creates reputational risk
"While AI will not completely replace junior consultants, but it will not necessarily increase the need for juniors." (INT_008)		
"I did consulting for the first one and a half, two years before ChatGPT and learned a lot by hand. This is taken from new junior consultants" (INT_001)	Decreasing learning opportunities for junior talent	
"Junior analysts may have less opportunity to learn because smaller tasks are gradually processed by AI." (INT_003)		
"A certain creativity is taken away from you ... Sometimes you don't try so hard anymore." (INT_013)		
"There is a danger of becoming too relaxed and not questioning outputs enough." (INT_014)		
"There was a scandal that a government report was only prepared by AI, something like that must not happen." (INT_002)	Reputational risks have increased through AI	
"Reputational damage caused by poor AI use will become an important factor in the selection of consultancies." (INT_003)		
"The regulatory and confidential handling of data is very important, otherwise there is a risk of negligence" (INT_011)		
"I think we're like the dot-com bubble; many things will not catch on, but some use cases such as AI-based knowledge graphs will." (INT_013)	Distinguishing sustainable AI use cases	
"If you say AI is a tool, you'll stay in the efficiency trap forever." (INT_016)		

"If we want to talk about growth, value, creativity, and real agency, we have to hand over agency to AI; currently everything relies on human-in-the-loop control" (INT_016).	from investment euphoria	
"Many companies see AI as a software tool (Office, SAP, CRM) that you implement and then run – that's 'extremely wrong and dangerous'." (INT_018)		
"You can't blindly rely on AI […] Information is attributed, things are not right, context is misperceived." (INT_001)	Technical constraints of AI capabilities	4. Structural Limitations of AI integration
"The issues are hallucinations, overly creative approaches and misleading summaries if you don't prompt enough." (INT_011)		
"Every output from AI has to be cross-checked manually. Formulations are sometimes bloated, AI invents things." (INT_008)		
"We are far from a general intelligence that completely understands the client and can help on its own." (INT_007)		
"The challenge is not so much in the selection of the ML process, but in trying out parameters and working with data. […] Companies rarely have a central, harmonized database; they are living organisms with acquisitions, legacy systems and distributed data" (INT_018)		
"Regulatory and confidential handling of data are super important, otherwise there is a risk of negligence." (INT_011)	Regulatory and compliance constraints	
"There are regulations as far as AI application is concerned; the use is highly dependent on the client and use case." (INT_003)		
"We're so heavily regulated because of data privacy... we feel like we're five years behind the market." (INT_001)		
"A customer also has an internal AI chat, but it says: Please don't put any data in; they are very strict about compliance." (INT_015)		
"Banks are not yet doing much with AI because of the black box [problem]. They have to maintain governance and control, which is currently not possible with AI." (INT_015)		
"Partners and seniors drive AI adoption; If the partners are behind it, it gives us confidence and the permission to use AI." (INT_006)	Leadership-based adaptation	5. Organizational enablement
"The technical challenge is manageable; the difficulty lies in the Human-AI Chemistry." (INT_016).		
"We only received 100 corporate licenses for ~2000 employees during the pilot." (INT_010)		
"We have mandatory training courses on how to use AI and many learning formats; new tools will be introduced company wide. The formats ensure that you become aware of tools more quickly and can benefit sooner." (INT_005)	Systematic AI upskilling	
"Prompt engineering has been added, including training and cheat sheets (persona, clear prompts, etc.)." (INT_010)		
"These trainings have influenced the way I work... help to understand how to use AI and what roles (e.g. AI officers) you need." (INT_013)		
"We no longer go into projects with the usual number of consultants; Some customers don't want that anymore." (INT_005)	Project staffing transformation	
"Teams have positioned themselves differently, stronger AI focus ... new roles such as prompt engineer, AI strategy, use case covering." (INT_013)		
"Projects will be run with director, manager, consultant and 10 AI agents who analyse and prepare data and create presentations." (INT_018)		

"How does AI change the pyramid, cost structure, young experts and work-life balance (more output vs. shorter working hours)?" (INT_017)		
"As AI advances, expectations for project results have increased: bigger scope, faster delivery, better output, and more customer centric." (INT_005)	Rising client performance expectations	6. Business Model Transformation
"Customers want to understand: What worked/didn't work, why and what does that mean for them in concrete terms." (INT_012)		
"There is a gap between expectation (you can optimize/augment everything) and what AI and consultants can currently do." (INT_014)		
"More […] customers might question projects if it's 'just GPT'; Transparency is important." (INT_008)		
"We have introduced a technology fee that finances our AI systems as a compromise: fewer consultants, small additional fee." (INT_005)	Pressure on traditional consulting pricing models	
"Customers expect AI to be used and argue: It's easier with AI, so daily rates and total stake have to come down." (INT_007)		
"AI leads to a decreasing willingness to pay and shorter project times for certain projects, especially those that require research." (INT_018)		
"Value-based pricing and profit-sharing (sharing costs) are an alternative logic to the classic consulting fee." (INT_018)		
"Advisors have to provide transfer services more quickly: Develop frameworks with AI and then adapt them to customer requirements." (INT_012)	AI-enabled pre-emptive solution development	
"Significant project changes occur when we show the customer concrete AI solutions/assets, e.g. our Agentic Workbench." (INT_014)		
"We have an internal AI-driven knowledge system that provides potential answers based on past projects and data and links directly to relevant slides/decks." (INT_009)		
"Don't wait for the customer to come up with a topic, but use [previous] project data to derive pre-emptive challenges and prepare offers." (INT_016)		
"It's about new commercial models, new customer collaboration, different delivery models; Tool stories are not enough." (INT_016)	Transition from knowledge assets to ecosystem orchestration	
"many clients want to integrate AI into their entire system." (INT_002).		
"We have our own department that develops and implements AI solutions" (INT_002)		
"There are 'out of the shelf' software offerings from startups/providers that can be implemented immediately." (INT_018)		
"Methodological knowledge (phases, roles, project approaches) and technical know-how used to be a huge asset [for consultancies], now it’s a commodity at the push of a button." (INT_012)		

4.1. Market dynamics in the age of AI

Experts report that their consultancies experience growing external market pressure, in which AI competence increasingly determines which firms secure project mandates. Clients seem to directly link contract awards to demonstrated AI proficiency, as evidenced by one director recounting a conversation with a global CIO: “In the age of agentic AI, I don’t know if you’ll still be around in five years. I can’t sign a five-year contract.” (INT_016). This pressure permeates the entire consulting pyramid, with one consultant emphasizing that “AI competence determines who gets projects and who does not” (INT_003). Consequently, consultancies appear eager to provide sufficient evidence of AI literacy to the market, thereby reinforcing industry-wide AI adoption and the expansion of service portfolios. Market participants describe this dynamic as an *arms race*, characterized by “competitors using the same AI tools” while “more offers are managed in parallel” (INT_018).

This external dynamic also seems to have internal implications, as hiring profiles for entry-level consultants evolve. A basic understanding and proficiency in AI tools is increasingly regarded as a standard requirement, as one expert noted: “In the past, people would have asked: Have you already worked with PowerPoint, Excel, Word? Today, the equivalent is AI” (INT_016). This shift appears to go further, as experts involved in recruitment processes report changing entry requirements: “The classic role of business administration is becoming more irrelevant. Technical background (maths, physics, engineering) are becoming more important” (INT_002). Consultancies therefore seem to build a workforce that is more specialized around AI, as one manager described: “We are specifically hiring people who have AI skills. Not only technically, but also theoretically, who can understand and explain the topic” (INT_014). At the same time, experts repeatedly emphasise that technical capabilities alone are insufficient if they are not complemented by strong soft skills. One interviewee stressed that “communication skills remain very important, because you have to get information from the customer and ultimately reflect complex topics in an understandable way” (INT_015). This underlines that clear communication, the simplification of complex ideas, and the ability to integrate diverse knowledge remain central to successful project work.

Despite the competitive pressure and evolving skill profiles, the interviewed experts consistently highlight that consulting remains fundamentally a people business, as “customer relationships will remain face to face” (INT_002). Several consultants underline that “the daily routine has not changed fundamentally; classic consulting, understanding challenges, applying solutions, remains” (INT_007). Even with rapidly advancing tools, experts note that the core business of consulting, understanding client challenges, structuring complex problems, and identifying viable solutions, remains intact. Clients reinforce this expectation by demanding deliverables that go “beyond normal ChatGPT output” (INT_012), requiring consultants to address the specific contextual situation and to draw from prior experience on what has succeeded or failed elsewhere.

4.2. AI as Catalyst for Consultant Performance

Across seniority levels, consultant’s report that AI has seamlessly integrated into their daily workflows, making it a constant companion rather than an occasional tool. One consultant noted: "I use AI every day" (INT_001), while another described its routine presence: "Copilot 365 is the first application I open and it stays open until I shut down in the evening" (INT_014). Instead of treating AI as an add-on, interviewees use it continuously throughout their daily tasks: "Everything I write goes through agents who know my style, my history, and my target group and optimize it live" (INT_016). This extends to communication, where AI refines language, reduces syntax errors, and structures ideas for more professional deliverables. As several experts emphasized, "If you don't use AI, you will perform worse" (INT_013).

Beyond augmenting individual capabilities, interviews also indicate that AI is frequently treated as a virtual colleague, using it to challenge reasoning and fill knowledge gaps. Multiple respondents described AI as a sparring partner: "I see Copilot as a partner with whom you discuss, structure and fill white spots in your own thinking" (INT_011) or "I often use Copilot as a sparring partner to question ideas or to check whether something has been overlooked" (INT_004). AI also grants consultants instant access to specialized expertise that would otherwise require meeting senior colleagues or domain experts: "If I don't know an Excel formula, I describe the problem and get a solution from the AI" (INT_002).

These use cases translate not only into tangible quality improvements, but also into efficiency gains. Experts report consistently substantial time savings, with one senior director estimating time reductions from hours to minutes in certain settings: "I created a reliable solution and effort indication in 30 minutes with Copilot, which would previously have taken 2-3 hours with 10-12 architects" (INT_012). Especially for repetitive and research-intensive tasks like understanding client documents, these "tools accelerate simply endlessly. Personal productivity gain as an absolute game changer" (INT_012). An expert reported: "I let the AI summarize hundred-page contracts for me instead of reading them in their entirety" (INT_002). Managers emphasize that the freed-up capacity is used to shift resources towards higher-value and strategic activities: "The time saved is not used for free time, but for additional thinking loops and quality improvement" (INT_009).

4.3. Challenges of AI Integration

Interviewees consistently highlight technical and regulatory constraints as primary barriers to effective AI adoption. Current AI tools remain error-prone and can generate misleading content: "The issues are hallucinations, overly creative approaches and misleading summaries" (INT_011). This fosters distrust among consultants, who caution that "you can't blindly rely on AI" (INT_001), necessitating manual verification at every step of the consulting process: “Every output of the AI has to be cross-checked manually” (INT_008). These technical limitations are enhanced with client-specific restrictions, as consultancies must navigate diverse industry regulations and governance requirements: "There are regulations as far as AI application is concerned. The use is highly dependent on the client and use case" (INT_003). Particularly in financial services, stringent data privacy rules often prohibit external tools, forcing reliance on slower, over-regulated internal models: "Banks are not yet doing much with AI because of the black box [problem]. They have to maintain governance and control, which is currently not possible with AI" (INT_015). Even internal solutions face limits, as "a customer also has an internal AI chat, but it says: Please don't put any data in. They are very strict about compliance" (INT_015). As one manager summarized this challenge: "We are far from a general intelligence that completely understands the client" (INT_007).

Building on these technical and structural constraints, heavy reliance on error-prone AI introduces reputational risks. Daily AI use heightens exposure: "The regulatory and confidential handling of data is very important, otherwise there is a risk of negligence" (INT_011), and "reputational damage caused by poor AI use will become an important factor in the selection of consultancies" (INT_003). Senior leaders also identify an *efficiency trap*, prioritizing short-term productivity over long-term capability building: “If you say AI is a tool, you will stay in the efficiency trap forever" (INT_016). While AI boosts short-term quality and efficiency of consultancies, experts recognize long-term risks of workforce deskilling: "Junior analysts may have less opportunity to learn because smaller tasks are gradually processed by AI" (INT_003), alongside reduced demand for entry level roles: “At junior level, you will need significantly fewer people in 2+ years" (INT_017). This efficiency trap also extends to the AI investment euphoria experts experience: "I think we are [in] like a dot-com bubble; many things will not catch on" (INT_013). True transformation requires ceding control, with AI acting autonomously. Yet, current AI systems from consultancies require human oversight: "If we want to talk about growth, value, creativity, and real agency, we have to hand over agency to AI; currently everything relies on human-in-the-loop control" (INT_016).

4.4. Key Success Factors

With these challenges in mind, consultancies seem to successfully adapt, integrate, and leverage AI under certain conditions. Throughout the interviews, respondents highlighted the fundamental role of leadership in shaping cultural openness toward AI: "Partners and seniors drive AI adoption. If the partners are behind it, it gives us confidence and the permission to use AI" (INT_006). Leadership must also calibrate the right balance between human and AI resources, as one director framed it: "The technical challenge is manageable; the difficulty lies in the Human-AI Chemistry" (INT_016). This directly affects project staffing, where traditional teams are being reconsidered: "We no longer go into projects with the usual number of consultants" (INT_005). Instead, interviewees describe hybrid human-AI teams as an emerging norm, with humans controlling and providing the project direction and AI taking on the time consuming tasks: "Projects will be run by one director, one manager, one consultant, and 10 AI agents who prepare and analyse data and create the presentations" (INT_018). Leaders are also expected to guide workforce upskilling. Consultants at all seniority levels appreciate newly implemented trainings that specifically fosters AI proficiency and keeps them updated on the latest developments: "We have mandatory training courses on how to use AI and many learning formats; new tools will be introduced company-wide. The formats ensure that you become aware of tools more quickly and can benefit sooner" (INT_005).

The commitment of leadership to AI reflects a broader business model transformation driven by rising client expectations: "As AI advances, expectations for project results have increased: Bigger scope, faster delivery, better output, and more customer-centric" (INT_005). Respondents note that consultancies must effectively manage the "gap between expectation (you can optimize/augment everything) and what AI and consultants can currently do" (INT_014). This gap becomes especially visible in clients' price sensitivity, thereby directly impacting profitability levels of consultancies: "AI leads to a decreasing willingness to pay and shorter project times" (INT_018) or "Customers expect AI to be used and argue: It's easier with AI, so daily rates and total stake have to come down" (INT_007). Consultancies seem to respond to this dynamic by experimenting with new commercial models, trying to offset decreasing revenue. Some firms try to be compensated for the heavier use of AI: "a technology fee that finances our systems" (INT_005) or try a result-driven approach: "value-based pricing or profit-sharing" (INT_018).

To further counter the rising expectation gap between clients and consultancies, firms have started reorganizing internal resources to expand and differentiate their offerings. Experts report expanding IT departments specifically for AI: "We have our own department that develops and implements AI solutions" (INT_002). These efforts are already transforming client engagements, with customers seeming intrigued by existing solutions: "significant project changes occur when we show the customer concrete AI solutions, e.g. our agentic workbench" (INT_014). Consequently, the focus of traditional project deliverables is shifting from pure knowledge transfer towards ecosystem orchestration. One director observed: "Methodological knowledge (phases, roles, project approaches) and technical know-how used to be a huge asset [for consultancies], now it's a commodity at the push of a button" (INT_012). In this context, "new commercial models, new customer collaboration, different delivery models" are required, as "tool stories are not enough" (INT_016). Finding the best solution to a client's challenge seems insufficient in the age of AI. New project deliverables will encompass solution identification, integration, and long-term maintenance, since "many clients want to integrate AI into their entire system" (INT_002). Another director pointed to "out-of-the-shelf software from startups/providers that can be implemented immediately" (INT_018) as emerging competitors, emphasizing that consultancies should develop and implement their own software solutions for clients. Aligning with this development, consultancies seem eager to maintain integrated solutions and become long-term advisors. Respondents report their firms developing "an internal AI-driven knowledge system that provides potential answers based on past projects and data and links directly to relevant slides/decks" (INT_009). Consultancies want to become more proactive and support clients holistically, across entire transformations: "Don't wait for the customer to come up with a topic, but use [previous] project data to derive pre-emptive challenges and prepare offers" (INT_016). Together, these efforts enable consultancies to capture the full value of a client's transformation rather than focusing solely on specific advisory tasks.

5. Discussion

5.1. Theoretical Contributions

The interviews describe the emerging transformation of the consulting industry from what the literature has previously theorized. Traditionally, knowledge management has been a defining capability of the industry. Consultancies that can transfer knowledge from previous experiences to new clients had a competitive edge (Sarvary, 1999). However, clients now expect more from individual projects than applied theories or best practices, which AI can generate instantly. Project scopes seem to extend beyond identifying optimal solutions for specific challenges toward comprehensive ecosystem orchestration. These type of projects not only cover traditional consulting phases such as problem identification, solution design, and implementation, but also extend to solution maintenance and managing downstream impacts across client departments, processes, and external technologies. These additional efforts enable consultancies to deliver a holistic, sustained transformation. For example, a consultancy supporting a client in implementing AI-driven customer analytics may no longer limit its role to designing the analytical model and handing over recommendations. Instead, the project extends to integrating the solution into the client's existing IT infrastructure, continuously monitoring model performance, updating algorithms based on new data, and coordinating with multiple internal departments such as marketing, sales, and IT. At the same time, the consultancy may connect external technology providers or proprietary tools to ensure scalability and long-term functionality. In this setting, the consultancy acts as an orchestrator of a broader ecosystem rather than a temporary advisor, ensuring that the solution remains effective, aligned with business objectives, and adaptable to evolving conditions. Consultancies are responding the broaden project scopes by expanding internal capabilities in two ways. First, they are strengthening IT departments for development, integration, and maintenance of tailored solutions, reallocating internal resources and prioritizing hires with MINT or AI expertise over traditional business profiles. Second, they are developing AI-driven internal knowledge systems that are trained on past project data. These systems accelerate the replication of proven solutions and enable the proactive acquisition of clients by anticipating future challenges arising from ongoing engagements. Similarly, project staffing for consultancies are evolving to the next phase. Experts at all levels indicate that teams in the future will not only include AI experts but also move towards hybrid human-AI teams. Interviewees expect AI agents to handle research, data preparation, and presentation drafting independently, while consultants provide contextual, quality, and relationship management. This fast-paced development of AI also reduces the willingness to pay of customers. Experts describe a decreasing headcount-per-project trend, which ultimately affects the traditional revenue model of consultancies that consists of billable hours per consultant depending on seniority level and project scope (Ng, 2008). To counter this development, consultancies have already started to experiment with new potential pricing structures. Some firms have introduced technology fees to offset their own IT costs, while other experts report their company exploring new models based on gained value, in which consultancies are compensated a share of the increased profit or saved costs from the project results. These dynamic AI-driven developments also bring risks. Senior leadership indicates an emerging theory referred to as the efficiency trap of AI adoption. Overreliance on AI replaces junior-associated tasks and risks deskilling junior consultants. As tasks such as conducting market research, analysing datasets, or drafting slide structures are increasingly automated, entry-level consultants lose opportunities to develop foundational skills and progress along traditional learning curves, thereby threatening the long-term capabilities of consultancies for short-term productivity gains. Additionally, amid the ongoing arms race, consultancies are eager to demonstrate AI proficiency by investing in AI-driven solutions, which risks ineffective investments and the emergence of a bubble. Consultancies might allocate significant resources to unproven or low-value use cases that fail to deliver sustainable returns. In sum, these novel findings directly answer RQ2: “How is artificial intelligence affecting the business model of consultancies?”. Given the recent development of AI and resulting client expectation, the business model of consultancies changes from knowledge transfer to end-to-end ecosystem orchestration, human-AI hybrid project staffing, and commercial model changes. Due to this fast paced development, the business model is facing an emerging efficiency trap, where efforts for short-term competitiveness risk long-term sustainability.

The interviews also highlight two contradicting developments with the literature. First, the diffusion of innovations theory predicts a gradual, S-shaped adoption depending on the firms' attributes like relative advantage and compatibility (Rogers, 1983). Instead, interviews indicate an industry-wide arms race, where all experts report similar tool adoption at comparable speeds. Interviews indicate two reasons for this development: on one side, experts report prominent benefits from using AI, as these systems augment the consultants’ capabilities. Using AI has become a routine part of consultants’ daily tasks, from communicating with clients and conducting research to analysing data and drafting reports. They are intrinsically motivated to use AI to improve their individual performance. On the other side, as clients' start to notice these productivity gains and experiment themselves with AI-driven solutions, they raise their expectations around project performance with consultancies. Second, this arms race seems to mitigate the value gain that innovations are theorized to bring companies (Teece et al., 1997). Findings suggest that AI-driven efficiency and productivity directly translate into expanding workloads for consultancies at a stagnant or even decreasing profitability level. Higher expectations from clients result in larger project scopes and higher output expectations that absorb the freed capacity. Consequently, value gains are largely captured by clients through expanded demands rather than firm-level profits. These two contradictions directly answer RQ1: “How does artificial intelligence reshape the day-to-day work of consultants?”. An industry-wide arms race embeds AI routinely into the consultants core tasks, augmenting their capabilities and thereby fuelling intrinsic motivation to leverage AI. However, these productivity gains are offset by rising client expectations, channelling gained value into expanded workloads rather than individual or firm-level benefits.

Lastly, the findings also support existing literature. The dynamic capabilities theory emphasizes the responsibility of leadership to sense, seize, and transform opportunities into real organizational value. It is their responsibility to foster cultural openness and build organizational capability (Teece et al., 1997). Experts confirm this theory by consistently highlighting that the level of AI adoption in projects depends on the partners involved, and that structured workforce upskilling is dependent on leadership's commitment to AI. Furthermore, the TOE framework emphasizes the importance of external factors as persistent adoption barriers (Tornatzky & Fleischer, 1990). Client specific regulations around compliance and data privacy highly impact the AI adoption on projects for consultancies. Interviews indicate this to be extremely prominent in more conservative industries like the financial services, as projects in this sector have a slower AI integration rate compared to other sectors.

5.2. Managerial Contributions

The theoretical findings provide four actionable implications for strategy managers in consulting firms navigating their AI-driven transformation.

First, consultancies should actively redefine their value proposition beyond knowledge management. As AI generates theoretical knowledge at an instant, competitive advantage for consultancies will increasingly depend on the ability to orchestrate end-to-end solutions. Consultancies should be able to integrate technologies into client ecosystems and deliver sustained impact. As a result, managers should prioritize building internal capabilities in development, implementation, and integration. This shifts the value preposition from solution recommendations to single client challenges to taking ownership of long-term transformations.

Second, consultancies must deliberately design human-AI project team models. While AI can significantly enhance productivity, it should not fully replace junior-level tasks that are critical for capability development. Otherwise, consultancies could risk long-term capability decline. Managers should ensure structured learning pathways by selectively retaining foundational tasks, complementing them with AI usage rather than fully automating them. Furthermore, leadership should invest in targeted upskilling programs not only to develop technical or AI specific hard skills, but also to prevent soft skills like problem solving or creativity from declining long-term. Third, consultancies need to rethink their commercial models to better capture value from AI-driven services. Traditional headcount- and time-based billing is increasingly misaligned with productivity gains, requiring a shift toward hybrid pricing structures. These may include technology fees to offset rising AI-related costs or outcome-based compensation models to counter declining revenues driven by reduced headcounts per project. At the same time, firms should carefully manage the AI-related expectation gap between clients and consultancies to prevent efficiency gains from being fully absorbed by clients through expanded project scopes without corresponding increases in revenue. Finally, managers should adopt a disciplined approach to AI investments. In the context of an industry-wide arms race, there is a risk of overinvesting in unproven or low-value use cases due to the investment euphoria the industry is experiencing. Managers should prioritize use cases with clear strategic relevance, measurable impact, and scalability, while avoiding symbolic investments to solely signal AI capability.

Overall, for consultancies to successfully navigate through AI transformation requires firms to move beyond applied theory to ecosystem orchestration and strategically managing the human-AI chemistry. To achieve this, managers should develop a strong foundation by developing internal capabilities and implementing effective mechanisms to capture value from AI.

5.3. Limitations and Future Research

This exploratory qualitative study has three limitations that should be considered when interpreting these findings. First, the sample of 18 strategy consultants from six larger consultancies limits generalizability to the broader industry, as results may not transfer to other consultancies with different specializations or of different sizes (Lincoln & Guba, 1985; Patton, 2015). However, as an exploratory design, this study's strength lies in uncovering novel patterns and contributions in an under-researched area, aligning with qualitative research's emphasis on depth over breadth (Lincoln & Guba, 1985). Second, participant selection relied on convenience and snowball sampling through the researcher’s own networks, which inherently introduces potential bias (Bogner et al., 2009; Patton, 2015). Experts with different academic and professional backgrounds might have experienced and emphasized different aspects of AI adoption. Closely linked to this is the potential bias without triangulation or client perspectives, as experts might report data influenced by firm incentives or social desirability (Corbin & Strauss, 2015). While these risks were considered, the approach was appropriate for accessing a hard-to-reach population of strategy consultants. Additionally, utilizing networks from prior collaborations ensured high-trust and rich insights, that would otherwise be hard to attain. Finally, while theoretical saturation was reached within this sample, the Gioia methodology relies on researcher interpretation during the coding stages. This risks overlooking nuances in linking interviewees terms to aggregate dimensions (Gioia et al., 2012). To counterbalance this limitation, the process remained rigorously close to empirical evidence, following established protocols for credibility and rigor.

With these limitations, findings could be used to generate propositions to emphasize patterns for theory development in an under researched area (Corbin & Strauss, 2015). Future research could address these highlighted gaps by building on the study's findings through targeted extensions (Patton, 2015). For instance, quantitative surveys might test the generalizability of the industry-wide arms race adoption pattern across smaller consultancies, non-strategy practices, and global regions. Complementing this, longitudinal studies over 2-5 years could track AI's evolving workforce impacts, quantifying the efficiency trap through junior deskilling risks and structural shifts in the consulting pyramid amid declining headcounts and rising human-AI teams. Comparative multi-firm case studies could further explore leadership strategies for achieving optimal human-AI chemistry, evaluating upskilling program effectiveness and the role of internal IT expansions in enabling ecosystem orchestration. Meanwhile, client-side surveys or dyadic consultant-client interviews would help validate the perceived expectation gaps driving price resistance, while assessing the practical viability and adoption barriers for emerging models like value-based pricing.

6. Conclusion

This thesis examined how artificial intelligence is transforming the consulting industry, addressing the paradox that consultancies advise sectors on digital transformation while the implications of AI for their own practices remain insufficiently explored. Drawing on 18 semi-structured expert interviews, the study investigated changes in consultants' daily work (RQ1) and the broader implications for the consulting business model (RQ2).

The findings suggest that AI has become an integral part of consultants' daily project work, embedding a technology-augmented process across core consulting tasks. From communicating with clients and conducting research to analysing data and drafting documents, AI augments consultants' capabilities and enhances individual performance. However, rather than reducing workload, these efficiency gains are absorbed by higher output expectations and expanded project scopes, transferring value to clients rather than increasing individual or firm-level profitability. At the same time, AI adoption introduces significant challenges. Industry-specific regulatory constraints, data privacy requirements, and technical limitations restrict AI usage in client engagements. More critically, the study identifies an emerging efficiency trap: while AI accelerates short-term execution, the industry-wide arms race creates excessive reliance on AI and threatens the long-term capability development of consultancies.

These operational effects of AI also appear to fundamentally transform the consulting business model. Traditional strategy projects have been centred around identifying client challenges and transferring knowledge by applying theory and best practices to solve them. AI shifts projects beyond these conventional phases toward long-term, end-to-end ecosystem orchestration, including more proactive client acquisition through ongoing solution maintenance and the anticipation of challenges during engagements. In response, consultancies are developing internal AI-driven capabilities and increasingly hiring specialized, technically skilled entry-level consultants rather than traditional business generalists. These developments challenge established team structures by reducing headcounts and introducing AI agents, forcing consultancies to rethink their economic model in order to offset rising technology costs and potential pressure on revenues.

Overall, this thesis concludes that artificial intelligence is not replacing the consulting industry but redefines how value is created within the industry. While AI enhances efficiency and analytical capacity, the core consulting process remains a people business. Consultancies that effectively design and govern human-AI collaboration will secure sustainable value creation and lasting competitive advantage.

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Appendix

Appendix 1: Interview Participants

Identification	Position	Industry	Tenure in years
INT_001	Senior Consultant	Technology	2
INT_002	Consultant	Automotive	1
INT_003	Consultant	Energy	1
INT_004	Senior Consultant	General	3
INT_005	Senior Consultant	General	2
INT_006	Senior Consultant	Automotive	3
INT_007	Manager	Financial Services	5
INT_008	Senior Consultant	Automotive	2
INT_009	Senior Consultant	Automotive	3
INT_010	Senior Consultant	Retail	3
INT_011	Manager	Financial Services	4
INT_012	Senior Director	Financial Services	19
INT_013	Manager	Automotive	5
INT_014	Senior Consultant	Financial Services	1
INT_015	Senior Consultant	Financial Services	2
INT_016	Director	General	15
INT_017	Consultant	General	3
INT_018	Director	Retail	18

Appendix 2: Expert Interview Questionnaire English

Introduction

1. Could you briefly describe your current role and background in consulting?

Section 1: Context and Degree of AI adoption

2. According to your experience, what are the main phases of a typical consulting engagement, and on which do you work on the most?
3. How do you contribute to your main workstreams and which tools (e.g. PowerPoint, Excel, Python, …) do you usually use?
4. How often do you typically use AI-based tools during your work, and what kind of tools or applications are involved? (e.g., ChatGPT, Sora, Gemini, …)
   a. Has this changed in the past 1–2 years?
5. From your perspective, how has AI affected your role and daily tasks?
   b. Have certain tasks changed, been automated, or emerged? (e.g., data analysis, document creation, automation, research support)?
6. In your experience, what factors have most influenced successful (or unsuccessful) integration of AI in client projects?
   c. What role do organizational readiness, consultant skills, or client openness play?
7. What benefits or challenges have you experienced when using AI tools for your work?

Section 2: AI's Impact on Client Expectations

8. Have you noticed any changes in what your clients expect from consulting projects as AI becomes more prevalent?
9. Have expectations changed regarding project conditions (delivery times, innovation, costs, …)?
10. Have expectations changed regarding project deliverables (transparency, analyses, AI solutions)?
11. Can you share a specific example where AI played a role in shaping client expectations, project scope, or the consulting approach?
12. Do you think the expectations of your clients that you have described will change in the future?

Section 3: Talent and Skills in the Age of AI

13. Have you noticed any shifts in the profiles HR favours when scanning for new consultants?
   d. Which degrees or specific skills become more important for your firm?
14. If you conduct interviews, have you noticed shifts in the characteristics you prioritize when interviewing new recruits?
15. Is your firm preparing its consultants to adapt to AI-related changes and if yes, how?
   e. Have you changed the way you work with AI as a result of these internal initiatives?
16. What specific path (education, skills, experiences) after graduating high school would you recommend to someone aspiring to become a consultant in your team?

Section 4: Outlook

17. Looking ahead to the near future (1–2 years), how do you see AI transforming consulting work and client relationships?
18. Is there anything we haven't discussed that you consider important regarding AI's current or future impact on consulting?

Closing

Thank you for your time and support. In the end of my thesis, I will send you a brief management summary with the key findings.

Appendix 3: Experteninterview Fragebogen

Einleitung

1. Könnten Sie bitte Ihre aktuelle Rolle und beruflichen Hintergrund in der Beratung beschreiben?

Abschnitt 1: Kontext und Umfang der KI-Nutzung

2. Welche Phasen gibt es Ihrer Meinung nach in einem typischen Beratungsprojekt, und in welchen sind Sie persönlich am häufigsten eingebunden?
3. Welche Aufgaben übernehmen Sie und welche Programme nutzen Sie in Ihrer täglichen Arbeit?
4. Wie häufig nutzen Sie KI-Lösungen, und um welche Tools handelt es sich konkret?
    a. Hat sich der Einsatz solcher Tools in den letzten ein bis zwei Jahren verändert?
5. Inwiefern hat der Einsatz von KI Ihren Arbeitsalltag oder Ihre Rolle im Projekt beeinflusst?
    b. Sind bestimmte Aufgaben weggefallen, hinzugekommen oder haben sich verändert
    c. Wie nutzen Sie die Zeit, die Sie durch die Nutzung von KI einsparen?
6. Welche Faktoren beeinflussen Ihrer Meinung nach den erfolgreichen Einsatz von KI-Anwendungen in Kundenprojekten?
    d. Welche Rolle spielen organisatorische Vorbereitung, Fähigkeiten der Berater, oder die Offenheit des Kunden?
7. Welche Vor- oder Nachteile haben Sie persönlich bei der Nutzung von KI in Ihrer Arbeit erlebt?

Abschnitt 2: Auswirkungen von KI auf Kundenerwartungen

8. Haben Sie in letzter Zeit Veränderungen in den Erwartungen Ihrer Kunden bemerkt, seit KI im Alltag eine größere Rolle eingenommen hat?
9. Haben sich Erwartungen hinsichtlich der Projektrahmenbedingungen (Lieferzeiten, Innovationsgrad, Kosten, …) verändert?
10. Haben sich Erwartungen hinsichtlich der Projektergebnisse (Transparenz, Analyse, integrierten KI-Lösungen, …) verändert?
11. Können Sie ein Beispiel nennen, bei dem KI den Verlauf eines Kundenprojekts beeinflusst hat?
12. Glauben Sie, dass sich die Erwartungshaltung Ihrer Kunden zukünftig ändern wird?

Abschnitt 3: Talente und Kompetenzen im Zeitalter der KI

13. Haben Sie Veränderungen in den Profilen bemerkt, die HR bei Neueinstellungen priorisiert?
    e. Welche Fähigkeiten oder Qualifikationen gewinnen dabei an Bedeutung?
14. Sofern Sie selbst Interviews durchführen, haben Sie Veränderungen bei den Eigenschaften festgestellt, die Sie bei neuen Bewerbern priorisieren?
15. Wie bereitet Ihr Unternehmen Mitarbeitende auf den Umgang mit KI vor?
    f. Haben solche Initiativen Ihre eigene Arbeitsweise im Umgang mit KI beeinflusst?
16. Welche konkrete Laufbahn (Studium, Fähigkeiten, Erfahrungen) nach dem Abitur würden sie heute jemanden empfehlen, der zukünftig als Berater in Ihrem Team anfangen möchte?

Abschnitt 4: Ausblick

17. Wie wird KI Ihrer Meinung nach die Beratungsbranche und die Kundenbeziehungen in den nächsten ein bis zwei Jahren verändern?
18. Haben wir Ihrer Meinung nach einen wichtigen Aspekt zum Einfluss von KI auf die Beratungsbranche noch nicht angesprochen?

Abschluss

Vielen Dank für Ihre Zeit. Nach Abschluss meiner Masterarbeit sende ich Ihnen gerne eine kurze Management-Zusammenfassung mit den zentralen Ergebnissen der Studie zu.