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OPTIMIZING DECISION-MAKING IN MANAGEMENT CONSULTING: LEVERAGING SYNERGIES BETWEEN ARTIFICIAL INTELLIGENCE AND CONSULTANT EXPERTISE

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Abstract

This study explores how synergies between artificial intelligence and human expertise can optimize decision-making in management consulting. Drawing on qualitative interviews with 14 consultants and observations from AI training workshops, the research identifies challenges such as unclear use cases, trust dynamics, and data security concerns. Findings reveal AI's role in enhancing routine tasks, data analysis, and strategic insights while human judgment ensures contextual relevance. A structured Human-AI framework is proposed, integrating AI's computational strengths with consultants' expertise to improve decision efficiency and quality. Recommendations focus on training, organizational culture, and feedback mechanisms to foster successful AI adoption.

Keywords: Artificial Intelligence, Management Consulting, Decision-Making Optimization, Human-AI Collaboration, Consultant Expertise, AI Integration

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1. Introduction

Despite advances in technology and industry dynamics, the management consulting business model has been persistently resistant to change for years. The resistance to change that management consultants have long aimed to address in their clients has now become a challenge within their own profession (Deelmann 2019). However, the growing adoption of Artificial Intelligence (AI) is driving transformational change across industries, including management consulting, by reshaping decision-making processes and traditional practices (Canals and Heukamp 2020). In the context of management consulting, where decisions often involve navigating ambiguity and high stakes, AI offers high potential to enhance analytical capabilities, improve decision accuracy, and unlock new strategic insights (Samokhvalov 2024). By automating repetitive tasks, structuring data, and providing actionable insights, AI empowers consultants to focus on higher-order activities such as strategic planning (Canals 2020). Nonetheless, while AI excels at processing large datasets and identifying patterns, its implementation is not without challenges. However, despite the technological advancements, AI remains a complementary tool rather than a replacement for human expertise. The real value lies in the synergistic collaboration between Human and AI systems (Jain, Garg, and Khera 2023). However, recent advancements in generative AI tools have enabled them to rank qualitative options more effectively, bringing their judgment closer to human expertise, particularly in management decision tasks. This evolution signals AI's increasing ability to support not only quantitative analyses but also decisions requiring more nuanced, context-driven evaluations. This evolution signals AI's increasing ability to support not only quantitative analyses but also decisions requiring more nuanced, context-driven evaluations (Choudhary et al. 2023).

This work project, conducted as part of a Direct Research Internship, explores how synergies between human expertise and AI can be effectively leveraged to improve decision-making processes within the management consulting industry. As one of the largest global management consultancies, the organization under analysis has developed and implemented several AI tools, including proprietary, self-developed solutions, aimed at enhancing decision-making efficiency and quality. Despite significant investments in AI technologies, the firm has identified inefficiencies and untapped potential, particularly in integrating AI-driven insights with the human expertise of consultants.

The primary challenge lies in combining the strengths of AI and human decision-making. While AI offers computational power, advanced data analysis, and predictive capabilities, human expertise provides critical elements such as contextual understanding, intuition, and strategic judgment—factors that AI alone cannot replicate. This research seeks to address the following key question: How can the synergies between AI tools and human expertise be leveraged to optimize decision-making in the management consulting context?

By answering these questions, this project aims to identify actionable solutions that improve collaboration between AI and human expertise, ensuring decision-making processes are both data-driven and contextually informed.

This report contains a literature review of key concepts surrounding AI integration, human expertise, and decision-making styles. Section 3 outlines the methodology used to address the research questions, followed by Section 4, which presents the findings of the analysis. These findings serve as the foundation for the recommendations detailed in Section 5, which propose strategies to optimize decision-making processes through the integration of AI and human expertise. Finally, Section 6 concludes the report by summarizing the key insights, highlighting the study’s limitations, and providing suggestions for future research.

2. Literature Review

2.1 Artificial Intelligence

AI has been the subject of intense research for decades. In 1950, British mathematician Alan Turing's pioneering study "Computing Machinery and Intelligence" explored the question of whether machines are capable of thinking like humans (Turing 1950). Although AI has gained enormously in importance in social and economic areas in recent years, there is still no single definition of the term "artificial intelligence" (Buxmann and Schmidt 2021). One of the founders of this field was the American computer scientist John McCarthy. He defined the first official AI development project as follows: “For present purposes, the problem of AIis taken to be that of getting a machine to behave in a way that would be called intelligent if a human were to behave in such a way” (McCarthy et al. 1955). AI techniques applied in decision-making can be divided into several categories. Rule-based systems function by following a set of pre-established rules, making choices based on specific conditions and outcomes. Expert systems differ by using expert insights to replicate human decision processes. Machine learning algorithms add another layer, enabling systems to analyze data, detect patterns, and make predictions or classifications grounded in models derived from data learning (Shalev-Shwartz and Ben-David 2014). AI in decision-making is already applied and improving decision making process across various areas, including healthcare (Balicer and Cohen-Stavi 2020), consumer behavior (Luo et al. 2019) and finance (Musleh Al-Sartawi, Hussainey, and Razzaque 2022). The application of AI enables businesses to undertake real-time decision-making, to streamline processes, to reduce costs, and to enhance efficiency (Davenport et al. 2020; Csaszar, Ketkar, and Kim 2024; Demir 2022). In the context of management consulting, the adoption of AIis experiencing significant growth. In 2023, Accenture announced a $3 billion investment to enhance its Data & AI practice by developing internal AI tools and training employees to adopt these technologies effectively (Accenture 2023). PricewaterhouseCoopers (PwC) committed $1 billion to integrating generative AI, including deploying ChatGPT Enterprise for 100,000 employees to streamline workflows and decision-making (PricewaterhouseCoopers 2023). Similarly, KPMG allocated $100 million, partnering with Google Cloud to develop enterprise AI agents and train its workforce for optimized internal operations (KPMG 2024). These investments reflect a growing emphasis within the consulting industry on leveraging AI not only for client-facing services but also for transforming their own internal processes and capabilities. However, despite these substantial investments, the application of AI in decision-making comes with inherent limitations. While AI can enhance efficiency and provide predictive insights, it does not fully address all managerial challenges. For instance, the value of leveraging data and predictive analytics can diminish in contexts of high uncertainty, where simpler decision-making rules may prove more effective (Sull and Eisenhardt 2015). Furthermore, the critical question is not merely whether to use AI but how to apply it effectively. While some decisions can be automated, many managerial choices rely on human judgment, which incorporates elements such as intuition, ethics, and experience that extend beyond algorithmic predictions (Choudhury, Starr, and Agarwal 2020; Raisch and Krakowski 2021).

2.2 Managerial Decision-Making

Managerial decision-making is central to organizational success, as it enables effective resource allocation, drives strategic direction, and ensures operational efficiency. Rather than a singular act, decision-making is a structured and iterative process that spans all organizational levels, from top management to operational staff (Kozioł-Nadolna and Beyer 2021). Decisions are critical because they directly impact managerial performance and organizational outcomes, influencing both short- and long-term success (Drucker 2007).

Decision-making involves evaluating alternatives to select the most effective option for achieving specific goals, a process guided by individual abilities, values, preferences, and beliefs (Broche-Pérez, Herrera Jiménez, and Omar-Martínez 2016; Williams and Noyes 2007). The efficacy of decision-making is influenced by managerial styles, which can generally be categorized into a spectrum ranging from rationality to intuition (Calabretta, Gemser, and Wijnberg 2017).

Rational decision-making is systematic and analytical, emphasizing structured evaluations and data-driven approaches to identify optimal solutions (Dane and Pratt 2007). It is particularly effective in predictable and structured environments (Sinnaiah, Adam, and Mahadi 2023). The rational decision-making process is structured into distinct phases, including identifying the problem, outlining the solution scenario, conducting a gap analysis, gathering data and alternatives, assessing outcomes and selecting the optimal solution (Uzonwanne 2016). By relying on extensive information, rational decision-making reduces cognitive biases, such as sunk-cost and confirmation biases, thereby fostering objectivity (Idson et al. 2004). However, critics argue that the pursuit of unattainable "optimal" decisions can introduce inefficiencies and delays (Snyder and Paige 1958; Braybrooke and Lindblom 1964).

In contrast, intuitive decision-making is based on experience and subconscious insights, enabling rapid responses in ambiguous or uncertain environments (Dane and Pratt 2007). While it aligns with the rational framework, intuition operates faster, integrating prior experiences through pattern recognition and holistic cognitive schemas, but can overlook critical threats and opportunities due its reliance on experience and subconscious processing (Calabretta, Gemser, and Wijnberg 2017; Miller 2008). Unlike rational approaches, intuitive decision-making emphasizes associative mapping and subconscious processing to achieve agility in complex situations (Dane and Pratt 2007).

Although historically treated as distinct, the integration of rational analysis and intuitive flexibility enhances strategic and operational outcomes, offering a synergistic approach to decision-making (Kolbe, Bossink, and Man 2019; Petrou et al. 2020).

Managerial discretion further influences decision-making by determining the freedom managers have to adopt rational or intuitive methods. Managerial discretion reflects the balance between external constraints and individual agency, enabling leaders to exercise judgment and adapt strategies effectively (Wangrow, Schepker, and Barker 2015). While discretion allows innovation, it also risks misalignment with organizational goals. Its extent is shaped by factors such as executive characteristics (e.g., locus of control), organizational resources, and the task environment (Youssef, Hussein, and Christodoulou 2019). Executives with significant discretion can have a pronounced impact on organizational strategy and performance, leveraging their skills to navigate constraints effectively (López-Cotarelo 2018). However, managerial discretion is most effective when coupled with expertise and ethical decision-making, as managers with higher expertise are better equipped to apply discretion transparently and reduce opportunistic behaviors (Myers et al. 2022).

Expertise, particularly in the context of management consulting, is a critical success factor in addressing challenges that exceed internal organizational capabilities (Germain and Enrique Ruiz 2009). Expertise, defined as the integration of knowledge, experience, and skills within a specific domain, enables consultants to deliver strategic, operational, and technical solutions. This expertise provides value beyond algorithmic tools by offering end-to-end, comprehensive support across processes, people, and systems (Tavoletti et al. 2021).

2.3 Human-AI Collaboration in Decision-Making

AI has significantly transformed managerial decision-making by providing advanced tools for data analysis and predictive insights. Compared to human decision-making, AI-driven algorithms leverage statistical models to deliver decisions with greater speed, objectivity, and precision (Jung et al. 2018). While AI excels at optimizing routine tasks and improving operational consistency, human oversight remains essential to ensure that decisions are context-sensitive and strategically aligned, particularly in high-stakes or ambiguous scenarios such as management consulting (Kaplan and Haenlein 2019; Amershi et al. 2019). While human-AI collaboration offers substantial potential benefits, the successful adoption of AI systems depends on their acceptance and integration into decision-making processes by both organizations and consumers (Kim et al. 2024). Reluctance to engage with algorithms remains a significant barrier, often stemming from factors such as a perceived loss of decision-making autonomy and a misalignment between intuitive human decision-making processes and the transparency of algorithmic systems (Burton, Stein, and Jensen 2020). Furthermore, Lebovitz, Lifshitz-Assaf, and Levina (2022) highlight that both domain expertise and technical experience can be critical for effective human-AI collaboration. Domain expertise enables professionals to interpret AI outputs within their specific context, while technical experience allows them to engage with and interrogate the AI's results, ensuring its recommendations are meaningfully integrated into their decision-making processes.

To classify Human-AI collaboration, Dellermann et al. (2019) defined socio-technological ensembles, or hybrid intelligence, as the synergy of human and AI strengths to achieve superior outcomes. The core idea underpinning these systems is task division and specialization, where each agent is responsible for distinct, non-overlapping sub-tasks, based on their strengths (Agrawal, Gans, and Goldfarb 2018). However, overreliance on AI in such a replacement-based approach can lead to unintended consequences, such as the erosion of critical human skills—illustrated by the decline in navigation abilities due to dependence on GPS (Balasubramanian, Ye, and Xu 2022). Another aspect this concept may overlook is that combining both human and AI capabilities can outperform either alone (Choudhary et al. 2023).

To address these challenges, Puranam (2021) offers a structured approach to integrating human and AI capabilities effectively. The Human-AI Collaborative Decision-Making (HACD) framework divides the overall goal into subtasks that are distributed between human and AI agents, characterized This framework divides decision-making tasks based on two key dimensions: interdependence and specialization**.**

Interdependence refers to the relationship between tasks, which can be sequential or parallel. While, sequential tasks involve AI processing data for human interpretation or, conversely, humans providing input for AI to process.

Parallel tasks involve humans and AI independently contributing to the decision-making process, where the value of their combined outputs can be either super-additive or sub-additive. The HACD framework identifies three types of tasks based on the current state of technology. Type A tasks are those where AI matches or outperforms humans, such as image or handwriting recognition. Type B tasks are human-centric, where humans outperform AI, such as evaluating a job applicant's integrity, though subtasks like reading a CV may still be AI-driven.

Type C tasks involve collaboration, where humans and AI perform the same task, and combining their outputs through assembling can produce results that surpass those achieved by either alone. Research has highlighted the need to redesign decision-making processes to incorporate private managerial knowledge while maintaining discretion and flexibility. Further research is needed to determine when and how organizations can capture value from algorithms while preserving managerial discretion. In the organizational context, this involves training decision-makers to effectively integrate their private knowledge with data-driven insights and redesigning decision-making processes to better align with these dynamics (Kim et al. 2024; Makarius et al. 2020).

3. Methodology

This study adopts a qualitative research approach to explore complex phenomena in their real-life context through emergent questions, naturalistic data collection, and thematic analysis. This methodology allows for a deeper understanding of issues where variables are not easily quantifiable, making it particularly suited for examining context-specific phenomena (Creswell and Creswell 2017). Additionally, the research incorporates an applied dimension to explore the organizational context and complexity, with qualitative analysis used to inform a structured framework for addressing the challenge (Adams, Khan, and Raeside 2014).

3.1 Data Collection

Qualitative, unstructured interviews are employed to investigate the emerging phenomenon of Human-AI collaboration in decision-making. Unstructured interviews are particularly effective for capturing participants' subjective perspectives, allowing for an in-depth exploration of their experiences and interpretations in this context (Rubin and Bellamy 2022). Given the exploratory nature of this research, this approach was chosen to allow participants to express themselves freely while providing the flexibility to delve into specific topics as they arose during the conversation (Lim 2024). The interviews were conducted with 14 management consultants from the researched company, including three pilot interviews that were used to gain an initial understanding of key areas of relevance, but were not included in the final analysis. To ensure participants could engage regardless of their geographical location, interviews were conducted via video call. Recordings were made with participants' consent to facilitate transcription and analysis, with explicit assurances that the data would be anonymized (Bryman 2016). To guarantee the comprehensive collection of data, the study utilized saturation sampling, concluding data collection after 14 interviews, as no new themes emerged during the analysis. This aligns with the literature, which suggests that saturation is often reached with 9 to 17 interviews in qualitative studies (Hennink and Kaiser 2022). Participants were selected to ensure diversity in technical expertise and professional experience, ranging from highly technical to less technical consultants and from individuals with significant professional experience (3–10 years) to those with limited experience (1–3 years). A brief overview of the interview themes, including current AI usage, strengths and weaknesses of AI tools, and perspectives on future AI integration, was shared with participants one day in advance to facilitate thoughtful responses (Creswell and Poth 2018). Follow-up questions were sent via email to selected participants to enhance data comparability across responses. While this method provides significant depth, a common limitation is the frequent discrepancy between participants' reported actions or intentions and their actual behaviors, highlighting the inherent inconsistency in self-reported data (Robson 2002). Participant observation complemented the interviews by offering real-time insights into behaviors and interactions not easily captured in verbal accounts. This method provided a nuanced understanding of organizational dynamics by focusing on interactions, collaboration patterns, and implicit practices (McDonald and Simpson 2014). Observations were conducted during two Generative AI (GenAI) training workshops, each lasting 1.5 hours, and involving 22 and 25 consultants, respectively, from mixed technical and professional backgrounds . The workshops focused on two primary themes: effective prompting techniques and exploring AI tools applicable to consulting practices. Among these participants, seven also took part in the unstructured interviews. Immersing in these sessions allowed to document emergent practices and contextualize the findings from the interviews (McDonald and Simpson 2014).

Table 1: Data Collection Sources

Interviews

Source	**Codes**	**Frequency**	**Duration**
Consultants with less technical background and high professional experience	I1, I2, I3, I4	4	30 min.
Consultants with less technical background and low professional experience	I5, I6, I7	3	30 min.
Consultants with high technical background and high professional experience	I8, I9, I10	3	30 min.
Consultants with less technical background and low professional experience	I11, I12, I13, I14	4	30 min.

Observations

Source	**Codes**	**Frequency**	**Duration**

AI workshops with 20 consultants (mixed backgrounds and experience levels)	-	2	90 min.

3.2 Data Analysis

This study employed qualitative content analysis based on Mayring's and Fenzl's (2019) methodology, which provides a systematic framework for interpreting textual data. The method was selected for its structured yet flexible approach, allowing the analysis to remain grounded in participants' experiences while addressing the study's research objectives on Human-AI collaboration in decision-making workflows. Interview transcripts were chosen as the primary data source for their rich content on consultants' real-world experiences with AI tools, while observations complemented this data by providing insights into behaviors and interactions within practical settings. Each transcript was reviewed iteratively to gain a holistic understanding of the data, identifying emerging patterns and recurring themes. Mayring and Fenzl (2019) emphasize the importance of defining analysis units, which in this study were individual sentences and paragraphs, allowing for precise coding. The coding process followed inductive category development, with themes emerging organically from the data. Statements were grouped into categories such as "usability challenges," "trust dynamics," and "organizational constraints." This approach mirrors an iterative refinement process, ensuring that categories evolve in response to the data while maintaining theoretical alignment. Once categories were established, they were analyzed for Interconnections and broader patterns. For instance, the relationship between task complexity and trust in AI outputs emerged as a critical theme, reflecting how consultants' confidence in AI varied with task-specific requirements. Similarly, peer support and informal learning mechanisms were identified as key factors mitigating barriers to AI adoption. The final stage of analysis involved synthesizing insights into actionable findings. Themes were contextualized within the broader literature on Human-AI collaboration, emphasizing the interplay between technical proficiency, trust, and usability.

4. Findings

The analysis of the interview data revealed several critical themes regarding the integration of algorithmic tools into consultants' workflows. These findings provide a nuanced understanding of how consultants perceive, interact with, and derive value from algorithmic inputs, particularly in relation to their contextual knowledge and expertise.

4.1 Challenges to Effective AI Integration in Consulting Workflows

The interviews revealed several challenges consultants face when integrating AI tools into their workflows. A key issue is the lack of clarity regarding suitable use cases, which often leads to underutilization. Many participants struggle to identify tasks where AI adds value, instead completing tasks manually. One consultant noted, "Nearly every day, a new AI tool emerges, and to be honest, I have completely lost track of them." (I10) highlighting the need for clearer guidance on practical applications (Logg, Minson, and Moore 2019).

Concerns about data security further inhibit effective AI adoption. Consultants expressed reluctance to input sensitive client data into AI systems due to fears of violating confidentiality agreements. One consultant noted. One consultant stated, "We deal with highly sensitive client data, and it's unclear whether these AI tools fully comply with our confidentiality requirements. It's a risk I'm not willing to take." (I2) This reflects a significant communication gap, as the organization's AI tools were already fully compliant with data protection standards. Many participants were unaware of the internal safeguards in place, perpetuating cautious behavior and limiting the use of AI for tasks involving client data.

Another common challenge is the time and effort required to craft effective prompts, which often outweighs the perceived efficiency gains. As one participant explained, "Formulating prompts can require more time than simply thinking through the task and writing the text." (I13) Additionally, some consultants expressed that they perceive no immediate necessity to explore AI tools, as they can still achieve their goals using existing methods. This tendency allows them to stay within their comfort zones, further inhibiting the effective adoption of AI tools in their workflows. Combined with tight deadlines and the fast-paced nature of consulting projects, this reluctance leaves little time to explore and understand the full potential of AI tools. As one participant explained, “Given the pressure of deadlines, it’s difficult to allocate time learning something new.” (I5)

4.2 Current Applications and Benefits of AI Tools in Management Consulting

Consultants widely rely on AI tools, with the internally developed GenAI tool being the most commonly used across all participants. This tool, based on a large language model (LLM), ensures data privacy and enables the upload of large client datasets to provide precise and context-aware insights. While some participants were unaware of its robust data security, others highlighted its transparency, as it clearly indicates content sources. As one consultant noted, *“*It’s extremely useful because I can upload entire datasets, and it understands the context very precisely.” (I4) Additionally, eight out of fourteen consultants utilized another company-developed LLM, which is also compliant with data protection standards and enables real-time access to web-based data, improving speed and accuracy. One participant explained, “The real-time web data makes my research faster and I don´t use Google anymore.” (I7) Microsoft Copilot was adopted by five consultants as a reliable assistant for everyday tasks such as drafting, summarizing, and organizing information. Furthermore, six consultants leveraged the AI model in Power BI to analyze and visualize data, benefiting from its ability to work with client-specific and internal information. These tools collectively streamline workflows, enhance research capabilities, and enable consultants to deliver more precise and actionable insights.

For some consultants AI has become an essential tool for consultants, enhancing both research efficiency and real-time client communication. In research, AI helps gather insights, analyze datasets, and summarize complex information, enabling quick understanding of unfamiliar topics. As one consultant noted, “AI helps me cluster, collect, and organize information quickly." (I11) During client interactions, AI supports credibility by providing real-time definitions and examples for industry-specific terms, ensuring seamless communication. One participant shared, "AI helps me clarify terminology during conversations, enhancing my engagement." (I1) By providing rapid access to relevant information, AI improves consultants' preparation and performance in high-stakes situations.

AI also streamlines routine tasks such as drafting emails, summarizing documents, and creating report outlines, allowing consultants to focus on higher-value activities. One consultant remarked, "I use AI for proofreading and summarizing, it significantly reduces time and effort." (I8) By automating these repetitive tasks, AI frees up time for strategic decision-making and complex problem-solving, making it an essential tool for enhancing productivity (Canals 2020).

In addition to text-related tasks, AI is for some consultants invaluable for data analysis and technical support, including crafting formulas, debugging, and interpreting complex spreadsheets. These tools simplify data manipulation and reduce technical barriers, enabling consultants to work more efficiently. As one consultant explained, "AI helps me understand complex formulas in inherited datasets." (I6). By simplifying such technical tasks, AI facilitates faster decision-making and allows consultants to focus on generating meaningful insights .

Moreover, AI supports the organization of information by clustering ideas and creating initial drafts for presentations or reports. One participant shared, "AI helps me create a basic structure for presentations, which I can then refine." (I10) By transforming unstructured findings into coherent frameworks, AI boosts productivity and enables consultants to concentrate on refining and customizing outputs rather than starting from scratch. Together, these capabilities demonstrate how AI enhances efficiency and effectiveness across various aspects of consulting workflows.

4.3 Trust Dynamics in Different Contexts

The interviews revealed that trust in AI-generated outputs does not vary based on technical background but depends on task complexity, as even more technically experienced experts faced similar challenges. For simpler tasks, such as generating solutions for predefined ideas, AI is trusted to streamline processes. As one participant noted, “If I already have a concrete solution in mind, I just use AI to save the effort of writing it out.” (I7) However, trust diminishes in complex scenarios that require integrating diverse references, such as expertise, client documents, and internal capabilities. “The more complex the tasks are, the more I scrutinize the output.” (I6) explained one participant.

User expertise also plays a critical role in shaping trust. Participants with limited knowledge of a topic expressed greater uncertainty about AI outputs. One participant shared, “When I know little about a topic and rely on AI, I feel a significant level of uncertainty about how accurate the output is.” (I3) Conversely, those with sufficient expertise to evaluate and validate the content showed higher trust: “I can trust AI when I have my own knowledge to assess the output and ensure its quality.” (I12) These findings underscore that trust in AI depends on task complexity and the user’s ability to critically evaluate content. Trust is higher for structured tasks and lower for complex or specialized scenarios, highlighting the need to align AI usage with users’ expertise and the task’s requirements.

4.4 Feedback on the AI tools

Feedback on AI tools was found to be limited, as many participants admitted they often bypass the feedback process and resolve issues themselves when dissatisfied with AI-generated outputs. One participant shared, “When the output doesn’t meet my expectations, I just fix it on my own.” (I3) Despite this, all interviewees reported being asked to provide feedback on internally developed AI tools, although this feedback was collected through company-wide initiatives rather than directly within the tools.

A key challenge identified is the diverse nature of consulting practices, such as Management Consulting, which makes providing specific and actionable feedback difficult. As one participant explained, “We don’t provide much feedback because AI tools like Copilot are optional assets, not essential daily tools. The way they are used is often too superficial to generate meaningful feedback.” (I13) These findings suggest that while feedback mechanisms exist, the optional and varied usage of AI tools across consulting practices limits the depth and utility of the feedback provided. To enhance adoption and development, there is a need for more targeted feedback mechanisms tailored to specific use cases and consulting domains.

4.5 Training and Peer Support in AI Adoption

Training programs at the company play a crucial role in supporting consultants’ effective integration of AI tools. These include mandatory sessions, often culminating in certifications, and optional workshops covering AI trends and practical applications. As one participant explained, “Our company doesn’t allow anyone to use the tool without proper training.”(I2) However, observations during GenAI workshops revealed that these mandatory training programs are often not carefully followed, and feedback indicated they are too general to address specific needs. Further training sessions focus on areas such as understanding LLMs, prompt optimization, and practical tasks like data analysis with AI tools. Participants highlighted the value of these programs in building confidence and improving skills. One consultant shared, “Prompting is a big topic, and learning how to do it properly helped me a lot.” (I2) However, some noted time constraints as a barrier to participation, as one explained, “The last two times, I couldn’t attend because I had conflicting meetings.” (I1) Informal learning also plays a key role, with consultants often seeking support from colleagues or internal taskforces. One participant shared, “I’d ask my teammates or reach out directly to our GenAI taskforces we’ve established within our consulting industry account. These taskforces, which meet weekly to share AI use cases, discuss challenges, and explore ways to use AI tools more effectively, are something I find very useful for fostering collaboration and continuous improvement.” (I12) Overall, the combination of structured training initiatives and informal peer support helps reduce uncertainty, enhance technical skills, and improve productivity, ensuring successful AI adoption across the company.

5. Recommendations

5.1 Boundary Conditions for Leveraging Synergies between AI and Consultants

To effectively harness the synergies between AI and the expertise of management consultants, several foundational conditions must be met. These conditions, identified through qualitative interviews and supported by relevant literature, include enhancing awareness of AI's potential, clarifying data usage policies, addressing training gaps, fostering a supportive organizational culture, and ensuring transparency and feedback mechanisms.

A proactive organizational culture is vital for fostering an environment where AI enhances consultant expertise. Participants highlighted their organization's openness to generative AI, which promoted innovation and collaboration. To advance this, organizations could form an AI advocacy network with champions guiding teams in integrating AI into workflows and showcase successful applications to inspire broader adoption (Jarrahi et. al. 2023).

Awareness of AI's capabilities is crucial for maximizing its potential in enhancing consultant expertise. Consultants often restrict AI use to familiar tasks, overlooking its broader applications. Organizations can address this by promoting deeper understanding of AI's diverse use cases. For example, as mentioned by consultant I12 an AI task force helped team members share innovative use cases, broadening their understanding and improving efficiency. The described task force could be expanded to other management consulting industry accounts to ensure the effective leveraging of proven practices.

Additionally, effectively harnessing synergies between AI and consultant expertise requires employees to comprehend the purpose of AI within their work context, including its specific role within the team and its implications for reshaping employee responsibilities (Makarius et al. 2020). Such initiatives could be formalized through structured workshops, providing practical demonstrations tailored to each individual role and emphasizing realistic applications and limitations (Whittle et al. 2019). Furthermore, dedicated domain experts at each account could contribute extensive practical knowledge of tasks, workflows, and business models, enabling them to understand and assess the rationale behind deriving business value from AI implementation (Herath Pathirannehelage, Shrestha, and von Krogh 2024).

The integration of AI into decision-making workflows also requires clarity on data usage policies. As previously stated in the interviews, consultants frequently refrain from utilizing client data in AI processes due to compliance uncertainties and potential conflicts, even when they have undergone training on that subject. Addressing this requires the development of comprehensive real-world examples to illustrate permissible practices. Additionally, appointing dedicated data compliance officers who can offer on-demand guidance would empower consultants to leverage client data responsibly while ensuring adherence to regulatory requirements (Gupta, Dwivedi, and Shah 2023).

Transparency in AI-generated outputs is critical for fostering trust and ensuring effective collaboration between consultants and AI systems. Participants emphasized the need for greater visibility into the sources and logic behind AI recommendations. Organizations should prioritize the integration of reference-tracing capabilities within AI tools and provide consultants with training on interpreting these outputs (De Vreede, Raghavan, and De Vreede 2021). Furthermore, structured feedback mechanisms should be established to evaluate AI tools' performance and user satisfaction, enabling continuous refinement and optimization.

5.2 Framework for Enhancing Decision-Making Through AI

This framework draws on insights from the interviews and Puranam's (2021) classification of tasks into Type A, Type B, and Type C, providing a structured approach to effectively integrating AI into decision-making. Type A tasks, where AI excels due to its speed and scalability, involve repetitive and data-intensive activities. Type B tasks require human judgment and domain-specific expertise, while Type C tasks benefit from collaboration between humans and AI to achieve superior outcomes through aggregation of the outputs. To account for the qualitative nature of many management consulting tasks described by participants extended this framework to include qualitative tasks. Unlike quantitative tasks, where aggregation methods such as averaging are straightforward, combining human and AI-generated qualitative outputs is more complex (Choudhary et al. 2023). This chapter examines the integration of AI into decision-making processes within management consulting, using a hypothetical scenario to illustrate the division of labor between humans and AI. The scenario is based on a real-life example where no AI was utilized during the project. It involves the development of a digitalization strategy aimed at analyzing over 900 processes within a large organization, with the goal of determining which IT processes should be outsourced, maintained, or discontinued. Initial datasets, including IT system costs and other relevant factors, are provided as part of the analysis. This scenario, defined by Consultant 3, was selected due to the fact that 9 out of 14 interviewed consultants had practical experience in creating digitalization strategies, highlighting the organization's strong digitalization focus and providing a relevant basis for the recommendations offered.

AI-Driven Tasks (Type A)

AI-driven tasks are critical for automating data-intensive processes and analyzing quantitative aspects of decision-making. In the problem definition phase, AI tools, such as Power BI, structure and analyze large datasets to identify inefficiencies like delays, operational costs, or bottlenecks. Visualizations, including heatmaps and bottleneck analyses, highlight measurable performance gaps, enabling consultants to prioritize areas for improvement.

During the gathering information phase, GenAI tools expedite the research process by aggregating external best practices, industry benchmarks, and case studies. These tools provide actionable insights by identifying proven solutions and strategies from similar industries, forming a solid foundation for decision-making.

In the gap analysis phase, AI tools quantify and visualize discrepancies between current performance and success benchmarks. By automating comparisons, such as identifying operational delays or cost inefficiencies, AI enhances the precision of performance assessments.

In the analyzing option outcomes phase, AI tools streamline evaluations by automating KPI visualizations, including ROI, time efficiency, and cost savings. Features like "What-If Analysis" simulate scenarios, such as resource adjustments, to project potential impacts. While manual configuration may still be necessary to define criteria, AI ensures objective and real-time insights into each alternative's viability, simplifying decision evaluation.

Human-Driven Tasks (Type B)

Human expertise remains indispensable for addressing contextual complexities, providing qualitative insights, and validating AI outputs. In the problem definition phase, consultants play a pivotal role in refining the scope of inefficiencies identified by AI and prioritizing problems based on strategic importance and feasibility. For example, consultants assess factors such as operational significance, resource optimization, and alignment with long-term goals to ensure the problem scope reflects organizational priorities.

In the defining solution scenario phase, consultants incorporate qualitative success factors that extend beyond quantitative measures. By engaging stakeholders through workshops or interviews, consultants identify broader success indicators such as employee satisfaction, workload reduction, or enhanced client experiences, ensuring alignment with both operational and strategic goals.

During the gap analysis phase, human expertise is used to validate and refine AI-driven findings. Consultants integrate factors like cultural considerations, workforce readiness, and resource availability to contextualize performance gaps within the organization. Additionally, they define success criteria and improvement milestones that reflect both tangible outcomes and qualitative organizational needs.

In the gathering information phase, consultants bridge the gap between stakeholder input and AI-driven data by collecting qualitative insights through interviews, surveys, and focus groups. This ensures the integration of real-world perspectives into the analysis process.

In the analyzing option outcomes phase, consultants assess qualitative dimensions that AI alone cannot capture, such as stakeholder reactions, cultural implications, and long-term alignment with organizational strategy. Finally, during the selecting the best option phase, the consultant takes responsibility for choosing the preferred solution to ensure managerial discretion and expertise play a central role. This step emphasizes the importance of thoroughly understanding the chosen option, as human judgment provides critical validation, contextual alignment, and strategic refinement that AI alone cannot achieve.

Collaboratively-Driven Tasks (Type C)

Collaborative tasks represent the integration of AI's computational strengths and human judgment, creating a balanced approach to decision-making.

In the problem definition phase, AI tools, including GenAI connected to real-time data, analyze and summarize large volumes of external data, while the internal GenAI tool identifies recurring inefficiencies, trends, and emerging issues based on past projects that might otherwise be overlooked. These tools provide a comprehensive perspective by combining internal insights with external benchmarks and real-time trends. Simultaneously, human consultants engage stakeholders to contextualize AI findings, ensuring that cultural, operational, and organizational nuances, such as resistance to change or resource limitations, are accounted for.

In the process of defining the solution scenario, AI and human consultants collaborate to prioritize success indicators by combining computational insights with qualitative judgment. GenAI tools can ideate and rank quantitative success metrics such as ROI, time efficiency, and cost savings based on predefined criteria. For example, AI may highlight cost savings as the most critical indicator due to its measurable impact on resource allocation. However, consultants refine and validate these rankings by incorporating broader strategic goals and qualitative considerations, ensuring alignment with the organization's long-term priorities.

In the gap analysis phase, collaborative tasks involve a synergistic approach where AI tools, such as GenAI, and human consultants work independently yet complementarily to define actionable steps and identify constraints. With the knowledge gathered from previous steps, GenAI can propose initial pathways for bridging the identified gaps. For example, by analyzing uploaded insights, benchmarks, and historical data, GenAI can suggest prioritized steps, such as automating inefficient IT systems or consolidating redundant processes.

The proposed framework integrates AI-driven tasks, human expertise, and collaborative efforts to enhance decision-making in management consulting. AI-driven tasks focus on automating data-intensive processes and analyzing quantitative aspects, such as identifying inefficiencies, benchmarking performance, and simulating outcomes using tools like Power BI and GenAI. Human-driven tasks rely on consultants' qualitative judgment, contextual understanding, and stakeholder engagement to refine AI findings, validate solutions, and ensure alignment with organizational goals. Collaborative tasks combine the strengths of both AI and human consultants, with each working independently on the same task. AI analyzes real-time data and past projects, while consultants contextualize these insights with qualitative inputs, leading to superior aggregated outcomes.

Additionally, AI tools can support minor tasks such as drafting emails, summarizing documents, and organizing information, enabling consultants to focus on higher-value activities. This balanced approach ensures more efficient and informed decision-making.

6. Conclusion

This study examined how synergies between human expertise and AI tools can optimize decision-making processes within the management consulting industry. Drawing on insights from interviews, observations, and existing frameworks, the research highlights the complementary strengths of AI and human judgment. AI excels in automating data-intensive tasks (Type A), while human expertise remains essential for contextual understanding and navigating complex, qualitative decisions (Type B). The study further underscores the importance of collaborative approaches (Type C), where integrating AI and human inputs can produce superior outcomes.

However, the study is not without limitations. First, the research is context-specific, focusing on a single organization, which may limit the generalizability of the findings to other firms or industries. Second, while the qualitative approach provided in-depth insights, the reliance on interviews and observations introduces the possibility of bias or discrepancies between reported actions and actual behaviors. Additionally, the evolving nature of AI technologies means that the frameworks and recommendations outlined here may require continuous adaptation as new tools and capabilities emerge.

Future research could address these limitations by incorporating a broader sample across multiple organizations and industries. Further studies could also explore quantitative analyses to validate the findings and assess the long-term impact of AI-human collaboration on decision-making outcomes.

In conclusion, while AI has transformative potential for the management consulting industry, its real value lies in its integration with human expertise. By fostering a balanced and collaborative approach, organizations can leverage AI to drive data-driven insights while ensuring decisions remain contextually grounded and strategically informed.

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Appendices

Appendix 1 – Adapted Model of Inductive Category Formation and Application

(Based on Mayring and Fenzl, 2019)