NOVA SCHOOL OF BUSINESS & ECONOMICS

A Work Project, presented as part of the requirements for the Award of a Master`s degree in

(International) Management from the Nova School of Business and Economics

The Role of Generative AI in Management Consulting:

A Descriptive Exploration of the Strategic Use and Business Model Integration of Generative AI

Theresa Christina Nöcker – 65829

Work project carried out under the supervision of:

Prof. Marco Berti

Management and Organisations

Nova School of Business and Economics

23rd of February 2026

Abstract

Generative Artificial Intelligence (GenAI) is reshaping knowledge-intensive work and has become a strategic priority for management consulting firms. However, systematic evidence on how consulting organisations implement GenAI and manage the associated organisational transition remains limited. This study addresses this gap through an exploratory qualitative design based on 18 expert interviews across Tier-1, Tier-2 and Big Four consulting firms in Germany. The findings show that GenAI primarily acts as an augmentative tool, accelerating research and content production while shifting effort toward evaluation and judgment. Adoption patterns vary across firms and are shaped by the interaction of organisational conditions, consultants' sensemaking of GenAI, and emerging capability requirements.

Keywords: *Generative AI; Management Consulting; Strategic Integration; Operational Transformation; Organisational Adoption; Sensemaking; Change Management*

This work was funded by Fundação para a Ciência e a Tecnologia (UID/00124/2025, UID/PRR/124/2025, Nova School of Business and Economics) and LISBOA2030 (DataLab2030 - LISBOA2030-FEDER-01314200).

Table of Contents

List of Figures

List of Abbreviations

Abbreviation	**Full Term**
AI	Artificial Intelligence
CAQ	Centre for Audit Quality
CEO	Chief Executive Officer
GDPR	General Data Protection Regulation
EU AI Act	EU Artificial Intelligence Act
GenAI	Generative Artificial Intelligence
GPT	Generative Pre-Trained Transformer
ISO	International Organisation for Standardisation
I-[n]	Expert Interview [1;2;3;18]
KIBS	Knowledge-Intensive Business Services
LLM	Large Language Model
MECE	Mutually Exclusive, Collectively Exhaustive
ROI	Return on Investment
RQ	Research Question

1 Introduction

1.1 The Strategic Imperative of GenAI in Management Consulting

"*Artificial intelligence […] will infuse everything within a few short years.*" - Arvind Krishna, CEO of IBM, IBM Think 2024 Keynote (Krishna, 2024)

Only a short time after the public release of ChatGPT in late 2022, Generative Artificial Intelligence (GenAI) has become a pervasive element of organisational practice. Its rapid diffusion marks a decisive turning point in the digitalisation of knowledge work and has particular significance for knowledge-intensive industries such as management consulting. With its capacity to generate text, synthesise unstructured information, construct quantitative models, and produce client-ready material within seconds, GenAI reshapes long-standing assumptions about how consulting work is organised. Early empirical evidence shows that GenAI accelerates cognitive tasks, strengthens analytical depth, and streamlines documentation-heavy processes, all of which are central to consulting value creation (Ruokonen and Ritala 2025; Kanbach et al. 2024). In the German context, GenAI adoption has advanced rapidly since 2022, supported by national digital transformation initiatives, regulatory debates, and growing investment in AI infrastructure. Although consulting firms have historically been early adopters of technological innovation, the disruptive potential of GenAI is of a different order. The technology challenges established work routines, prompts adjustments to business models, and alters the skill requirements for maintaining competitiveness. At the same time, its diffusion exposes consulting firms to new organisational and ethical risks, including data-protection issues, model hallucinations, and emerging governance demands (Gelashvili-Luik et al. 2025). As competitive pressures intensify and clients demand higher value delivery within increasingly compressed time horizons, GenAI promises both efficiency gains and enhanced innovative capacity, making its adoption strategically necessary while also creating significant organisational complexity.

Consequently, developing a systematic understanding of how GenAI can be integrated into strategic decision-making, operational workflows, and organisational structures becomes essential. This challenge is not only of scholarly relevance but also constitutes a pressing managerial concern for consulting firms navigating the ongoing technological transformation.

1.2 Aim of the Thesis

The aim of this thesis is to examine how management consulting firms operating in Germany are currently integrating GenAI into their strategic practices. Adopting a descriptive and exploratory perspective, the study focuses on enacted GenAI use rather than speculative future developments.

Guided by the research question, this individual part of the thesis examines the strategic use of Generative AI, as illustrated in Figure 1.

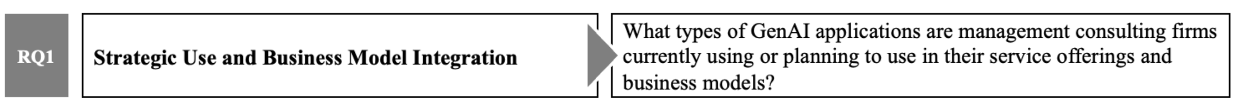

Figure 1: Research Questions

While RQ1 also captures firms' orientations toward future GenAI applications, the empirical emphasis of this study is deliberately placed on current and enacted uses. Forward looking planning around GenAI remains limited, reflecting the rapid pace of technological change and the high level of uncertainty characterising the domain. As a result, the analysis prioritises present adoption practices over speculative future scenarios.

The overarching objective of the thesis is to provide a systematic account of current GenAI adoption in German consulting firms and to derive, from observed practices, the key success factors that shape effective, responsible, and scalable GenAI integration under conditions of ongoing technological change.

1.3 Overview of the Thesis Structure

This thesis consists of eight chapters that collectively examine how GenAI is reshaping management consulting. Chapter 1 introduces the topic, research aims, and thesis structure. Chapter 2 provides the theoretical foundation by outlining the characteristics of management consulting and the emergence of GenAI as a general-purpose technology. Chapter 3 reviews the current state of research on GenAI in organisations, professional services, and consulting, and synthesises these insights to frame the analytical focus of the study. Chapter 4 details the qualitative research design, including sampling, interviews, and analytical procedures. Chapter 5 presents the empirical findings along the three RQs, covering strategic integration, operational transformation, and organisational change. Chapter 6 translates these findings into recommendations on strategic direction, governance, capability building, tooling, workflow integration, and leadership. Chapter 7 reflects on the limitations of the study and outlines avenues for future research. Chapter 8 concludes the thesis by summarising the central findings and offering an outlook on future developments in the use of GenAI in management consulting.

2 Theoretical Foundation

2.1 The Role of Management Consulting

2.1.1 Definition & Scope

Management consulting refers to professional advisory services that assist organisations in solving complex problems, improving performance, and developing strategic direction. Consultants contribute analytical tools, specialised expertise, and structured problem-solving approaches to support decision-making across both private and public sectors (Mosonyi et al. 2019; Bijnens and De Rock 2025). Typical activities include diagnosing organisational challenges, designing corporate and operational strategies, implementing change programmes, and enabling large-scale transformation initiatives (Bijnens and De Rock 2025; Doloreux et al. 2025).

Management consulting is widely recognised as a form of Knowledge-Intensive Business Services (KIBS), which can be described as a sector whose value creation depends primarily on professional expertise, innovation, and the transformation of knowledge into solutions (Teixeira et al. 2023; Doloreux et al. 2025). Within this framework, consulting firms act as knowledge brokers, linking client organisations with specialised external insights and best practices to foster innovation and performance improvement (Bühlmann 2023; von der Heid and Blome 2024). Consultants rarely assume operational responsibility; instead, they function as analytical partners who provide frameworks, evidence-based analyses, and strategic guidance tailored to client contexts (Mosonyi et al. 2019; Teixeira et al. 2023).

2.1.2 Management Consulting as a Knowledge-Intensive Service

Building on this classification, management consulting exemplifies a knowledge-intensive business service (KIBS), in which value creation depends primarily on the generation, processing, and application of knowledge rather than physical production (Kaczorowska-Spychalska et al. 2024). A defining feature of consulting is its reliance on intellectual capital as the primary productive asset, with firms drawing on methodological frameworks, data-driven analysis, and professional judgment to address complex client challenges (Rhee Park and Cooper 2023; Schlee et al. 2024).

Consulting outputs are largely intangible and co-produced with clients, rendering effective knowledge management central to service quality and innovation (Rhee et al. 2023; Schlee et al. 2024). Digitalisation further strengthens knowledge sharing, organisational learning, and innovation performance within KIBS through AI-enabled collaboration tools and data-driven systems (Kaczorowska-Spychalska et al. 2024). Accordingly, consulting firms rely on structured knowledge systems, mentoring processes, and firm-specific methodologies to retain and scale intellectual capital.

Value creation in consulting depends on the interplay between explicit knowledge, codified in frameworks and databases, and tacit knowledge grounded in experience, intuition, and interpersonal skill. The conversion of tacit insights into explicit and transferable forms remains a central mechanism of value creation in consulting projects, reinforcing the profession's character as a knowledge-intensive industry (Dutta and Kumar 2022).

2.1.3 Economic Significance of Management Consulting

The economic significance of management consulting is substantial. Recent estimates value the global market at more than one trillion US dollars, with steady expansion projected over the coming years and annual growth rates of approximately four to five percent (The Business Research Company 2025; Mordor Intelligence 2024). Although figures vary due to different definitions of consulting services, the overall evidence points to a large and consistently growing sector. A similar pattern is visible at the national level. In Germany, for instance, the consulting market has shown continuous growth over the past decade, rising from around EUR 30 billion in 2016 to an expected EUR 46 billion in 2025, as illustrated in Figure 2. This trend underscores the industry's resilience and expanding economic relevance within Europe.

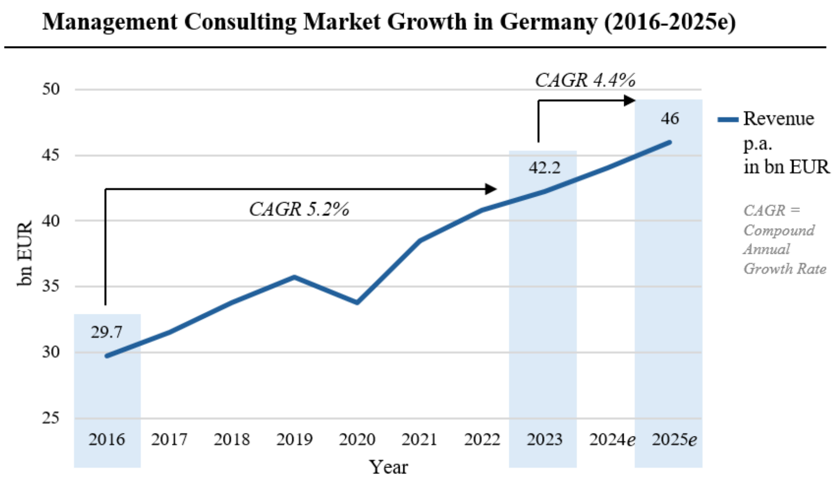

Figure 2: Consulting Market Growth in Germany (Own Illustration based on BDU, 2024)

Beyond its economic scale, consulting also plays a strategic role in organisational transformation, public sector reform, and digital initiatives. Consultants are frequently involved in government modernisation programmes, digital transformation projects, and sustainability or energy-transition initiatives, illustrating their influence across industries and policy domains (Machljankin et al. 2024). The industry therefore extends its impact far beyond economic metrics, shaping how organisations respond to technological, regulatory, and societal shifts.

2.1.4 The Evolving Role of Technology in Consulting Practice

Technology has long been integral to consulting, but its influence has accelerated dramatically over the past decade. Historically, consultants relied on spreadsheets, ERP systems, and business intelligence tools to analyse client data and generate recommendations. Today, consulting firms increasingly leverage advanced technologies such as big data analytics, artificial intelligence (AI), cloud computing, and visualisation tools as part of their core service delivery. Among these, AI and digital platforms have become particularly transformative, reshaping analytical work, client engagement, and value creation (Tavoletti et al. 2022; Mamedova and Savchenko-Belskaya 2022).

The COVID-19 pandemic further accelerated digital adoption within consulting firms. It forced consultancies to redesign engagement models and governance structures for virtual collaboration, integrating AI-driven and cloud-based platforms that enabled teams to co-create insights remotely. Studies show that the crisis significantly accelerated the use of digital technologies and virtual delivery models in the consulting sector, fundamentally reshaping client interaction and service execution (Kronblad and Pregmark 2021; Leyh et al. 2023).

Technology therefore constitutes a crucial enabler of consulting practice, enhancing efficiency through automation, supporting scalability through digital toolkits, and strengthening competitiveness through data-driven analytics. Nevertheless, the success of technological adoption continues to depend on human expertise, judgment, and contextual understanding, which remain central to effective consulting (Tavoletti et al. 2022).

2.2 The Emergence of GenAI as a General-Purpose Technology

GenAI refers to a class of algorithms capable of autonomously producing novel content such as text, images, code and multimodal outputs like audio or video. Unlike earlier AI systems focused on predictive or classification tasks, GenAI leverages large-scale transformer architectures to generate original and contextually appropriate material. The most prominent examples are Large Language Models (LLMs) such as ChatGPT (Generative Pre-Trained Transformer), Gemini, and Claude, which are "*trained on vast corpora of unstructured data*" (Min et al. 2024; Zhao et al. 2024). Due to their emergent capabilities in reasoning, synthesis, and cross-domain generalisation, LLMs are increasingly viewed as a general-purpose technology with profound implications for knowledge-intensive sectors (Bubeck et al. 2024; Brynjolfsson et al. 2024).

The development of GenAI has been shaped by rapid advances in model scale and accessibility. The release of GPT-3 in 2020 demonstrated the potential of scaling laws in deep learning, while the launch of ChatGPT in late 2022 triggered mass adoption. Subsequent generations, including GPT-4, Gemini 1.5, and Claude 3, introduced multimodal reasoning, improved instruction-following, and enterprise-grade integrations that increasingly embed GenAI into professional workflows (Min et al. 2024; Wang et al. 2025; Zhao et al. 2024). Empirical research characterises 2023–2024 as a breakout period marked by widespread experimentation but uneven organisational integration (Brynjolfsson et al. 2024; Dwivedi et al. 2024).

Applications in knowledge-intensive work are already evident. Experimental evidence shows that LLMs enhance productivity in tasks such as drafting, summarisation, and problem solving, particularly for less-experienced workers (Noy and Zhang 2023). In practice, enterprise tools such as Copilot, Notion AI, and Harvey AI have been adopted across professional services, including consulting, law, and finance (Dwivedi et al. 2024). However, many organisations continue to experiment with these tools rather than embedding them into core processes (Brynjolfsson et al. 2024).

At the same time, GenAI entails significant limitations and risks. Technical challenges include hallucinations, weak numerical reasoning, and unstable outputs (Bubeck et al. 2024; Zhao et al. 2024), while ethical and legal concerns centre on bias, copyright, and data privacy (Dwivedi et al. 2024; Yu et al. 2025). Security vulnerabilities such as prompt injection and data leakage further complicate enterprise deployment (Li et al. 2024). For consulting firms in particular, the heavy reliance on text-based analysis and client-facing deliverables renders GenAI highly relevant yet also raises concerns about knowledge commoditisation and erosion of professional distinctiveness (Brynjolfsson et al. 2024). This tension between productivity gains and professional disruption underscores the need for deliberate and strategically governed integration.

2.3 Regulatory Foundations of GDPR and the EU AI Act

The use of GenAI in management consulting is increasingly shaped by regulatory frameworks such as the GDPR and the EU Artificial Intelligence Act (EU AI Act). The GDPR, applicable since May 2018, is particularly relevant, as consulting firms routinely process sensitive personal and business data and must adhere to principles such as purpose limitation, accountability, and data minimisation (European Union 2016).

The EU AI Act complements this framework through a risk-based approach to AI governance emphasising transparency, human oversight, and organisational responsibility. Having entered into force on 1 August 2024, it introduces legally binding requirements that will be applied in a phased manner between 2025 and 2027, requiring organisations to continuously adapt their practices as compliance obligations become applicable over time (European Union 2024; European Commission 2024a). Together, GDPR and the EU AI Act frame GenAI use in consulting as a regulated managerial practice, requiring formal governance structures and adjustments to service delivery models.

3 Literature Review

3.1 State of Research on GenAI in Organisations, Professional Services and Consulting

The purpose of this literature review is to synthesise recent academic and practitioner insights into how GenAI affects organisations, adjacent knowledge-intensive professions and, ultimately, management consulting. The review follows a three-tiered structure. The first part surveys general research on productivity gains, automation potential and associated risks across industries. The second part examines evidence from law, auditing and financial services to derive lessons for consulting and the third part analyses the nascent academic and practitioner literature on GenAI in management consulting. This arrangement creates a coherent red thread that moves from broad organisational impacts to sector-specific adoption and culminates in in a focused examination of management consulting. Throughout, the analysis highlights both universal findings and context-specific nuances and indicates how the forthcoming expert interviews will build upon these insights.

3.1.1 GenAI in Organisations

GenAI promises substantial productivity gains by automating cognitive tasks and enabling new forms of work creation. Kanbach et al. (2024) estimate that up to 300 million jobs may be affected globally and that around 40 percent of working hours could be automated. High-income occupations requiring advanced communication and analytical skills are particularly exposed, while repetitive white-collar tasks face a higher risk of displacement. More broadly, GenAI reduces the marginal cost of content production and shifts human roles toward curating, verifying, and contextualising AI outputs. Empirical evidence supports this shift. Brynjolfsson Li and Raymond (2024) find that access to a GenAI assistant increases worker productivity by 15 percent, with stronger effects for less-experienced employees.

Qualitative research suggests that GenAI does not simply reduce effort but reconfigures how work is performed. Based on interviews with European knowledge workers, Memmert et al. (2025) show that professionals actively reallocate or even increase effort when collaborating with GenAI. They invest time in learning to steer the technology, verifying outputs, and reinvesting efficiency gains into higher-order tasks. These findings characterise professionals as process administrators who remain responsible for quality and outcomes, highlighting the learning and coordination costs associated with GenAI use.

Practitioner reports echo both the momentum and challenges of adoption. The Internal Audit Foundation (2024) reports that 55 percent of organisations are pursuing limited or aggressive AI adoption and projects that the global AI market will more than double between 2024 and 2027. However, large-scale value realisation remains uneven. KPMG (2025) finds that while GenAI is widely prioritised as an investment, only 32 percent of firms report generating returns at scale, citing constraints related to legacy systems, data integration, and governance.

Risk-oriented studies further underscore the need for robust oversight. The Center for Audit Quality (2024) documents emerging use cases in which GenAI supports financial reporting while warning that risks related to accuracy, data provenance, and ethical use necessitate enhanced human-in-the-loop controls.

Overall, prior research indicates that GenAI combines significant productivity potential with non-trivial organisational costs. Efficiency gains are accompanied by increased effort related to training, prompt engineering, and verification, constituting forms of AI managerial labour that require sustained investment in people and processes (Law and Varanasi 2025). Managing these trade-offs is therefore critical for organisations seeking to deploy GenAI responsibly and effectively.

3.1.2 GenAI in Knowledge Work and Professional Services

Legal Services

Legal services offer a relevant comparator for consulting because they rely heavily on text-based analysis and expert judgment. Recent survey data show that interest in GenAI is widespread, with 59 percent of law firms reporting that the technology should be applied to their work and 26 percent of legal professionals already using it in practice (Thomson Reuters 2025). Adoption concentrates on tasks such as document review, legal research and drafting, which together account for more than half of all reported use cases. Clients also express growing expectations, with most corporate clients indicating that they want their legal advisers to use GenAI. At the same time, many organisations do not yet measure the performance or reliability of GenAI, and concerns persist regarding accuracy and potential unauthorised practice. These patterns underscore the importance of client communication, systematic evaluation and clear safeguards when integrating GenAI into professional services.

Auditing and Internal Audit

Auditing exemplifies another adjacent profession where GenAI adoption must balance efficiency with assurance. The CAQ (2024) notes that firms use GenAI to draft financial-statement disclosures and to generate SQL code for internal reporting, but employees review and test these outputs to ensure adherence to Generally Accepted Accounting Principles. Auditors caution that the technology introduces new risk considerations such as accuracy, bias and confidentiality, and requires new controls and staff training. Similarly, the Institute of Internal Auditors (2024) emphasises that GenAI is well positioned to enhance audit activities such as data visualisation, anomaly detection and workflow automation. The Institute of Internal Auditors (2024) reports that AI adoption is already widespread, with 55 percent of organisations indicating limited or aggressive adoption, but successful integration demands human oversight, robust data governance and a commitment to upskilling.

Financial Services

Financial services provide a contrasting case of heavy investment in GenAI. A 2024 KPMG survey reports that 81 percent of banking and insurance CEOs and 75 percent of asset-management CEOs identify GenAI as a top investment priority. Despite this enthusiasm, only 32 percent of firms generate returns at scale. KPMG (2024) highlights that the successful adoption of GenAI depends on the modernisation of legacy infrastructures, the institutionalisation of data-driven decision-making practices and sustained investment in cloud-based “Everything-as-a-Service” models, in which 82 percent of firms intend to invest. Financial services leaders also worry about regulatory complexity. Approximately 70 percent of insurance CEOs regard the lack of AI regulation as a barrier, prompting calls for new standards like ISO 42001 for AI management. These insights underscore the importance of infrastructure, governance and regulatory clarity.

3.1.3 Cross-Industry Implications for Consulting

The experiences of law, auditing and financial services offer several lessons for management consulting. First, client demand can drive adoption: corporate legal clients are actively requesting GenAI use, suggesting that consulting clients may soon expect similar capabilities. Second, use cases cluster around document summarisation, research and draft generation, that are activities common to consultants. Third, risks and controls are paramount; auditing standards emphasise human oversight and verification, and legal professionals worry about accuracy and unauthorised practice. Consulting firms must therefore institute robust review processes and ethical safeguards. Fourth, practitioners note that GenAI adoption is resource-intensive and requires modernising systems and measuring ROI. Lessons from banking and auditing thus highlight that technology alone does not guarantee value. Instead, investments in training, governance and infrastructure are crucial. These cross-industry insights set the stage for analysing how consulting can harness GenAI’s potential while avoiding pitfalls.

3.2 GenAI in Management Consulting

3.2.1 Knowledge-Intensive Characteristics as Drivers of GenAI Adoption in Consulting

Building on the classification of consulting as a form of KIBS (see Section 1.3), research highlights two distinctive features that make the profession particularly susceptible to GenAI. First, unlike legal or accounting services, where deliverables are subject to strict regulatory standards, consulting outputs are largely self-defined and evaluated on perceived insight, persuasiveness, and contextual relevance. This flexibility renders them especially amenable to automation through GenAI's text- and data-synthesis capabilities (Pimentel and Veliz 2024). Second, consulting is inherently client-facing. Value creation depends on trust, tailored recommendations, and contextual interpretation. While GenAI can accelerate information processing, it cannot replace the relational and judgmental dimensions of client engagement.

Thus, these characteristics suggest that GenAI has the potential to profoundly reshape consulting workflows, amplifying efficiency while simultaneously reinforcing the need for human oversight and contextual expertise. To illustrate these dynamics more concretely, the following section examines consulting's text-heavy and analysis-driven workflows, which align particularly closely with GenAI's capabilities in information processing and synthesis.

3.2.2 Text-Heavy and Analysis-Driven Workflows

Consulting workflows are inherently research- and synthesis-intensive. Consultants spend significant time searching, summarising, and reconfiguring information into structured artefacts. GenAI aligns closely with these activities through its affordances in text generation, data summarisation, and real-time retrieval. Studies show that GenAI can automate the generation of knowledge artefacts and improve discovery across large repositories of structured and unstructured data (Pimentel and Veliz 2024).

3.2.3 Impact of Automation on Skill Requirements

Macroeconomic analyses also confirm measurable productivity gains. Kanbach et al. (2024) estimate that up to 300 million jobs could be affected and that approximately 40 percent of working hours could be automated. High-income occupations requiring strong communication skills are particularly exposed, while repetitive knowledge-work tasks such as data entry or proofreading may largely disappear. Kanbach et al. (2024) further argue that the marginal cost of generating content approaches zero and that "judgment and critical thinking will become crucial for curating and editing AI-generated material." In other words, consultants are likely to transition from content producers to curators of AI-generated insights, focusing on verifying accuracy, contextualising recommendations and exercising strategic judgement.

Empirical evidence supports this re-orientation. Brynjolfsson et al. (2024) found that access to a GenAI assistant raised productivity by 15 percent on average, with larger gains for less experienced workers. Novice consultants may thus close skill gaps more quickly.

However, adoption is not frictionless. Pimentel and Veliz (2024) caution that generative systems require careful oversight and strong AI literacy. Beyond formal training, employees themselves actively reshape their roles in response to GenAI adoption. This is particularly visible among early-career professionals, whose job-crafting behaviours provide insight into how the next generation of consultants integrates AI into daily work practices.

3.2.4 Job Crafting and the Reframing Work Design among Early-Career Professionals

Job crafting refers to employees' proactive efforts to adjust tasks and relationships to align work activities with individual skills and career goals (Mayer et al. 2025). In management consulting, this concept is particularly relevant for early-career professionals, whose roles have traditionally been characterised by routine analytical and documentation-intensive tasks.

Prior research indicates that the introduction of GenAI reshapes job crafting practices by reframing, rather than reducing, patterns of effort. Memmert et al. (2025) show that knowledge workers frequently reallocate or even increase effort when using GenAI, as time is invested in learning to steer the technology, verifying outputs, and reinvesting efficiency gains into higher-priority tasks. This highlights that professionals remain responsible for quality and outcomes, underscoring the learning and coordination costs associated with GenAI use.

Building on this perspective, Mayer et al. (2025) examine GenAI-enabled job crafting among entry-level professionals in a European consultancy. Their analysis identifies interrelated forms of job crafting that shape how GenAI is integrated into daily work. Task crafting involves automating routine activities and reallocating time toward client interaction and ideation, thereby accelerating learning and enhancing job meaningfulness. Relational crafting emerges when GenAI is used as a source of guidance, which may reduce interaction with senior colleagues and complicate established mentoring and performance evaluation processes. While these practices illustrate GenAI's empowering potential, they also introduce risks related to over-reliance, skill erosion, and rising performance expectations.

These micro-level adaptations align with what Raisch and Fomina (2024) conceptualise as hybrid problem solving, in which AI performs initial analytical work while human professionals critically refine insights and jointly develop final recommendations. Overall, prior research positions job crafting as a central mechanism through which GenAI reshapes work design, effort allocation, and early career trajectories in consulting. At the same time, these effects depend strongly on organisational context and cultural norms, a contingency that the following section examines in greater detail.

3.2.5 Cultural and Organisational Contexts of Adoption

The sensemaking study by Yan et al. (2025) explains why the same GenAI technology can lead to very different adoption patterns, as employees interpret organisational cues, leadership signals, and prevailing cultural expectations differently. High internal corporate social responsibility, signalling genuine investment in employees, is associated with harmonious passion and approach-oriented job crafting, whereas high external corporate social responsibility can trigger obsessive passion and avoidance behaviours driven by fear of replacement. Even in supportive environments, employees may disengage from GenAI use when they seek to conserve personal resources. Although situated in China's high power-distance context, the study demonstrates that professionals interpret GenAI through organisational signals and cultural expectations.

These dynamics align with change management research that emphasises the role of leadership communication. Kotter (1996) highlights the importance of clear and consistent vision, while Armenakis and Harris (2009) stress the role of middle managers in translating strategic intent into concrete expectations. Sensegiving refers to deliberate leadership efforts to shape how employees understand, interpret, and enact organisational change, including the adoption of GenAI. In this context, vague or overly aspirational messaging can generate uncertainty, whereas coherent sensegiving helps anchor AI use in everyday work practices.

Beyond communication and formal structures, GenAI also has unintended effects on professional behaviour, norms, and decision-making. Larson et al. (2024) note that the authoritative tone of AI-generated outputs may reduce critical engagement, as professionals become more inclined to accept results without sufficient scrutiny. For consulting firms, this dynamic poses a broader cultural challenge. GenAI therefore needs to be integrated in ways that preserve reflective judgment, systematic verification, and established standards of professional rigor.

3.2.6 Hidden Managerial Labour and Collaboration Dynamics

Law and Varanasi's (2025) review highlights the emergence of AI-related managerial labour in knowledge-intensive work. While professionals may delegate routine tasks to GenAI, they must still invest in prompt engineering, verification, and oversight, often restructuring collaboration by using AI as a sounding board for ideation or critique. These shifts can increase efficiency but also risk reducing opportunities for peer learning and mentorship, which are central to consulting's apprenticeship culture. Recognising and compensating this hidden work is essential for sustainable adoption, as employees otherwise experience GenAI not as a productivity enhancer but as an additional cognitive burden.

3.2.7 Early Industry Initiatives and Practitioner Perspectives

Academic research is complemented by practitioner insights. The consulting industry has already begun to institutionalise GenAI adoption, illustrating both enthusiasm and competitive pressure. For example, McKinsey's GenAI platform Lilli enables rapid synthesis of the firm's extensive knowledge base and has been deployed broadly across the organisation; McKinsey has also been working with clients to bring Lilli-powered capabilities into their own knowledge and AI programmes (McKinsey & Company 2023). Moreover, Boston Consulting Group has partnered with Anthropic to integrate responsible GenAI technologies into its consulting workflows (Boston Consulting Group and Anthropic 2023), and Bain & Company collaborates with OpenAI to integrate generative models into client delivery processes (see Appendix A). Although these initiatives are documented primarily in industry reports rather than peer-reviewed studies, they nevertheless signal an industry-wide arms race among consultancies to leverage proprietary data and generative models to accelerate project delivery and sustain differentiation.

However, practitioner reports caution that adoption must be strategic. Thomson Reuters

(2025) note that most legal professionals do not measure ROI, while the CAQ (2024) emphasises human oversight, and KPMG (2025) warns that generating returns requires modernising systems and building governance frameworks. Consulting firms should therefore avoid a technology push mentality and instead align GenAI implementations with business models, client expectations and ethical standards. Case studies from law and auditing show that implementing GenAI also entails establishing review protocols and training programmes.

3.3 Synthesis and Link to Empirical Research

The literature review indicates that GenAI produces a dual dynamic in organisational settings. On the one hand, it accelerates cognitive and knowledge-intensive tasks by enhancing research, drafting, and analytical workflows. On the other hand, these efficiency gains generate new forms of labour, most notably verification, prompt refinement, and risk management. Evidence from adjacent professional fields such as law, auditing, and finance reveals well-defined use cases alongside persistent concerns regarding accuracy, bias, ethics, and governance. Across these domains, scholars emphasise the importance of client communication, regulatory assurance, and measurable value creation.

Emerging work on management consulting suggests that the profession's dependence on text-based deliverables and intensive client interaction renders it especially susceptible to GenAI adoption. Although consultants can deploy GenAI to summarise documents, analyse data, and generate slides, they must simultaneously uphold professional judgment, safeguard quality, and manage client expectations. Adoption trajectories are shaped by organisational culture, perceived fairness, and readiness for change, while the managerial labour required to coordinate AI-enabled work remains insufficiently theorised and empirically documented.

Despite these insights, existing research on GenAI in consulting remains largely conceptual. Prior studies focus primarily on productivity gains, automation potential, and task-level substitution, while offering limited empirical evidence on how consulting firms integrate GenAI into business models, operational routines, and workforce practices. Practice-oriented accounts of enacted adoption processes, concrete use cases, and organisational responses remain scarce, particularly in European and German contexts. This lack of systematic empirical evidence on everyday GenAI-enabled consulting work constitutes the central research gap addressed by this study.

To address this gap, the present study adopts an exploratory qualitative approach and examines how consulting firms currently engage with GenAI in practice through expert interviews across hierarchical levels and firm types. Rather than quantifying impact, the study focuses on identifying emerging use cases, organisational tensions, and ineffective practices that hold diagnostic value for understanding adoption dynamics. By doing so, the study contributes empirically grounded insights into the operational and organisational realities of GenAI-enabled consulting work. The resulting findings and recommendations provide both an analytical lens for scholars and a reflective reference point for consulting firms seeking to assess and guide their own GenAI transformation efforts.

4 Research Design and Methodology

To investigate the impact of GenAI on the consulting industry, a qualitative research design was chosen. Qualitative approaches are particularly suitable for capturing subjective assessments, implicit practices and meaning-making processes in complex and fast-changing environments (Döringer 2021). Semi-structured expert interviews were therefore selected as the primary method, as they allow for both systematic exploration and flexibility to probe individual experiences and emerging themes (Lim 2025).

Sampling and Selection of Interview Participants

A total of 18 interviews were conducted with consultants from leading German firms, including McKinsey, BCG, Bain, Tier 2 strategy consultancies, and the consulting practices of the Big Four. These firm archetypes differ in organisational logics, resource endowments, and governance structures and are therefore theoretically relevant for comparative analysis of GenAI integration (Bijnens and De Rock 2025; Doloreux et al. 2025). Prior research suggests that variations in scale, digital maturity, and knowledge infrastructure shape how consulting firms adopt emerging technologies (Kaczorowska Spychalska et al. 2024; Pimentel and Veliz 2024). Focusing on these archetypes ensures analytical comparability while retaining meaningful variance. Details on firm classification and the final sample are provided in Appendices B and C.

Boutique consultancies, specialist providers, and in-house consulting units were excluded due to differing institutional logics and governance structures, which would have compromised theoretical comparability (Jain 2024). Participants were recruited through purposeful sampling via professional networks and LinkedIn, targeting consultants with direct exposure to GenAI in project work, digital practices, or internal AI initiatives. To capture hierarchical breadth, the sample spans roles from Junior Consultant to Partner, enabling insights across executional, managerial, and strategic levels. Thematic saturation was reached after 18 interviews, as no new themes emerged in the final stages of data collection. An overview of the recruitment process and inclusion criteria is provided in Appendix D.

Conduct of Interviews

The interviews were conducted over a three-week period via Microsoft Teams. Although planned for approximately 30 minutes, several interviews lasted up to 60 minutes due to participants' detailed contributions. All participants were informed about the study's purpose, provided consent for recording, and were assured of data anonymisation. With permission, all interviews were recorded and fully transcribed.

Interview Guide

The interviews followed a semi-structured guide comprising ten open questions with optional probes. The guide covered GenAI use, task and workflow changes, skill shifts, opportunities and risks, organisational acceptance, and future developments, ensuring systematic coverage while allowing in-depth exploration. The full interview guide is provided in Appendix E.

The questions were closely aligned with the three RQs and designed according to established principles of semi-structured qualitative interviewing. A funnel logic was applied, beginning with descriptive questions to establish context and minimise interviewer bias, followed by interpretive questions to elicit perceptions and underlying mechanisms. Each question was linked to a specific analytical purpose, with the detailed mapping documented in Appendix F.

This design balances comparability across interviews with openness to emergent insights and provides a rigorous basis for qualitative content analysis and the generation of practice-oriented insights into GenAI adoption in management consulting.

Research Context

The study deliberately focuses on the German consulting market, which differs from other countries in terms of data protection requirements (DLA Piper, 2024), labour-market structures (Eichhorst and Marx 2025), and comparatively cautious cultural attitudes toward technology adoption (European Commission 2024b). As Germany represents one of the largest and most mature consulting markets in Europe, it provides a highly relevant context for analysing industry-wide AI adoption (see Section 2.1.3).

Data Analysis

All interviews were fully transcribed and analysed using structuring qualitative content analysis following Mayring (2000, 2022). ATLAS.ti was employed to manage the dataset and support systematic coding and analysis. The coding scheme combined deductive categories derived from theory and the RQs with inductive categories emerging from the data in a grounded-theory-inspired manner (Charmaz 2006). For each RQ, a hierarchical coding structure with three main categories and associated subcodes was developed, adhering to the mutually exclusive, collectively exhaustive (MECE) principle (Minto 2009). A detailed codebook with definitions and examples is provided in Appendix G.

In line with the Gioia Method, first-order in-vivo and descriptive codes were aggregated into second-order themes and overarching dimensions (Gioia et al. 2013). Illustrative coded excerpts and overviews of code structures, frequencies, and code-network visualisations are presented in Appendices H-J, providing transparency and an audit trail of the analytical process.

To support methodological rigour, the analysis followed an iterative procedure involving repeated code refinement, transcript review, and team discussions. ChatGPT 5.1 Pro was used solely to check redundancies and category boundaries without influencing interpretation (see Declaration of Software and AI Support).

Quality Criteria of Qualitative Research

To ensure methodological rigour, the analysis followed Lincoln and Guba's trustworthiness criteria of credibility, transferability, dependability and confirmability (Lincoln and Guba 1985).

Credibility was supported through team triangulation and iterative coding, while transferability was enhanced by providing contextual information on the German consulting market. Dependability was ensured through consistent interview procedures and transparent documentation of the analysis process. Confirmability was strengthened through the documentation of coding decisions and ongoing reflection on potential researcher bias (Lincoln and Guba 1985; Shenton 2004).

Quality Assurance and Limitations

To ensure methodological quality, all interviews were conducted under comparable conditions using a standardised interview guide. As with qualitative research more generally, the study is subject to limited generalisability, potential self-selection bias from LinkedIn-based recruitment, and a focus on large firms. However, these firms play a central role in shaping industry-wide AI adoption practices, lending the sample high informational value.

5 Analysis

This Chapter presents the empirical findings of the study and explains how consulting firms are integrating GenAI into their strategic, operational, and organisational practices. The analysis is structured around a data structure derived from the qualitative coding process, which organises interview insights into 1st-order concepts, 2nd-order themes, and aggregate dimensions, following a Gioia-inspired analytical approach. Figure 3 presents an illustrative excerpt of the Gioia data structure for RQ2, demonstrating the aggregation of interview insights across analytical levels and serving as a representative example. The complete codebook comprising all parent and subcodes is provided in Appendix G, while illustrative Gioia data structure examples for RQ1 and RQ3 are included in Appendix K.

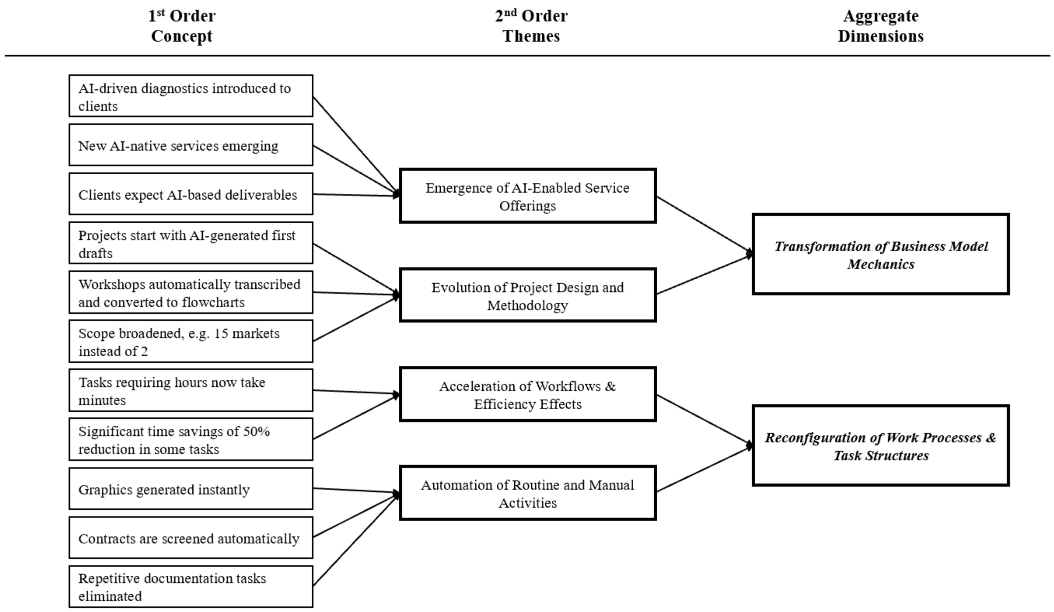

Figure 3: Example of Data Structure for RQ2 (Own Illustration)

The empirical findings for each RQ are presented in the subsections that follow, each structured around the respective aggregate dimensions.

5.1 Analysis of Strategic Use and Business Model Integration (T. Noecker)

This section addresses RQ1 by examining how management consulting firms currently use GenAI and integrate it into their business models from a strategic perspective. The analysis focuses on the tools and applications adopted, dominant use cases across consulting activities, and the strategic objectives guiding their deployment. Insights into future applications are considered where empirically evident.

5.1.1 Current AI Applications and Tools

Across the sample, consultants highlight three categories of GenAI tools that shape their daily work: (1) general-purpose and enterprise LLM infrastructures, (2) embedded productivity tools such as Microsoft Copilot and presentation support, and (3) document intelligence and knowledge-extraction systems. This parent code examines how these tool categories constitute the core technological layer through which GenAI enters consulting workflows, structures everyday work practices, and enables emerging service models. Together, they form the technological foundation that mediates GenAI adoption across projects and organisational contexts.

General-Purpose and Enterprise LLM Infrastructures

Across interviews, consultants' report extensive use of general-purpose LLMs, primarily ChatGPT, as the default entry point for analytical, drafting and problem-solving tasks. As one associate consultant notes, *"ChatGPT is used very, very heavily… internally in almost every project"* (I-5), and another adds that *"everything runs through ChatGPT"* (I-6).

In practice, "ChatGPT" almost always refers to enterprise-secured environments, since uploading confidential client information to public LLMs is strictly prohibited. Public ChatGPT is *"an absolute no-go"* (I-11) for client content. Even in protected systems, *"we are not allowed to enter real names or private data"* (I-5). Accordingly, firms rely on enterprise-grade GPT solutions, internally hosted instances, or proprietary LLM infrastructures. Before such secure, firm-approved solutions were introduced, public models were used only for *"research purposes or administrative tasks like rephrasing emails"* (I-11).

Several firms have built protected GPT environments linked to internal repositories like SharePoint, enabling secure uploads and knowledge extraction. These systems often *"load significantly more slowly"* (I-11), prompting some employees to use public models for minor, non-sensitive drafting tasks. Interviewees also describe a complex tool landscape with "*around 15 different applications*" (I-14) and new tools introduced *"sometimes monthly"* (I-11), making it unclear *"which tool you are supposed to use for which task"* (I-14). To manage this complexity, firms rely on strict governance, including mandatory AI trainings, clear upload guidelines (I-7) and bans on unapproved tools (I-1; I-8), which aligns with the formal upskilling initiatives outlined in Section 5.3.1.

Microsoft Copilot and Presentation Support Tools

The second category comprises AI tools embedded in productivity ecosystems, most prominently Microsoft 365. Eleven interviewees reported using Copilot across Outlook, Teams, PowerPoint and Excel. One manager calls it "*one of our most important tools*" (I-14), and a partner notes that "*we use ChatGPT and especially Copilot very strongly*" (I-15). Usage varies by firm; in some cases, "*we didn't roll it out for everyone; each employee had to explain why they needed it*" (I-2).

Beyond drafting and summarisation, Copilot supports communication workflows such as meeting recordings, note generation and transcription, and some firms use Copilot Studio to build custom AI agents (Partner I-16; Partner I-17).

Presentation add-ins further support slide production. Tools such as Dexter assist with executive summaries, icon suggestions and template-based structuring (Consultant, I-4; Consultant, I-12), while others use internal assistants like Lilli (Consultant, I-13) or GPT-based slide engines that automate early formatting, though final deliverables still require human refinement to meet client standards.

Perceptions are overwhelmingly positive across the interview sample. One partner described Copilot as *"working really brilliantly"* (I-15), and similar assessments were shared by most respondents. Only one associate consultant expressed a distinctly negative view, characterising the tool as *"a catastrophe"* and *"a worse version of OpenAI"* (I-18). Embedded tools therefore form a growing productivity layer that supports communication, drafting, and workflow automation, complementing the enterprise LLM infrastructures discussed in Section 5.1.1.

Document Intelligence and Knowledge Extraction

The third category covers AI systems for document analysis and knowledge retrieval, central to due diligence, regulatory review and knowledge-intensive strategy work. Several firms use internal applications such as document-chat interfaces and batch-analysis tools. As one manager explains, these tools *"allow you to upload documents and have them analysed, answer questions or generate reports"* (I-14), while batch systems can screen hundreds of files and produce summaries that would otherwise require days of manual review.

Across the sample, 14 of 18 interviewees report using document-driven or knowledge-extraction tools. Examples include internal navigation platforms that surface relevant past project materials; as one consultant notes, they *"lead you to the decks that contain the keywords you are looking for"* (I-4). Other organisations use document-aware AI assistants or secure GenAI environments that ground outputs in uploaded materials (Consultant I-13; Partner I-17). Interviewees also mention specialised tools for contract analysis in procurement and due-diligence contexts (Consultant I-3; Manager I-8) and GenAI-enhanced summarisation for regulatory texts or large document collections (Senior Manager I-7; Partner I-10).

These systems now underpin core consulting activities such as screening data-room materials, synthesising reports and retrieving firm-specific knowledge assets, making document intelligence one of the most institutionalised AI application areas.

5.1.2 Use Cases and Usage Patterns

Across interviews, four core GenAI applications dominate daily consulting work: (1) research and market intelligence, (2) document and content processing, (3) presentation and communication support, and (4) data analysis and quantitative assistance. This parent code examines how these use cases structure everyday GenAI engagement in consulting, how frequently they occur across the interview sample, and how their enactment varies by seniority and project context. Figure 4 provides an overview of the prevalence of GenAI use cases across the interview sample (n = 18), indicating how frequently interviewees reported using GenAI for different task categories and the extent to which these uses are embedded in everyday consulting practice. More advanced applications such as risk management, task automation, or agentic workflows are mentioned far less frequently, reflecting their limited institutionalisation and the absence of systematic governance or supporting processes. Usage varies across seniority levels and project types, shaping how frequently and for which tasks GenAI is applied.

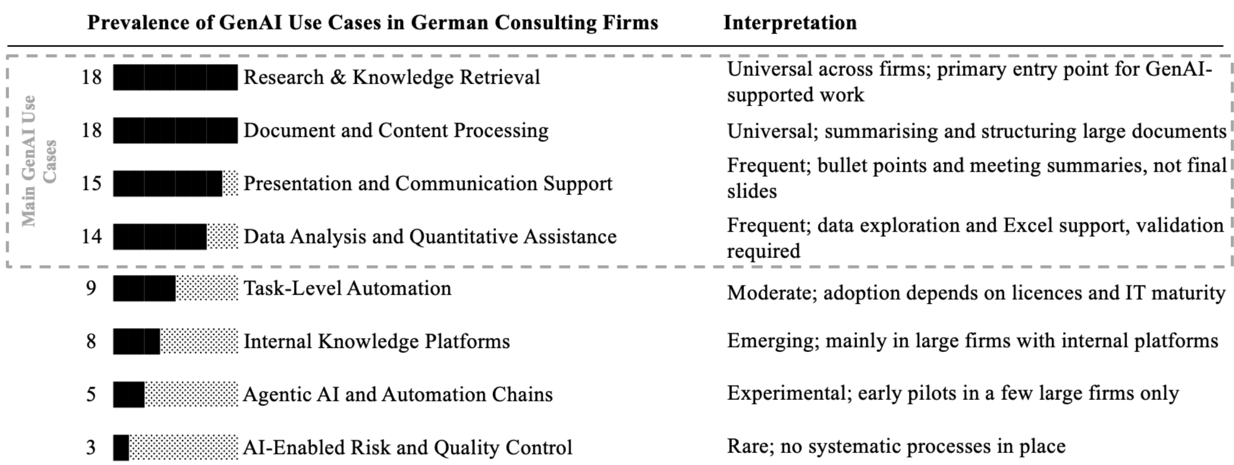

Figure 4: GenAI Use Cases in German Consulting Firms; n=18 (Own Illustration)

Research & Market Intelligence

Research is the most widely applied GenAI use case. Interviewees consistently describe using AI to accelerate early-stage understanding of markets, industries and regulatory topics. A consultant notes it is used *"to first get a basic understanding of a topic"* (I-9), and another confirms that AI is *"used especially strongly in the area of research"* (I-13).

The shift is from manual information gathering to rapid hypothesis scaffolding. One consultant explains that their internal system now provides first summaries and recommendations, reducing tasks that previously required *"a full day"* to *"half a day"* (I-11). Regulatory onboarding has also accelerated: a senior manager notes that reading complex regulations once took *"an entire Friday"* but now requires only minutes (I-7). As one senior consultant summarises, GenAI helps *"understand topics more quickly and make them more graspable"* (I-3).

Despite these gains, interviewees emphasise that GenAI provides only a starting point, as outputs must be validated to ensure they *"make sense and reflect the right underlying drivers"* (I-10). GenAI also improves access to firm knowledge: one partner highlights that colleagues now uncover *"far more nuggets in the global knowledge base,"* reducing tasks such as identifying IT-cost benchmarks from hours to *"45 minutes"* (I-17). Finally, prompting skills are becoming essential; as an associate consultant notes, effective research now depends on *"using AI correctly - what used to be operating Google is now operating AI"* (I-18).

Document & Content Processing

Document and content processing is one of the most mature GenAI use cases. Interviewees report that AI significantly accelerates work with long documents, regulatory texts and large information sets. A senior manager notes that uploading strategy papers or legislation into document-chat tools enables immediate extraction of key points, allowing consultants to *"very quickly create an initial assessment and get up to speed on new topics"* (I-7).

GenAI is also widely used for rewriting, translation and content reduction. An associate consultant notes that producing concise, client-ready points has become *"much easier"* (I-18), while another highlights that AI can turn *"ten paragraphs into ten bullet points"* (I-13). Managers use it to *"formulate the text more convincingly"* (I-14), and partners rely on it for translation and rewriting tasks previously done manually (I-2).

Consultants also use GenAI to compare documents, process large information sets and synthesise long inputs into clear storylines (I-9; I-12), capabilities that underpin many activities in due diligence and regulatory work.

Despite these advances, interviewees stress that human verification remains essential. Document-driven summaries are *“not yet fully reliable”* (I-7), and *“every tenth prompt”* may still hallucinate or mix information (I-5). As one senior manager concludes, *“You can’t take it 1:1; you still need to go over it and make sure it actually fits the client context”* (I-1).

Presentation & Communication Support

GenAI increasingly supports everyday communication and PMO tasks. Consultants commonly highlight its usefulness for drafting meeting minutes, scheduling and writing emails (I-8), and partners report *“massive improvements”* in extracting key points and structuring responses (I-17). Language refinement is also routine, with grammar and style checks *“increasingly supported by AI”* (I-15).

GenAI further streamlines presentation work by structuring arguments, proposing bullet points and generating early slide drafts. However, output quality remains limited. A manager notes that Copilot’s drafts are *“not yet mature enough to match corporate design”* (I-14), and partners stress that AI-generated slides are still far from client-ready (I-17). As a result, consultants typically transfer AI-generated text into manually designed decks.

To bridge these gaps, firms use specialised slide-generation tools that create layouts, icons and structured content aligned with firm templates (Consultant I-13), complemented by assistants that refine wording or adjust tone (see Section 5.1.1).

Data Analysis and Quantitative Assistance

Data analysis appears frequently across interviews. A partner notes that the Data & Analytics unit *“mainly uses GenAI tools”* and is already *“very advanced”* (I-17), and consultants similarly emphasise strong adoption *"in areas that are pretty data intensive"* (I-12). Classic first-year tasks such as repetitive evaluation, harmonisation and basic classification can now be offloaded to GenAI systems (Consultant I-6; Senior Consultant I-3).

Efficiency gains are substantial. One partner explains that analysing financial statements, which previously took *"two to three weeks with a team of three people,"* can now proceed much faster by feeding data into an AI tool to obtain an immediate assessment (I-15). GenAI also helps translate large datasets or text volumes into clear storylines (Consultant I-12).

Excel-related support is widespread but mixed. While interviewees report that GenAI is helpful for resolving formula or Power Query issues (Manager I-14) and for generating or debugging complex formulas (Consultant I-11; Consultant I-4), others caution that it remains "*quite error-prone*" (Consultant I-13) and may even miscalculate simple metrics (I-5). Two partners therefore stress that AI-assisted analyses must be checked for plausibility, since the tools "*are only as good as the questions you ask them*" and should not "*decide*" on their own (Partner I-15; Partner I-10).

Usage Variation by Seniority and Project Type

GenAI usage varies markedly by hierarchy. Juniors are the most intensive users, as many execution-oriented analyst tasks can be supported by AI. One consultant notes that "*pretty much all typical first-year tasks can now be supported by AI*" (I-6). GenAI mainly reduces execution work and helps overcome the blank-page problem.

Managers use GenAI more selectively, largely in coordination and quality assurance. A senior manager highlights a *"level-based application of AI tools"* (I-7), and another senior manager explains that GenAI supports early proposal drafts by providing *"a first initial approach"* (I-1), though managers still *"have to challenge whether the output is correct"* (I-7).

Among partners, usage varies widely and depends strongly on digital affinity. Some partners *"barely use it themselves"* (Consultant I-13), while tech-affine partners integrate GenAI more deeply into conceptual work. Interviewee 13 also notes that partners often use GenAI mainly for "*the last ten percent*" of refinement, whereas execution-heavy tasks remain with junior teams. One consultant adds that at partner level GenAI is used "*much more conceptually and for inspiration*" rather than operationally (I-8).

Usage patterns also vary by project type. GenAI is used intensively in product-oriented and deal-related work (Partner I-17) and in data-heavy projects (Associate Consultant I-18) but plays a limited role in operational cost-reduction programmes where "*not that much […] can really be used*" (Consultant I-6).

Sector differences affect prompting more than frequency. As one consultant notes, "*insurance and banking require completely different slide logic than consumer or media*" (I-13). Overall, project suitability and data availability shape usage more than industry.

5.1.3 Strategic Motivations and AI Objectives

This parent code captures the strategic rationales that underpin consulting firms' adoption of GenAI, focusing on why firms invest in and promote AI-enabled capabilities beyond isolated use cases. Across interviews, consultants describe three overarching motivations for adopting GenAI: (1) efficiency gains and time savings, (2) market differentiation and innovation signalling, and (3) knowledge scalability and AI-enabled offerings.

Efficiency, Time Savings and Quality Improvements

Efficiency gains are the most consistently cited motivation across interviews. Consultants emphasise that GenAI accelerates workflows and reduces manual effort. One consultant notes that *"you save an enormous amount of time […] we are much, much faster, but we don't work less,* *the output just increases"* (I-11).

These productivity improvements are closely linked to cost and quality effects. A consultant explains that contract reviews once requiring *"ten analysts for three weeks"* are now *"much faster and far more cost-efficient"* (I-8). A partner similarly stresses the ambition to improve both *"efficiency [...] and the quality of what we deliver"* (I-17), while another consultant adds that GenAI helps teams work *"more efficiently and also more error-free"* (I-13).

Beyond speed and cost reductions, GenAI also expands project capacity. A senior manager notes that GenAI enables teams to *"cover more projects at the same time"* (I-7), as analyses and content processing that previously took weeks can now be completed significantly faster.

At the same time, interviewees caution that AI outputs still require validation. One consultant warns that misunderstood prompts can *"ultimately make you less efficient"* (I-13), and another consultant summarises the shift in work: teams spend less time on execution and more on *"curating, evaluating and steering AI outputs"* (I-12).

Market Differentiation and Innovation Signalling

Beyond efficiency and quality, interviewees emphasise that GenAI has become a strategic tool for strengthening market position and signalling technological leadership. One consultant notes that firms invest heavily in AI "*to further solidify their standing*," supported by strong internal capabilities that allow them to "*implement AI more quickly*" (I-8).

External expectations reinforce this pressure. Clients increasingly assume that leading consultancies use GenAI by default: as one consultant remarks, "*If you don't work with GenAI, clients already wonder where you've fallen behind*" (I-4).

For many firms, GenAI adoption is directly tied to long-term competitiveness. A manager stresses that staying relevant requires delivering strategy and transaction work "*on an AI-supported* *basis*" to provide maximal value (I-14). Differentiation is also an explicit strategic objective, with one consultant noting that a core aim is *"differentiation,"* alongside efficiency and quality (I-12).

Knowledge Scalability and Expansion of AI-Enabled Offerings

A third motivation concerns scaling knowledge across the organisation and expanding AI-enabled client offerings. Consultants emphasise that GenAI improves access to firmwide expertise; a senior manager highlights a major initiative to consolidate insights "*in a data lake across our businesses [...] to enable AI-driven knowledge exchange*" (I-7). GenAI also strengthens global knowledge access: one partner notes that "*using knowledge across borders has become much easier*," making it crucial to build "*proprietary knowledge that others cannot access*" (I-17). Internal systems trained on past proposals further support delivery, making it "*much easier to approach new proposals based on my project history*" (Consultant I-12).

In parallel, firms are expanding AI-enabled offerings. One manager explains that Data and Analytics has evolved into "*Data, Analytics and AI*," signalling a broader service portfolio (I-14). Another interviewee highlights the rollout of "*data models, spend cubes or similar systems that operate with AI in the background*" (Associate Consultant I-18). A partner adds that firms increasingly "*develop our own tools for clients, moving closer to a technology company*" (I-17).

Across firms, scaling knowledge and building AI-based offerings are viewed as mutually reinforcing steps that gradually redefine the consulting business model.

5.1.4 Discussion of Strategic Use and Business Model Integration in the Adoption of GenAI

GenAI is increasingly used by consulting firms in a set of dominant application areas that extend beyond isolated efficiency gains and are embedded in broader strategic considerations. The empirical findings show that GenAI use is closely linked to underlying adoption objectives and to how it is positioned within service offerings and business models. Integrating the interview material with existing scholarship, this section shows that consulting firms are moving from ad hoc experimentation toward more deliberate and strategically guided patterns of GenAI use, marking early stages of institutionalisation that increasingly shape service portfolios and competitive positioning.

Hybrid Tool Use and the Reconfiguration of Knowledge Work

The findings show that general-purpose and enterprise LLMs form the backbone of GenAI adoption in consulting firms, consistent with literature emphasising their role in augmenting reasoning and text-based knowledge work (Brynjolfsson and McAfee 2017; Cockburn et al. 2018). Consultants routinely use ChatGPT, enterprise-secured GPT environments and internal assistants such as Lilli for drafting, summarisation and early-stage problem exploration, reflecting the three tool categories identified in Section 5.1.1.

The strong reliance on enterprise-secured systems aligns with research highlighting the importance of data governance and confidentiality in professional services (Davenport and Mittal 2023). Interviewees describe these protected environments as mandatory for handling client-sensitive material, underscoring the trust-based nature of consulting work.

The findings also extend existing literature by showing that enterprise systems do not replace public models but coexist with them. Consultants alternate between public tools for ideation and exploration and internal LLMs for compliant processing. This hybrid usage pattern is largely absent from current research, which often portrays internal infrastructures as more centralised.

The evidence further refines research on AI-enabled document processing. Document-intensive tasks such as due diligence, regulatory screening and contract analysis are among the earliest and most automated workflows, and the widespread use of document-chat interfaces and batch-analysis tools suggests a more advanced institutionalisation of document intelligence than reflected in academic studies.

Consultants' experiences with productivity tools such as Microsoft Copilot are largely positive, particularly for tasks like meeting summarisation or email drafting. However, isolated critical assessments point to limitations in their suitability for high-quality consulting output, indicating a gap between vendor claims and practical realities.

Taken together, the findings support literature framing GenAI as an augmentative technology while adding new insights into hybrid LLM usage, uneven tool performance and the growing institutionalisation of document-analysis systems.

Continuities and Boundaries in GenAI-Enabled Knowledge Work

The interview evidence reflects established themes in the literature, particularly GenAI's strengths in information retrieval, text processing and document-heavy tasks. Studies such as Agrawal et al. (2019) and Brynjolfsson et al. (2023) highlight summarisation, pattern extraction and rapid synthesis as core capabilities, which closely match consultants' use of GenAI for research, regulatory screening and high-volume document review. The strong uptake in due-diligence and contract-heavy contexts therefore aligns with expectations for early AI integration in professional services.

At the same time, the findings reveal boundaries less visible in existing scholarship. Presentation creation and quantitative analysis remain only partially supported and still require substantial manual quality control. The interviews also show variation across hierarchy levels and project types: juniors rely on GenAI for operational tasks, whereas senior consultants use it primarily for conceptual framing. These patterns illustrate that GenAI adoption unfolds unevenly within consulting teams, adding granularity to current theories of AI in knowledge work and highlighting the need for closer examination of intra-organisational adoption dynamics.

Efficiency, Differentiation and Knowledge Scalability as Strategic Drivers

The findings on strategic motivations largely confirm literature portraying AI as a driver of efficiency, quality improvements and competitiveness in knowledge-intensive industries (Davenport and Mittal 2023; Modha et al. 2023). Consultants frequently emphasise time savings and error reduction, supporting the view that early AI adoption focuses on productivity gains and baseline-task automation. The use of AI to strengthen market positioning and signal innovation capability similarly aligns with research on technology-driven differentiation.

The interviews also introduce refinements. While the literature often highlights the transformative potential of AI-enabled service innovation, the empirical evidence shows that service expansion remains cautious and incremental, with few firms offering fully AI-enabled products. The strong emphasis on knowledge scalability, particularly through internal GPT platforms that widen access to firmwide expertise, extends organisational-learning perspectives by illustrating how AI reshapes knowledge flows across consulting networks. Together, the findings provide a grounded view of firms' strategic priorities, revealing adoption logics that are ambitious yet shaped by pragmatism, governance demands, client expectations and talent considerations.

5.1.5 Synthesis of the Strategic Perspective on the Impact of GenAI in Management Consulting

In relation to RQ1, the findings show that consulting firms use GenAI primarily as an augmentative layer that supports rather than replaces existing workflows, consistent with literature framing AI as a complement to expert judgement in knowledge-intensive work. Public and enterprise-secured LLMs form the core infrastructure, with consultants alternating between public and protected systems depending on task sensitivity, illustrating how confidentiality-driven professions operationalise secure AI governance.

GenAI is most embedded in efficiency-oriented tasks such as rapid research, document review and structured analytical support, mirroring studies that describe early adoption as incremental and low-disruption. Practical constraints, including slower enterprise models, accuracy issues and limited automation, help explain why AI remains concentrated in specific phases of the consulting value chain.

Strategically, firms adopt GenAI to improve efficiency and quality, signal technological leadership and scale institutional knowledge across global networks. While RQ1 also captures planned future applications, the empirical material reveals limited visibility into concrete long-term trajectories, reflecting the rapid pace of technological change and uncertainty surrounding GenAI development. Accordingly, the strategic use observed in this study is grounded primarily in current and emerging practices rather than formalised future roadmaps.

Adoption, however, varies across project types and hierarchy levels, exposing gaps between strategic aspirations and daily practice. This suggests a degree of strategy–practice decoupling that research on AI in professional services has only begun to explore.

Taken together, the findings indicate that the strategic use of GenAI reflects the gradual institutionalisation of an AI-enabled infrastructure that supports existing services, enables incremental AI-enhanced offerings and lays the groundwork for future business-model innovation. These insights frame the subsequent analysis of how GenAI affects operational processes (RQ2) and how firms manage the transition toward AI-enabled consulting work (RQ3).

6 Recommendations

This Chapter derives recommendations for the effective, responsible, and sustainable integration of GenAI in management consulting firms. The recommendations are strictly grounded in the empirical findings and synthesis across RQ1 to RQ3 and reflect the study's core contribution that GenAI adoption is not driven by technological capability alone, but by the interaction of strategic intent, governance arrangements, capability development, workflow integration, leadership sensemaking, and continuous organisational adaptation. Each recommendation translates identified mechanisms into actionable design principles that address the strategic, operational, and organisational dimensions of GenAI adoption.

Strategic Direction and Explicit Use-Case Definition

The findings demonstrate that consultants' confidence in using GenAI is strongly shaped by the clarity of organisational expectations regarding its purpose and scope. Where firms articulated a concrete operational intent that positioned GenAI as a tool for early-stage research, synthesis, and first-draft creation (e.g., background research, issue structuring, or slide skeletons), consultants integrated it more readily into workflows. By contrast, environments that encouraged open experimentation without clear boundaries created uncertainty about professional standards, particularly regarding the use of GenAI outputs in client-facing deliverables.

Therefore, Consulting firms should define a clear and operational purpose for GenAI that specifies where its use is expected, where it is restricted, and how GenAI-generated outputs are expected to be reviewed and validated in line with professional standards. Beyond short-term guidance, firms should anchor GenAI in a long-term adoption vision that defines where it is embedded over time, which parts of the consulting value chain become AI-enabled, and what constitutes acceptable quality, risk, and client acceptance. This includes explicit policies defining permissible tasks (e.g. internal research and drafting) and prohibited uses (e.g. autonomous client communication or unchecked analytical outputs), supported by a prioritised use case roadmap that is reviewed and updated regularly as tools and risks evolve. These boundaries should not only reflect professional standards and client expectations but also align with evolving regulatory requirements governing data use, accountability, and transparency. By delineating boundaries and direction, firms position GenAI as a legitimate augmentation tool aligned with consulting norms rather than as an informal productivity aid.

Data Confidentiality-Centred Governance and Clear Usage Boundaries

Across cases, concerns related to data confidentiality, formal data protection obligations, and the handling of client-sensitive information emerged as fundamental constraints on GenAI adoption. Beyond data confidentiality concerns, evolving regulatory requirements as discussed in Section 2.3 further intensify uncertainty at the project level, reinforcing the need for clear, organisation-wide governance rather than ad hoc individual judgment. The analysis shows that in the absence of clear and usable governance, consultants either refrain from using GenAI altogether or revert to public tools, for example by manually paraphrasing client material to bypass restrictions, thereby increasing compliance and reputational risks. Governance thus operates not merely as a constraint but as a structuring mechanism that actively shapes how consulting work is organised and coordinated.

Thus, firms should establish data-centric governance frameworks that explicitly address how GenAI can be leveraged without compromising confidential or client-specific information. This includes policies specifying that client-identifiable data must never be entered into external LLMs, the use of enterprise GenAI tools with disabled model training, and mandatory human-in-the-loop validation for all client-facing outputs. Complementing technical safeguards, consultants require targeted training on data anonymisation, prompt hygiene, and escalation procedures for ambiguous cases. Such governance reduces uncertainty at the project level and enables consultants to rely on organisational judgment rather than individual interpretation.

Continuous and Role-Specific Capability Building

The findings further indicate that the primary challenges associated with GenAI adoption are interpretive rather than technical. Consultants struggle less with accessing tools and more with guiding models, evaluating output quality, and integrating AI-generated content into hypothesis-driven problem solving, for instance by using GenAI to generate alternative hypotheses that are subsequently stress-tested by consultants. One-off training initiatives proved insufficient, particularly given the pace at which GenAI capabilities evolve.

Therefore, capability development should be understood as a continuous process that prioritises analytical reasoning, verification skills, and the orchestration of human-AI collaboration. Firms benefit from implementing role-specific learning formats that reflect differing responsibilities across hierarchical levels and embedding these into ongoing project routines through structured comparison tasks, joint review sessions, and reflective exercises. Continuous capability building is essential to maintaining interpretive stability as both technological possibilities and organisational expectations change.

Secure Tooling Infrastructure and Workflow Integration

The analysis underscores that consultants' readiness to use GenAI depends heavily on tool reliability and the degree of integration into existing workflows. Adoption was strongest where GenAI functionality was embedded directly into core systems, such as slide creation tools or internal knowledge bases, and grounded in verified internal data sources. Conversely, unstable systems and access barriers led consultants to bypass internal solutions in favour of public models, effectively undermining governance and standardisation efforts.

Consulting firms should therefore invest in stable, enterprise-grade GenAI infrastructure that integrates seamlessly with established workflows and grounds outputs in verified internal data. Such infrastructure enhances practical value, signals organisational commitment, and strengthens consultants’ confidence in applying GenAI across projects while maintaining compliance.

Firmwide Knowledge Integration and Reuse through GenAI

Building on the empirical findings on knowledge scalability and cross-project reuse, GenAI creates the greatest value in consulting when embedded in firmwide knowledge infrastructures rather than used at the level of isolated projects. Several consultants reported that centrally provided prompt libraries and access to curated examples of prior project deliverables enabled faster onboarding, more consistent outputs, and closer alignment with firm-specific standards. In such settings, GenAI use shifted from ad hoc experimentation toward routine application. By contrast, where central knowledge access was lacking, consultants repeatedly recreated prompts or relied on generic outputs and informal personal archives. Fragmented repositories therefore constrained knowledge reuse and led to inefficiencies and variation in quality.

Hence, consulting firms should institutionalise organisational knowledge by integrating validated prompt libraries, controlled access to anonymised project materials, and AI-enabled internal knowledge platforms. Clear access rights and quality validation processes remain essential to ensure compliance and contextual relevance. When implemented effectively, GenAI-enabled knowledge systems reduce redundancy and strengthen organisation-wide intelligence.

Leadership Sensegiving and Cultural Stewardship

The analysis reveals that leadership behaviour plays a decisive role in shaping how consultants interpret the professional legitimacy of GenAI. Where partners and managers used GenAI visibly and transparently in project settings, consultants perceived the technology as endorsed and safe to use. In contrast, symbolic enthusiasm without behavioural follow-through created ambiguity and limited adoption, particularly in client-facing work. Leaders should therefore actively engage in sensegiving by demonstrating GenAI use in their own routines, openly discussing limitations, and modelling verification practices. By framing GenAI as a complement to professional expertise rather than a substitute, leadership stabilises professional identity and supports cultural anchoring of GenAI-supported work.

Continuous Adaptation as a Core Design Principle

A central insight across the empirical material is that GenAI adoption is most effective when structural enablers, interpretive stability, and evolving work practices reinforce one another. Given the rapid pace of technological change, static policies and one-off initiatives quickly lose relevance and risk misalignment with emerging use cases and risks. This need for continuous adaptation is further amplified by evolving legal interpretations and compliance expectations, which require firms to regularly reassess governance arrangements and acceptable use cases.

Firms should therefore treat GenAI integration as a continuous organisational design challenge that requires rapid iteration of policies, ongoing adjustment of training formats, and regular reassessment of governance arrangements. Embedding such adaptive mechanisms ensures that GenAI remains aligned with professional standards, regulatory requirements, and shifting client expectations over time.

An Integrated Multi-Level Framework for GenAI Adoption in Consulting

The integrated framework synthesises the study’s empirical findings and the resulting recommendations into a coherent visual representation. It conceptualises GenAI adoption in management consulting as an iterative, multi-level organisational process in which firms continuously align sensemaking, capability activation, and operational integration in response to evolving technological, regulatory, and client-related conditions. Reflecting the empirical findings across RQ1–RQ3, the framework illustrates that GenAI adoption is not a one-off implementation decision but an ongoing process of organisational adjustment, translating analytical insights into structured guidance for effective and responsible adoption (see Figure 6).

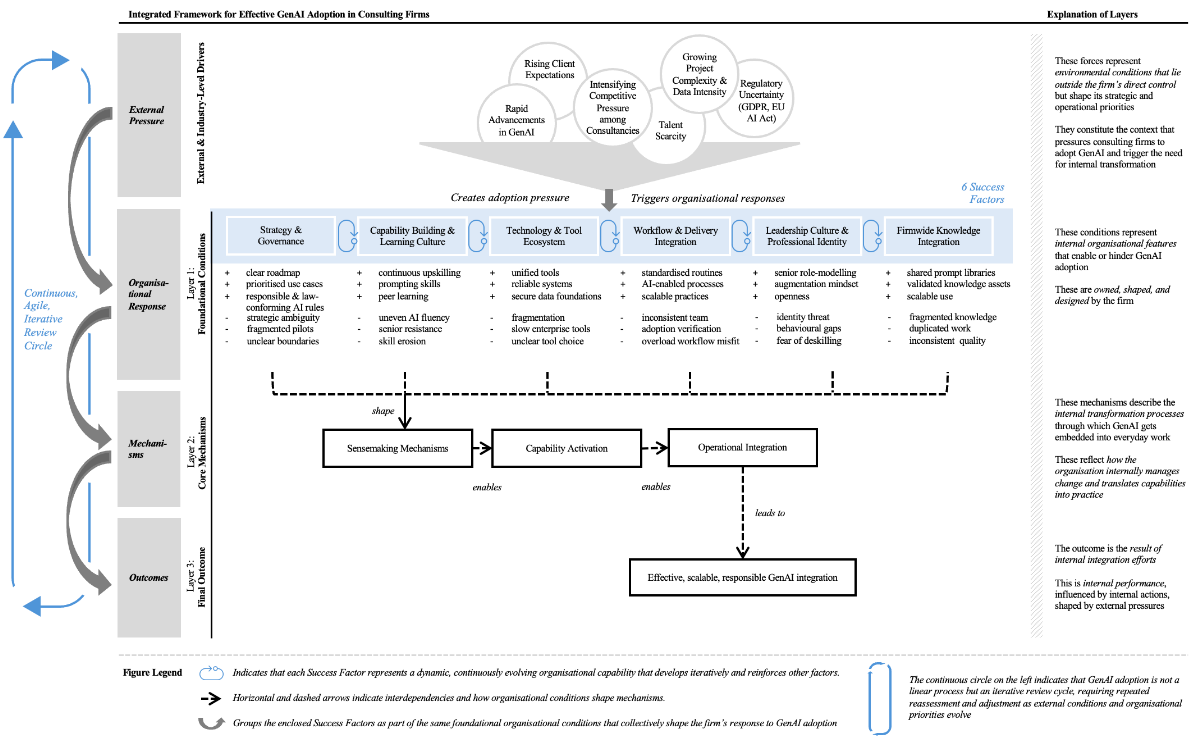

Figure 5: Framework for Effective GenAI Adoption in Consulting Firms (Own Illustration)

At its foundation, the framework distinguishes a layer that shapes the organisational context for GenAI use. This layer comprises strategic direction and governance, capability-building practices, technological infrastructure, workflow integration, leadership behaviour, and firmwide knowledge reuse. Drawing on sensemaking research (Yan et al., 2025), the framework shows that the clarity of strategic intent, the availability of governance guidance, the reliability of tools, and prevailing professional narratives shape how consultants interpret GenAI as either a legitimate and safe resource or a source of uncertainty. These interpretations condition whether capabilities such as prompting competence, human-in-the-loop validation, and AI-enabled workflow redesign are activated and translated into everyday project work.

At the outcome level, the framework highlights that effective, scalable, and responsible GenAI integration emerges from the sustained alignment of organisational structures, constructive sensemaking, and evolving work practices rather than from technological availability alone. As firms gain experience with GenAI and as tools, risks, expectations, and regulatory interpretations evolve, policies, training formats, and tool choices are repeatedly reassessed and adjusted. Therefore, the framework captures GenAI adoption as a dynamic process of organisational alignment and adaptation over time. A detailed close-up version of the framework is provided in Appendix L to enhance readability of the individual elements and relationships.

7 Limitations and Need for Further Research

This study is subject to several limitations arising from its scope and methodological choices. Figure 7 summarises the key limitations of the study and outlines corresponding directions for future research.

First, although 18 expert interviews offer rich qualitative insights, the sample is limited to large management consulting firms in the German market. While this ensures comparability, it restricts generalisability. Including boutique consultancies, specialised advisory firms or in-house consulting units in future studies would broaden the understanding of how GenAI is adopted in different organisational contexts.

Second, the geographic focus on Germany constitutes a contextual limitation. Although the firms studied operate globally, the findings reflect GenAI adoption within the European regulatory context, shaped by the GDPR and the emerging EU AI Act. National interpretations and enforcement practices may further influence governance choices and adoption patterns, suggesting value in future cross-country comparisons.

Third, participant recruitment via personal networks and LinkedIn may introduce self-selection bias. Several interview partners were referred to internal AI experts or GenAI specialists, which mitigates but does not eliminate this risk. The distribution of hierarchical levels is uneven, with more Consultants and Partners than Managers or Senior Managers. Likewise, Tier-1, Tier-2 and Big Four firms are not represented in equal proportions. Future studies should examine how AI adoption and enablement differ across these firm types.

Fourth, the methodological scope of this study is limited by its exclusive reliance on qualitative interviews, which introduces constraints related to subjectivity, recall and interpretation. While interviews provide deep contextual insight, the study lacks observational data, internal documentation and quantitative indicators that could triangulate participants' accounts. Relatedly, the integrated framework developed in this study does not aim to test causal relationships or propose generalisable hypotheses but instead serves as an empirically grounded conceptual synthesis that structures how GenAI adoption unfolds across organisational levels in consulting practice. Future research could build on this framework by operationalising and quantitatively testing the relative strength, interaction and performance impact of the identified enabling and constraining factors.

Fifth, this study focuses on GenAI adoption within consulting firms and does not capture how increasing GenAI use on the client-side effects client–consultant interaction and value creation. As clients increasingly rely on GenAI to interpret and evaluate consulting outputs, future research could adopt dyadic or client-inclusive designs to examine how GenAI reshapes collaboration and expectations.

Finally, this study captures a snapshot of GenAI adoption based on interviews conducted in the second half of 2025. Given the rapid pace of technological change, organisational practices and governance arrangements observed here may evolve over time. Future research using longitudinal or mixed-method designs would therefore be valuable to track these developments and assess their longer-term implications.

These limitations define the boundaries within which the findings should be interpreted while highlighting promising avenues for further research.

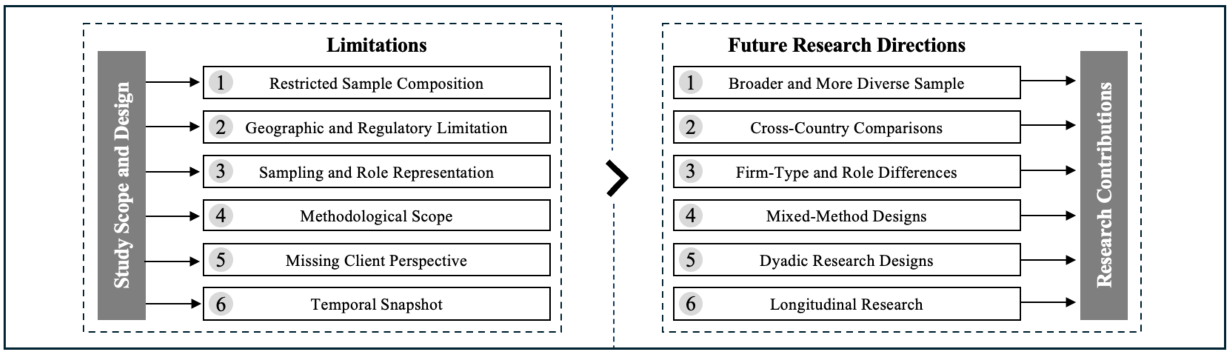

Figure 6: Limitations and Future Research Directions (Own Illustration)

8 Conclusion and Future Outlook

This thesis examined how large consulting firms in Germany are adopting GenAI and how the technology is reshaping strategic priorities. Based on 18 expert interviews, the study provides a systematic empirical account of how GenAI is currently integrated into consulting firms' value-creation logic and everyday project work and offers clear answers to the RQ.

First, the findings show that GenAI currently functions primarily as an augmentative rather than a transformative technology in management consulting. Firms have developed a growing ecosystem of tools and dominant use cases aimed at efficiency gains, quality improvements, and knowledge scalability. These applications accelerate analytical work and documentation processes but do not fundamentally alter the consulting business model, which remains centred on expert judgement, contextual interpretation, and client interaction. Explicit long-term GenAI deployment plans remain limited, as the rapid pace of technological development constrains reliable planning beyond the short term.

Second, the empirical evidence demonstrates that GenAI reshapes consulting operations by automating routine analytical and documentation intensive tasks and shifting human contribution toward interpretation, judgement, and client facing activities. Tasks such as research, first draft creation, and information structuring are increasingly executed by AI, enabling consultants, particularly at junior levels, to engage earlier in higher value work. At the same time, GenAI introduces new responsibilities related to quality assurance, validation, and data governance, reinforcing the continued need for human oversight.

Third, effective GenAI integration depends on organisational enablers that remain unevenly developed across firms. Adoption is shaped by leadership signals, governance mechanisms, technological infrastructure, learning systems, and cultural openness, which often operate inconsistently across teams and hierarchies. Although firms have begun formalising GenAI use through internal platforms, training initiatives, and guidelines, persistent ambiguity regarding compliance requirements, tool reliability, and appropriate usage indicates that organisational embedding remains at an early stage.

Across these findings, a recurring operational tension becomes visible. While GenAI enables substantial efficiency gains, these gains are frequently reinvested into expanded analytical scope and higher client expectations rather than translating into reduced workloads. This efficiency-expansion dynamic highlights that GenAI adoption cannot be assessed solely in terms of productivity optimisation.

Beyond addressing the RQs, the thesis synthesises these empirical insights through the integrated multi-level framework developed in Chapter 6. The framework consolidates the findings into a structured set of strategic, operational, and organisational capabilities that support consulting firms in assessing and benchmarking their AI transformation and provides guidance for institutionalising GenAI in a responsible and scalable manner.

Looking ahead, the trajectory of GenAI in consulting remains highly uncertain. At the same time, for consulting firms operating within the European Union, compliance with the EU AI Act constitutes a critical boundary condition for the scalable, responsible, and client-facing use of GenAI. The EU AI Act adds an important forward-looking dimension by formalising expectations around responsible AI use, requiring consulting firms not only to apply GenAI effectively, but also to demonstrate robust governance, transparency, and human oversight. Innovation cycles and the emergence of agentic AI systems capable of autonomously executing multi-step tasks may further reshape the division of labour between humans and intelligent agents.

Against this backdrop, the central challenge for the consulting profession is not whether automation will replace or augment existing roles, but how human-AI collaboration will be structured. Consultants will require stronger competencies in interpretation, workflow design, creativity, and the orchestration of AI-enabled processes, while maintaining critical thinking, contextual judgement, and ethical responsibility.

In sum, this thesis provides an early perspective on how consulting firms in Germany navigate the transition toward AI augmented work. As technological capabilities advance and regulatory frameworks become fully applicable, firms that align GenAI adoption with strategic intent, organisational capabilities, and responsible governance are likely to shape their future competitiveness, even as that future remains uncertain.

References

Armenakis, Achilles A., and Stanley G. Harris. 2009. "Reflections: Our Journey in Organisational Change Research and Practice." Journal of Change Management 9 (2): 127-142.

ATLAS.ti Scientific Software Development GmbH. 2023. "ATLAS.ti (Version 25)." Qualitative data analysis software. Berlin: ATLAS.ti Scientific Software Development GmbH.

Bijnens, Gert, and Bram De Rock. 2025. "The Changing Nature of Management Consulting: Integrating Digitalization and Client Collaboration." Journal of Business Research 172: 114092.

Boston Consulting Group and Anthropic. 2023. "BCG and Anthropic Announce New Collaboration to Bring Responsible GenAI to Enterprise Clients." Boston Consulting Group. September 14.

Bundesverband Deutscher Unternehmensberatungen (BDU). 2024. Facts & Figures: Der Consultingmarkt in Deutschland 2024. Berlin: BDU.

Bubeck, Sébastien, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, et al. 2024. "Sparks of Artificial General Intelligence: Early Experiments with GPT-4." Communications of the ACM 67 (4): 92-106.

Bühlmann, Felix. 2023. "Professional Service Firms and the Evolution of Expert Labor Markets." Socio-Economic Review 21 (2): 435-458.

Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond. 2023. "GenAI at Work." NBER Working Paper No. 31161. Cambridge, MA: National Bureau of Economic Research.

Center for Audit Quality. 2024. Auditing in the Age of GenAI. Washington, DC: Center for Audit Quality.

Charmaz, Kathy. 2006. "Constructing Grounded Theory: A Practical Guide Through Qualitative Analysis." London: SAGE.

Christensen, Clayton M., Dina Wang, and Derek van Bever. 2020. "Consulting on the Cusp of Disruption." Harvard Business Review.

DLA Piper. 2024. "Data Protection Laws of the World: Germany." https://www.dlapiperdataprotection.com/index.html?t=law&c=DE

Doloreux, David, Antoine Frigon, and Ekaterina Turkina. 2025. "Knowledge Dynamics in Management Consulting Firms: A Comparative Study of KIBS." Service Industries Journal 45 (3): 221-239.

Döringer, Stefan. 2021. "The Problem-Centred Expert Interview: Combining Qualitative Interviewing Approaches for Investigating Implicit Expert Knowledge." International Journal of Social Research Methodology 24 (3): 265-278.

Dutta, Subhankar, and J. A. Kumar. 2022. "Tacit and Explicit Knowledge Integration in Consulting Projects: A Dynamic Capabilities Perspective." Journal of Knowledge Management 26 (5): 1123-1145.

Dwivedi, Yogesh K., Daniel L. Hughes, Abdullah M. Baabdullah, et al. 2024. "So What If ChatGPT Wrote It? Multidisciplinary Perspectives on Opportunities, Challenges, and Research Directions." International Journal of Information Management 75: 102733.

Eichhorst, Werner, and Paul Marx. 2025. "The German Labor Market After the Long Boom: What's Next?" IZA Discussion Paper No. 17862. Bonn: IZA Institute.

European Commission. 2024a. „AI Act enters into force.” https://commission.europa.eu/news-and-media/news/ai-act-enters-force-2024-08-01_en

European Commission. 2024b. “Digital Economy and Society Index (DESI): Germany Country Report.” https://digital-strategy.ec.europa.eu/en/policies/desi-germany

European Union. 2016. „Regulation (EU) 2016/679 of the European Parliament and of the Council (General Data Protection Regulation).“ Official Journal of the European Union L 119.
https://eur-lex.europa.eu/eli/reg/2016/679/oj

European Union. 2024. „Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act).“ Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2024/1689/oj

Gioia, Dennis A., Kevin G. Corley, and Aimee L. Hamilton. 2013. “Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology.” Organisational Research Methods 16 (1): 15-31.

Institute of Internal Auditors. 2024. “Solving the Riddle: Harnessing GenAI for Internal Audit Activities.” Lake Mary, FL: IIA Research Foundation.

Jain, Souratn. 2024. “Revolutionizing Business Consulting with GenAI: Exploring Transformative Models for Strategic Decision-Making, Innovation, and Operational Excellence.” World Journal of Advanced Research & Reviews 22 (2): 2273-2284.

Kaczorowska-Spychalska, Dominika, Nina Kotula, Grzegorz Mazurek, and Łukasz Sułkowski. 2024. “GenAI as a Source of Change of Knowledge Management Paradigm.” Human Technology 20 (1): 131-154.

Kanbach, Dominik K., Louisa Heiduk, Georg Blueher, Maximilian Schreiter, and Alexander Lahmann. 2024. “The GenAI Is Out of the Bottle: Generative Artificial Intelligence from a Business Model Innovation Perspective.” Review of Managerial Science 18 (4): 1189-1220.

KPMG. 2025. Global Tech Report 2024: Financial Services Insights. Amsterdam: KPMG International.

Krishna, Arvind. 2024. “IBM Think 2024 Keynote.” IBM Events. Accessed November 30, 2025. https://www.ibm.com/events/think/watch/replay/think-2024-keynote-arvind-krishna

Larson, Brian Z., Leslie A. DeChurch, and Noshir S. Contractor. 2024. “The Cognitive Effects of Artificial Intelligence on Professional Judgment.” Academy of Management Review 49 (1): 123-145.

Law, Leah, and Nisha Varanasi. 2025. “GenAI & Changing Work: Systematic Review of Practitioner-Led Work Transformations through the Lens of Job Crafting.” Business & Information Systems Engineering (forthcoming).

Leyh, Christian, Matthias Lange, Annika Lorenz, and Yvonne Engelhardt. 2023. “Digital Technologies in Consulting - Impact of the COVID-19 Pandemic.” Information Technology for Development 29 (4): 879-897.

Lim, W. M. 2024. “What Is Qualitative Research? An Overview and Guidelines.” Australasian Marketing Journal 33 (2): 199-229.

Lincoln, Yvonna S., and Egon G. Guba. 1985. „Naturalistic Inquiry.“ Beverly Hills, CA: SAGE. https://books.google.com/books/about/Naturalistic_Inquiry.html?id=2oA9aWlNeooC

Li, Xin, Yong Wang, Yu Chen, and Jie Liu. 2024. “Security and Privacy Risks of Large Language Models: A Comprehensive Survey.” ACM Computing Surveys 57 (2): 1-34.

Machljankin, Julia, Oliver Neumann, Robert Steiner, and Jens Ege. 2024. “Exploring the Role of Consulting in Local Government Digital Transformation.” Public Money & Management 44 (2): 105-114.

Mamedova, Irina A., Viktoria Savchenko-Belskaya, and Sergio Velesco. 2022. “Management Consulting in the Digital Era.” In Global Trends in the Development of Management Consulting, edited by Springer, 55-67.

Maximize Market Research. 2025. Global Management Consulting Services Market Report 2024-2032. Pune: Maximize Market Research.

Mayer, Anne-Sophie, Reza M. Baygi, and Reinout Buwalda. 2025. “Generation AI: Job Crafting by Entry-Level Professionals in the Age of GenAI.” Business & Information Systems Engineering (forthcoming).

Mayring, Philipp. 2000. “Qualitative Content Analysis.” Forum Qualitative Sozialforschung / Forum: Qualitative Social Research 1 (2): Art. 20.

Mayring, Philipp. 2022. “Qualitative Inhaltsanalyse: Grundlagen und Techniken. [Qualitative Content Analysis: Basics and Techniques].” 13th rev. ed. Weinheim and Basel: Beltz.

McKinsey & Company. 2023. “Meet Lilli, our GenAI tool that’s a researcher, a time saver, and an inspiration”. McKinsey Tech & AI Blog. https://www.mckinsey.com/about-us/new-at-mckinsey-blog/meet-lilli-our-generative-ai-tool

Memmert, Lucas, Daria Soroko, and Eva Bittner. 2025. “From Effort Reduction to Effort Management: An Expectancy Theory Perspective on Professionals’ Work Practices with GenAI.” Business & Information Systems Engineering (forthcoming).

Min, Sewon, Kalpesh Krishna, Xinyuan Lyu, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. 2024. "Large Language Models: A Survey." Foundations and Trends in Machine Learning 17 (1): 1-290.

Minto, Barbara. 2009. "The Pyramid Principle: Logic in Writing and Thinking. Rev. ed. Harlow: Financial Times Prentice Hall." (Original work published 1985).

Mordor Intelligence. 2024. "Management Consulting Services Market - Growth, Trends, Forecasts 2025-2030." Mordor Intelligence.

Mosonyi, Szilvia. 2020. "The Craft of Management Consulting: Sources of Value Creation for Clients." Management Decision 58 (5): 901-920.

Noy, Shakked, and Whitney Zhang. 2023. "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence." Science 381 (6654): 187-192.

Pimentel, Marcelo, and Jose Carlos Veliz Palomino. 2024. "GenAI Solutions for Enhancing Knowledge Management: A Literature Review and Roadmap." In Proceedings of the 25th European Conference on Knowledge Management, Academic Conferences International Ltd.

Rhee, Joonmo, Taehyun Park, and Cary Cooper. 2023. "Knowledge-Based Value Creation in Professional Services: Evidence from Consulting Firms." Management Decision 61 (9): 2201-2221.

Schlee, Dominik, Tania von der Heidt, and Constantin Blome. 2024. "Buying Knowledge-Intensive Business Services: A Systematic Review." European Management Review.

Tavoletti, Ernesto, Michele Cerruti, and Andrea C. R. Rispoli. 2022. "Understanding Performance in Professional Services for Innovation Intermediation: Technology Consultants vs. Management Consultants." Technovation 126: 102535.

Teixeira, Aurora A. C., José J. M. Ferreira, and Nuno Lima. 2023. "An Empirical Taxonomy of Knowledge-Intensive Business Services Buyers: An Absorptive Capacity Approach." Research Policy 52 (4): 104756.

The Business Research Company. 2025. Management Consulting Services Global Market Report 2025. London: The Business Research Company.

Thomson Reuters. 2025. GenAI in Professional Services: Executive Summary for Legal Professionals. Toronto: Thomson Reuters.

Wang, Jiawei, Tao Zhang, and Meilin Chen. 2025. "Capabilities of GPT-5 on Multimodal Medical Reasoning." Artificial Intelligence in Medicine 165 (1): Article 102671.

Werr, Andreas, and Annika Schilling. 2022. "The Future of Management Consulting: Transformation of Knowledge and Value Creation." Journal of Organisational Change Management 35 (2): 229-247.

Yan, Yihang, Xiaoqian Qu, Hongzhen Lei, and Yao Geng. 2025. "Approach or Avoidance: How Does Employees' GenAI Awareness Shape Their Job Crafting Behavior? A Sensemaking Perspective." Behavioral Sciences 15 (6): 789.

Yu, Erlan, Wei Zhang, Hui Li, Fang Chen, and Lin Zhao. 2025. "Large Language Models in Medicine: Applications, Challenges, and Future Directions." International Journal of Medical Sciences 22 (4): 512-528.

Zhao, Wayne Xin, Yutao Hou, Xingyao Wang, et al. 2024. "A Survey of Large Language Models: From ChatGPT to GPT-4 and Beyond." Artificial Intelligence Review 57 (5): 1-74.

Appendix

Appendix A: Bain & Company Service Alliance with OpenAI

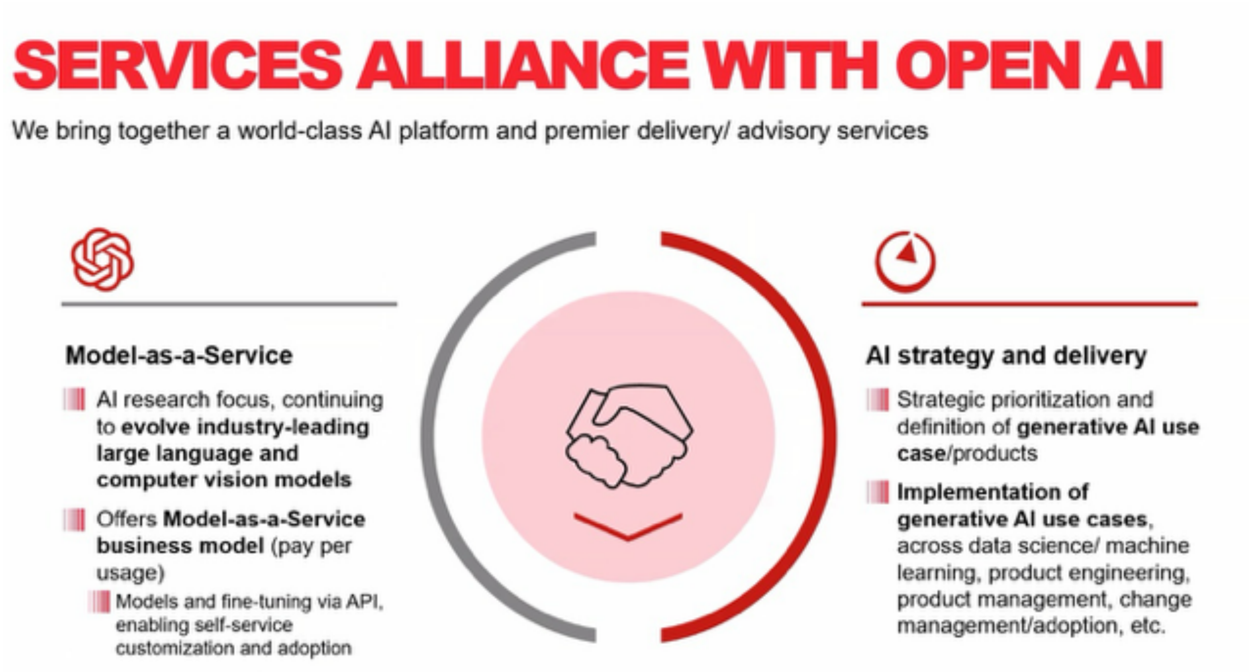

Figure 7: Bain & Company Service Alliance with OpenAI; Internal Document

Appendix B: Classification of Consulting Firm Archetypes Used in the Study

Archetype	**Description (Academic Definition)**	**Sample**
Tier 1 (Global Strategy Firms / McKinsey-, BCG-, Bain-equivalents)	Highly selective strategy consultancies with global brand equity, strong knowledge infrastructures, and a focus on high-complexity strategic projects. Characterised by premium pricing, global staffing models, and high internal knowledge codification. (*Based on Bijnens & De Rock 2025; Werr & Schilling 2022; Christensen et al. 2020)*	BCG, McKinsey, Bain & Company
Tier 2 (Strategy Specialists / Upper-Mid-Tier)	Large or mid-sized strategy consultancies operating with strong analytical capabilities but narrower global reach. Often focus on strategy, transformation, and sector expertise. High methodological maturity but lower institutionalisation compared with Tier 1. *(Based on Doloreux et al. 2025; Werr & Schilling 2022)*	Roland Berger, Strategy& (PwC), OC&C, Oliver Wyman
Big Four Consulting Practices	Consulting arms of global professional services firms with broad service portfolios (audit, tax, advisory). Strong operational focus, deep industry specialisation, and large-scale delivery capacity. Increasingly active in digital, transformation, and analytics consulting. *(Based on Christensen et al. 2020; Doloreux et al. 2025)*	Deloitte, KPMG, EY-Parthenon, PwC (non-Strategy&)
Boutique / Specialist Firms (Excluded)	Narrowly focused consultancies with strong specialisation in niche markets (e.g., supply chain specialists, tech boutiques). Their institutional logic, market positioning, and resource base differ significantly from large strategy competitors. *(Based on Doloreux et al. 2025; Christensen et al. 2020)*	e.g. Alvarez & Marsal, Stern Stewart, Bluemorow, Invetro, Etribes, Wavestone, Auxilo, Horváth, Superside, etc. (excluded by design)

Figure 8: Classification of Consulting Firm Archetypes used in Sample (Own Illustration)

Appendix C: Overview of Interview Participants and Firm Classification

# Interviewee	Role	Company Classification
1	Senior Manager	Big4
2	Partner	Big4
3	Senior Consultant	Tier 2
4	Consultant	Tier 1
5	Associate Consultant	Tier 1
6	Consultant	Tier 1
7	Senior Manager	Big4
8	Consultant	Tier 2
9	Consultant	Big4
10	Partner	Tier 2
11	Consultant	Tier 2
12	Consultant	Tier 1
13	Consultant	Tier 1
14	Manager	Tier 2
15	Partner	Tier 2
16	Partner	Tier 2
17	Partner	Tier 2
18	Associate Consultant	Tier 2

Code	X	Interviewee [1;2;3;n]

Figure 9: Expert Interview Partner (Own Illustration)

Appendix D: Overview of Potential Interview Partners and Selection Process

# Interviewee	Type	Geography	Industry/Focus	Function	Title	Contact Type
1	Tier2	Germany	AI and Data Analytics	Consulting	Vice President Analytics	Direct
2	Boutique / Specialist	Germany	Strategy	Consulting	Consultant	Direct
3	Boutique / Specialist	Germany	Management Consulting Finance	Consulting	Senior Associate	Direct
2	Big Four	Germany	AI Transformation	Conulting	Manager	Second
4	Tier2	Germany	Strategy	HR/Employer Branding	Employer Branding	Direct
5	Tier2	Germany	Data and Strategy	Consulting	Senior Associate	Direct
6	Tier2	Germany	Strategy and Operations	Consulting	Senior Associate	Direct
7	Boutique / Specialist	Germany	Strategic Transformation	HR/Talent Acquisition	Talent Acquisition Partner	Direct
8	Big Four	Germany	Financial Services	Consulting	Manager	Direct
9	Big Four	Germany	AI and Business Analytics	Consulting	Consultant	LinkedIn
10	Boutique / Specialist	Italy	Strategy (Big Data, Transformation)	Consulting	Manager	LinkedIn
11	Boutique / Specialist	Italy	Generative AI and Strategy	Consulting	Director	LinkedIn
12	Tier2	Germany	Strategy (Consumer Goods & Tech)	Consulting	Partner	Direct
13	Big Four	Germany	Business Analytics	Consulting	Senior Manager	Direct
14	Big Four	Germany	Strategy	Consulting	Analyst	Direct
15	Tier1	Germany	Strategy	Consulting	Consultant	Direct
16	Boutique / Specialist	Germany	Strategy	Consulting	Founder & Managing Director	Direct
17	Boutique / Specialist	Germany	Supply Chain Strategy	Consulting	Consultant	Direct
18	Big Four	Germany	Sustainability & Climate	Consulting	Consultant	Direct
19	Boutique / Specialist	Germany	Funds & Grants	Consulting	Founder & Managing Director	Direct
20	Tier2	Germany	Restructuring & Transformation	Consulting	Analyst	Direct
21	Tier1	Germany	Strategy	Consulting	Associate Consultant	Direct
22	Boutique / Specialist	Germany	Transaction Services	Consulting	Associate Partner	Linkedin
23	Tier2	Germany	Strategy	Consulting	Consultant	Linkedin
24	Tier2	Germany	Strategy	Consulting	Associate Consultant	Direct
25	Tier1	Germany	Strategy	Consulting	Consultant	Direct
26	Boutique / Specialist	Germany	Strategy	Consulting	Partner	Direct
27	Boutique / Specialist	Germany	Strategy	Consulting	Founder & Partner	Direct
28	Tier2	Germany	Strategy	Consulting	Managing Director (Partner) & Co-Head GErmany	Direct
29	Tier2	Germany	Automotive	Consulting	Partner & Geschäftsführer	Direct
30	Tier2	Germany	Strategy	Consulting	Associate	Direct
31	Tier1	Germany	Strategy (consumer Goods)	Consulting	Consultant	Direct
32	Tier2	Germany	Deals	Consulting	Managing Director (Partner)	Direct
33	Tier2	Germany	Retail & FMCG	Consulting	Managing Director (Partner)	Direct
34	Tier2	Germany	Telecommunications	Consulting	Managing Director (Partner)	Direct
35	Tier2	New York	Tech	Consulting	Director	Direct
36	Tier1	Germany	Strategy	Consulting	Associate	Direct
37	Tier1	Germany	Strategy	Consulting	Associate	Direct
38	Tier2	Germany	Operational Excellence	Consulting	Partner	Direct
39	Big Four	Germany	Transaction Strategy	Consulting	Head of Transaction Strategy & Execution Germany	Direct
40	Tier1	Germany	Strategy	Consulting	Associate	Direct
41	Tier1	Germany	Strategy	Consulting	Consultant	Direct

Legend: *individuals who ultimately participated in the interviews*
individuals who met the selection criteria but were unavailable.
individuals who were excluded due to insufficient fit regarding consulting firm type, geographic focus, or role

Figure 10: Potential Expert Interview Partners and Selection Process (Own Illustration)

Appendix E: Semi-Structured Interview Guide (English Version)

I. Strategic Use and Business Model Integration (RQ1)

Objective: Identify *what* is used and *for what purpose*.

1. **Current Applications and Tools**
   a) Which GenAI tools or applications are currently being used in your firm, both internally and in client projects?
   b) Which new tools or use cases are being planned or tested?
2. **Use Areas and Patterns**
   a) In which areas is GenAI most intensively used (e.g., research, presentation design, data analysis)?
   b) Are there noticeable differences in usage across hierarchy levels or project types?
3. **Motivation and Objectives**
   What were the main reasons or goals behind your firm's decision to integrate GenAI (e.g., efficiency, quality, innovation, competitiveness)?
4. **Planned Initiatives / Managing Resistance**
   What measures are planned to further support the adoption and integration of GenAI in your firm?
   (→ Operationalizes "AI resistance" as per Golgeci et al., 2025
   In your view, what are the key success factors for consulting firms to realize the full potential of GenAI (e.g., infrastructure, governance, culture)?

Potential Follow-up: From your perspective, would you describe the impact of GenAI on consulting as mostly supportive, substitutive, or transformative?

Figure 11: Semi-structured Interview-Guide

Appendix F: Overview of Interview Questions and Underlying Rationale for RQ1

#	**Interview Question**	**Purpose**
0	To start off, could you briefly describe your role and your firm's main consulting focus?	*Establishes contextual background of the interviewee and their organisational environment to situate subsequent responses analytically (sampling validation, contextual anchoring)*
1a	Which GenAI tools or applications are currently being used in your firm, both internally and in client projects?	*Elicits factual baseline information on current technological adoption to map the breadth of GenAI usage across organisational contexts*
1b	Which new tools or use cases are being planned or tested?	*Identifies emerging adoption trajectories and organisational innovation priorities, enabling assessment of forward-oriented strategy*
2a	In which areas is GenAI most intensively used?	*Captures domain-specific usage patterns to understand functional clustering and identify core value-adding applications*
2b	Are there noticeable differences in usage across hierarchy levels or project types?	*Reveals variation in adoption behaviour and potential structural or cultural enablers and barriers within the firm*
3	What were the main reasons or goals behind your firm's decision to integrate GenAI?	*Uncovers the strategic rationale behind adoption decisions, enabling interpretation of organisational intent and expected value creation pathways*
4	What measures are planned to further support the adoption and integration of GenAI in your firm?	*Identifies change-management initiatives and governance responses that influence long-term embedding*

Figure 12: Interview Questionnaire and Purpose (Own Illustration)

Appendix G: Codebook - Overview of Parent and Subcodes for RQ1

#RQ	#PC	Parent Code	Code	Definition	Anchor Example
1	RQ1.1	Current AI Applications & Tools	External General-Purpose LLMs	Use of publicly accessible large language models for ideation, drafting, translation, or exploratory research.	"Analysts use ChatGPT or Claude to generate first hypothesis drafts."
			Enterprise / Private LLM Environments	Deployment of secured enterprise-grade AI environments enabling compliant work with internal or client data.	"Teams rely on enterprise GPT to upload confidential documents."
			Microsoft Copilot & Office Embedded AI	AI functions embedded in Microsoft products supporting email drafting, meeting transcription, and slide generation.	"Copilot automatically drafts emails and meeting notes."
			Document Analysis & Knowledge Extraction Tools	AI tools used to extract, summarise, or classify large document sets such as contracts or regulatory texts.	"AI reviews hundreds of contracts to extract key terms."
			Workflow, Slide & Productivity Automation	Tools automating repetitive tasks such as slide formatting, template creation, and Excel routines.	"Slide automation tools generate first-draft layouts."
	RQ1.2	Use Cases & Usage Patterns	Research & Market Intelligence	Application of AI for fast information retrieval, market scans, and insight generation.	"AI synthesises market trends within minutes."
			Document Review & Due Diligence Work	AI-assisted analysis of regulatory texts, contracts, or data-room documents.	"AI summarises a 200-page regulatory update."
			Presentation Creation & Storylining	AI assistance in drafting, structuring, or improving slide content.	"Consultants use AI to refine storyline drafts."
			Data Analysis & Quantitative Assistance	AI support for data classification, forecasting, and Excel automation.	"AI identifies inconsistencies in datasets."
			Usage Variation by Seniority or Project Type	Differences in AI usage patterns across hierarchy levels and project archetypes.	"Partners use AI conceptually, analysts operationally."
	RQ1.2	Strategic Motivations & AI Objectives	Efficiency Gains & Time Savings	Reduction of manual workload and acceleration of recurring tasks through AI automation.	"Research processes are significantly faster."
			Quality Enhancement & Error Reduction	Improving the reliability and consistency of analyses through AI-enabled validation.	"AI identifies logical gaps in deliverables."
			Market Differentiation & Innovation Positioning	Using AI to strengthen competitive advantage and signal technological leadership.	"AI capabilities enhance client perception."
			Knowledge Scalability & Institutional Learning	AI used to synthesise and distribute global best practices quickly and consistently.	"Internal GPT provides instant access to firm knowledge."
			Expansion of AI-Enabled Offerings	Development of new consulting solutions directly enabled by AI.	"Launch of AI negotiation support tools."

Figure 13: Codebook (Own Illustration

Appendix H: Coded Interview Excerpts Illustrating the Analytical Approach for RQ1-RQ3 (Visualised in ATLAS.ti)

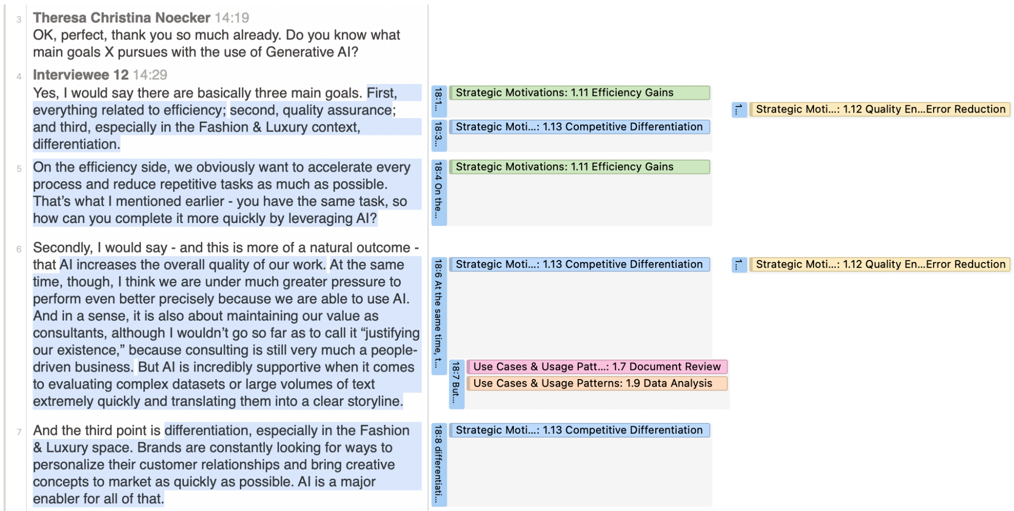

Figure 14: Example of Coded Interview Segment for RQ1

Appendix I: Overview of Code Structure and Code Frequencies by Analytical Category (Visualised in ATLAS.ti)

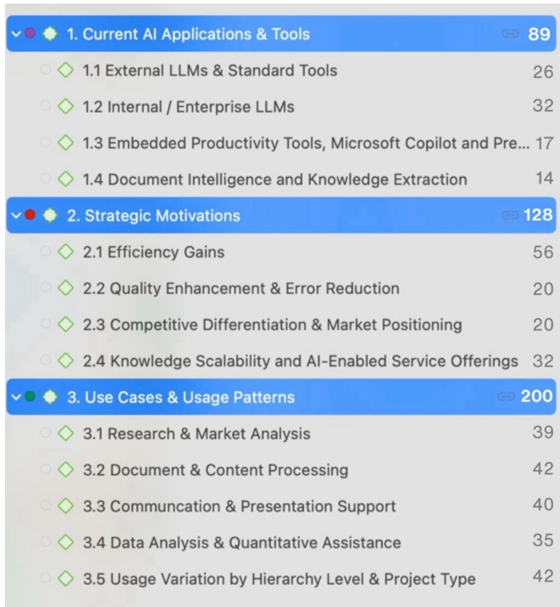

Figure 15: Example of Code Structure and Code Frequence for RQ1

Appendix J: Code-Networks per RQ (ATLAS.ti Code Network Visualisations)

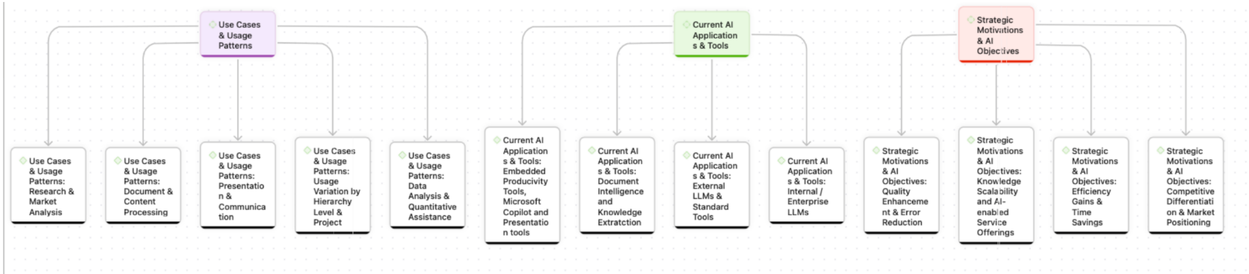

Figure 16: Code-Network for RQ1

Appendix K: Examples of Data Structure for RQ 1 and 3 according to the Gioia Method

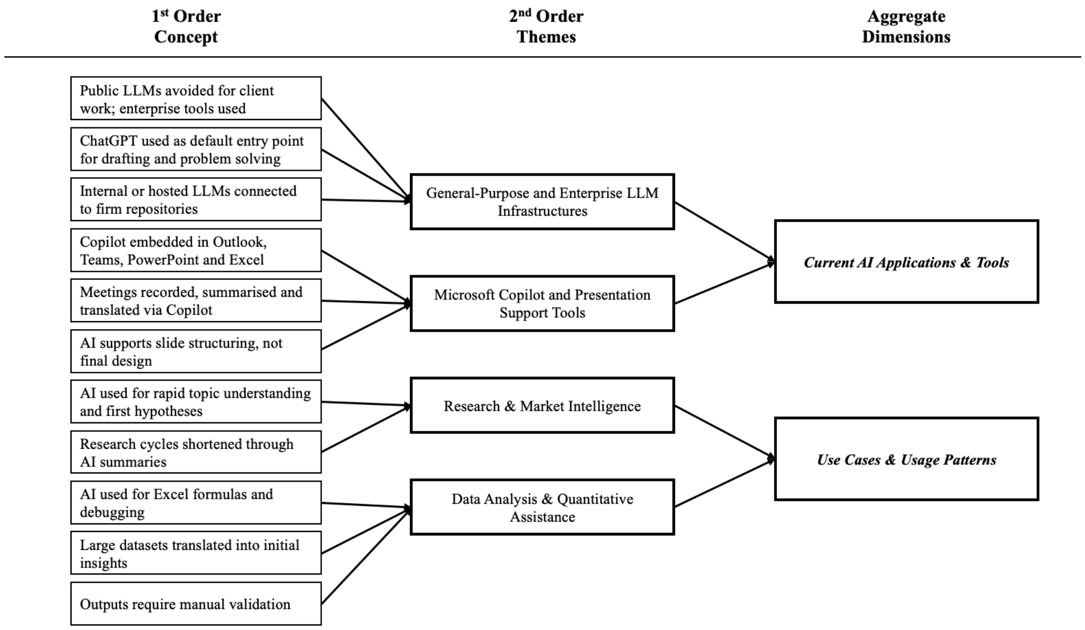

Figure 17: Example of Data Structure for RQ1 (Own Illustration)

Appendix L: Detailed Visualisation of the Integrated GenAI Adoption Framework

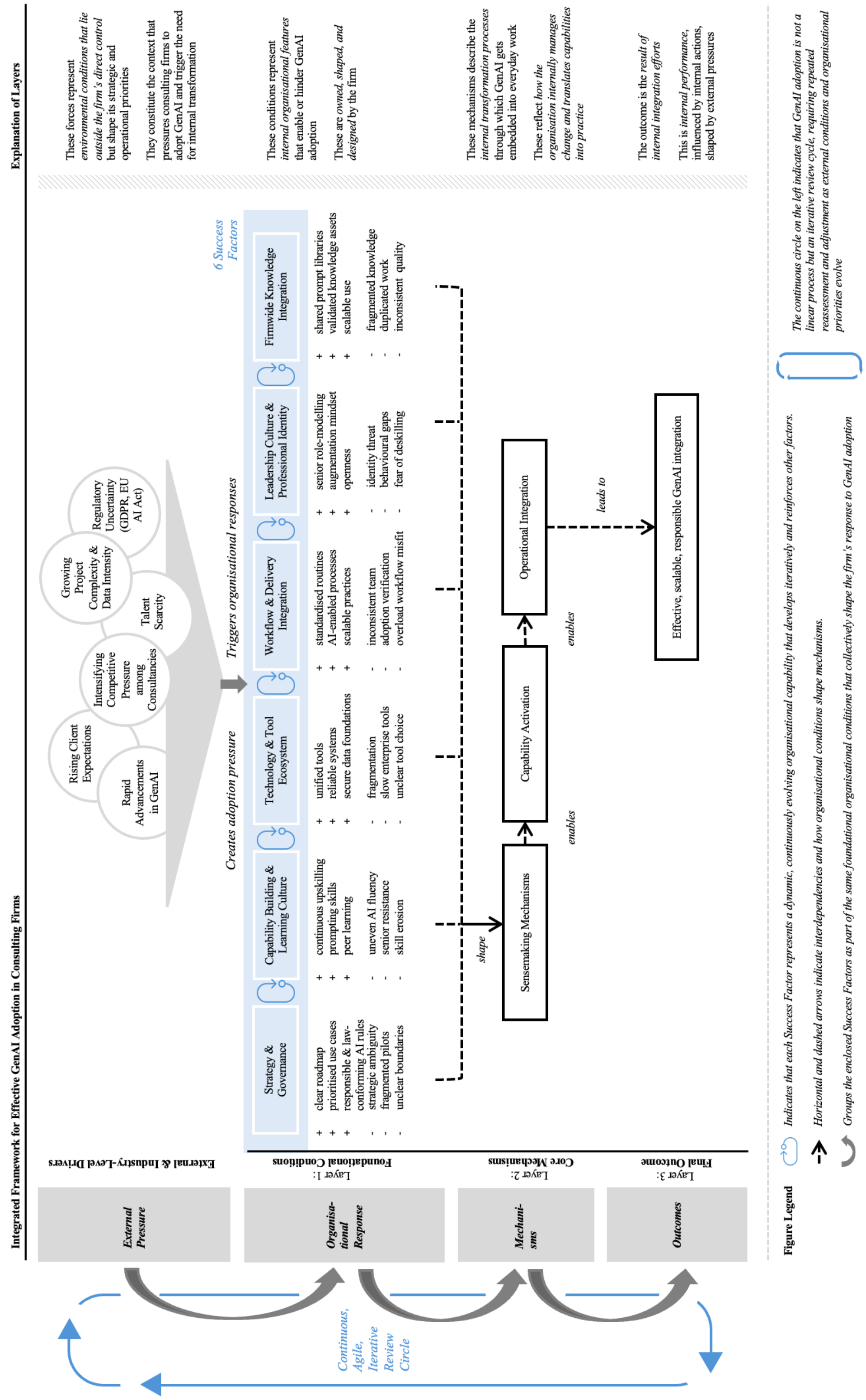

Figure 18: Detailed Visualisation of GenAI Adoption Framework in Consulting Firms

Declaration of Software and AI Support

Used Aid	Explanation
ATLAS.ti	Used as the primary software for qualitative data analysis, including the systematic coding of interview transcripts, the organisation of first- and second-order concepts, the creation of code groups, and the retrieval of coded segments to support the development of thematic structures for each research question.
ChatGPT	Used strictly as an auxiliary academic writing and reasoning tool. ChatGPT supported the refinement of argumentation flow, the sharpening of academic language, and the clarification of conceptual structures. It was also used to reflect on coherence across thesis sections and to develop preliminary text formulations that were subsequently reviewed and validated by the authors. No coding, data interpretation, or empirical conclusions were generated using ChatGPT.
DeepL	Applied selectively to translate industry-specific terminology and to refine English phrasing where nuanced linguistic precision was required. All translations were critically reviewed and adjusted by the authors.
Excel	Used as the primary environment for structuring interview materials, maintaining the qualitative codebook, consolidating coded segments, and preparing tables underlying the presentation of empirical results.
PowerPoint	Used to create graphical illustrations of the research methodology, including visual representations of the coding logic, data structure, and analytical procedures. PowerPoint served exclusively as a design tool for visuals that accompany and clarify methodological explanations.

Declaration of Authorship

I hereby declare

- that I have written this thesis without any help from others and without the use of documents and aids other than those stated above;
- that I have mentioned all the sources used and that I have cited them correctly according to established academic citation rules;
- that I have acquired any immaterial rights to materials I may have used such as images or graphs, or that I have produced such materials myself;
- that the topic or parts of it are not already the object of any work or examination of another course unless this has been explicitly agreed on with the faculty member in advance and is referred to in the thesis;
- that I will not pass on copies of this work to third parties or publish them without the University's written consent if a direct connection can be established with the Nova School of Business and Economics or its faculty members;
- that I am aware that my work can be electronically checked for plagiarism and that I hereby grant the Nova School of Business and Economics copyright in accordance with the Examination Regulations in so far as this is required for administrative action;
- that I am aware that the University will prosecute any infringement of this declaration of authorship and, in particular, the employment of a ghostwriter, and that any such infringement may result in disciplinary and criminal consequences which may result in my expulsion from the University or my being stripped of my degree.

Hamburg, 17th December, 2025 Duesseldorf, 17th December, 2025

Laura-Sophie Norden Lisa-Marie Sophie Bröske Theresa Christina Noecker

By submitting this academic term paper, I confirm through my conclusive action that I am submitting the Declaration of Authorship, that I have read and understood it, and that it is true.