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List of Abbreviations

AGI	Artificial General Intelligence
AI	Artificial Intelligence
CRM	Customer Relationship Management
CV	Computer Vision
ESG	Environmental, Social, Governance
GDPR	General Data Protection Regulation
GPT	Generative Pre-trained Transformer
HR	Human Resources
IPA	Intelligent Process Automation
LLM	Large Language Model
ML	Machine Learning
NLP	Natural Language Processing
PESTEL	Political, Economic, Social, Technological, Ecological, and Legal
RPA	Robotic Process Automation

1 Introduction

In today's world, the rapid advancements in Artificial Intelligence (AI) have begun to profoundly reshape various industries, with the consulting sector standing at the forefront of this transformation. As AI systems become increasingly sophisticated, their ability to perform complex tasks and emulate human behavior with remarkable accuracy is revolutionising traditional business models and decision-making processes. The integration of AI into consulting not only enhances efficiency and productivity but also holds the promise of driving significant economic growth in the future. This thesis explores the pivotal role of AI in the consulting industry, highlighting its potential to seamlessly blend with human expertise and redefine the landscape of modern consulting practices.[1]

The preceding paragraph was generated entirely by the latest Large Language Model (LLM) of OpenAI, ChatGPT 4o, and shows that the distinction between human and machine communication is no longer there, or at best only marginally discernible. AI is already impacting our everyday lives in countless ways and in a variety of forms; in the way the new series on Netflix is suggested to you, in the accuracy with which your smartphone understands and executes voice commands, in the personalised shopping recommendations on e-commerce websites, in the way your emails are automatically filtered for spam and even in the routes that navigation systems suggest to you to avoid traffic.

1.1 Problem definition and objective

In the previous decades, wide advances in the field of AI have shown the potential of this very technology: AI has evolved from a theoretical discipline, or practical applications in the background, to a prominent direct-touch technology that permeates our everyday lives in a variety of ways. These developments are not only impressive, but also technologically complex and multi-layered. Especially in the consulting sector, an industry that traditionally relies heavily on human knowledge and expertise, the integration of AI technologies poses a major and non-trivial ongoing challenge. The status quo shows that companies around the world are increasingly using AI to optimise their business processes, improve decision-making and gain a competitive edge. However, despite the numerous benefits, there are also considerable uncertainties and challenges in dealing with AI. In the consulting industry in particular, it is unclear how AI will change existing ways of working, what new skills and com-

[1]Generated by OpenAI's ChatGPT 4o on 25.06.2024

petences will be required and what impact this will have on consulting services and client relationships.

The objective of this thesis is to examine the impact of AI on the consulting industry and to analyse how this technology is transforming the industry. The research will focus on the questions, how AI is changing traditional consulting processes and methods, what new tools and approaches are made possible by AI, what competitive advantages can be achieved through the use of AI in consulting and what challenges need to be overcome, what trends and future developments can be expected in the field of AI and consulting and how can consulting firms prepare for this and adapt their strategies accordingly.

Or in one, short, central question: "How is AI changing the consulting industry?"

In order to answer these questions, a combination of qualitative interviews with experts from leading consulting firms and a target-oriented literature review will be conducted. The purpose is to draw a comprehensive picture of AI as technology and the current situation and future prospects in order to derive recommendations for practical action. This work should not only offer theoretical insights, but also provide practical impulses on how consulting companies can optimally utilise the potential of AI to increase their competitiveness and offer their clients continuously improving services.

1.2 Structure of the thesis

In chapter 2, the reader is initially given a broader impression of what AI is and how it works on a general technical level. It provides an introduction to the basic concepts and technologies of AI without going into too much technical detail. The intention is to give the reader a sufficient understanding of what types of AI there are, how they work and in which areas they can be used particularly well. The chapter also explains the basics of the various AI technologies, and gives insights into the consulting industry. The latter will provide a general overview of the consulting industry itself, as well as an overview of AI in consulting applications to date.

Chapter 3 is subsequently dedicated to the theoretical aspects and limitations of AI. At first, the theoretical limits and challenges, such as the black box problem and the need for large amounts of data, are discussed. The areas in which AI can be applied in the consulting industry are then analysed followed by a detailed Political, Economic, Social, Technological, Environmental and Legal (PESTEL) Analysis, which provides an overview of the external factors that influence the implementation and use of AI in consulting in the broader picture. Finally, the current status of the use of AI in the consulting industry is presented, with current applications, technologies and market analyses being discussed.

Chapter 4 provides a critical analysis and discussion of previous research on AI in the consulting industry. It includes a literature review and identifies research gaps as well as the most important findings from current studies. In addition, the methodology of the empirical studies conducted is described, including the research design and the formulation of the research question. Following, the results of the interviews and data analyses conducted are presented and critically discussed to highlight the implications for consulting practice, aswell as the ethical and social considerations.

Chapter 5 summarises the most important findings of the work in the conclusion and provides an outlook on future developments in the field of AI in the consulting industry, including the key results of the analysis and their implications. In addition, an outlook is given on how the use of AI in the consulting industry could develop further and what challenges and opportunities can be expected.

In the larger scheme of things the work is intended not only to provide a comprehensive overview of the current status and theoretical foundations of AI in the consulting industry, but also to show practical recommendations for the implementation and use of AI in this area. By combining theoretical analyses and empirical studies, the aim is to develop an in-depth understanding of the role and significance of AI in the consulting industry.

2 Basics of artificial intelligence and introduction to the consulting industry

To sustainably and profoundly understand the importance of AI in the consulting industry, it is necessary to know the key technologies and concepts that are shaping this development. AI has the potential to transform numerous industries and offers companies unprecedented solutions to complex challenges as well as new opportunities to optimise and better understand business processes.

A key new component of this transformation are LLMs, such as the Generative Pretrained Transformer (GPT) series developed by OpenAI. These models have enabled significant advances in Natural Language Processing (NLP). A deep understanding of their evolution and influence is crucial to fully realise their role and potential in guidance. Therefore, the development and importance of these models will first be considered in order to highlight their potential applications in counselling. These technologies are based on machine and deep learning, which are also analysed, as they form the backbone of predictive AI as well as the basis of new AI technologies. Another key area of AI is Computer Vision (CV), which gives machines the ability to interpret visual data and make decisions based on it. CV technologies have a wide range of potential applications, from medical image processing to autonomous vehicles. The importance and applications of CV will therefore also be analysed.

The consulting industry has developed in parallel with technological developments. It plays an important role as a mediator between technological progress and entrepreneurial needs. The consulting industry has established itself as an integral part of the global economy and encompasses a wide range of services, from strategic planning to operational optimisation. An understanding of the structure, dynamics and trends in the consulting industry is necessary to understand the integration of AI and the resulting changes. Thus, the development and importance of the consulting industry is explained in detail. It is also essential to consider the specific applications and impacts of AI in consulting; the intersection of these areas is complex and requires deeper insights. The integration of AI into consulting processes has not only increased the efficiency and effectiveness of services, but also enabled new business areas and services. AI systems can perform extensive data analyses, recognise patterns and make precise predictions, giving consulting companies a significant competitive advantage. A thorough grasp of the opportunities and challenges presented by the use of AI in consulting is pivotal to the long-term competitiveness and success of consulting firms.

In order to address these topics in a structured way, first it will be examined what exactly Machine Learning (ML) and Deep Learning are and how the LLMs based on them have changed NLP, before moving on to the importance of CV. The development and importance of the consulting industry is then explained and finally the role of AI in consulting and its impact on the industry is considered in detail.

2.1 Basics of AI

AI is a field of computer science that focuses on the development of systems and machines that are capable of performing tasks that normally require human intelligence. This includes skills such as learning, problem solving, recognition, speech recognition and decision making. The definition of AI can be divided into two main categories: strong AI and cautious AI (Cf. *Searle*, 1980, p. 417).

Weak AI, also known as cautious AI, also known as narrow AI, refers to systems that have been developed for specific tasks and do not possess general intelligence. These systems are specialised to perform a specific task or a limited number of tasks very well, but do not have the ability to learn or adapt to new tasks that are outside their given scope. Examples of weak AI include:

- Voice assistants such as Siri or Alexa, which can recognise and execute voice commands (Cf. *Raj, Devang, and Chanchal*, 2023, p. 352).
- Recommendation algorithms used in streaming services such as Netflix or Spotify to suggest more personalised content (Cf. *Garg, Shekhar, and Narwal*, 2024, p. 340).
- Facial recognition systems used in security applications or social media (Cf. *Bein and Williams*, 2023, p. 22).

Strong AI, also known as Artificial General Intelligence (AGI), refers to systems that have the ability to perform any intellectual task that a human can perform, or even surpass their capability. This form of AI has the ability to learn, understand and adapt to a variety of tasks and situations, much like the human mind (Cf. *Heaven*, 2023). Characteristics of strong AI include autonomous learning and adaptation to new situations without human intervention, the ability to solve problems across different domains and understanding and processing natural language in a broad context (Cf. *Abdüsselam*, 2023, p. 1). Although strong AI is theoretically possible, there are currently no practical implementations of it. The majority of AI systems that exist today fall into the weak AI category, as they are limited to specific tasks and lack the general intelligence that characterises strong AI.

The history of AI is characterised by many significant milestones and developments. The beginnings of AI can be traced back to the 1940s, when Alan Turing laid the foundations for the field with his work on theoretical computer science. In his famous article "Computing Machinery and Intelligence" (1950), Turing introduced the Turing test, which tests whether a machine can imitate human-like thinking (Cf. *Turing*, 1950, pp. 433–434).

The term "Artificial Intelligence" itself was coined in 1956 at the Dartmouth Conference organised by John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon. This conference marked the beginning of the formal discipline of AI research (Cf. *McCarthy et al.*, 2006, p. 13).

In the 1960s, the first successful AI programmes were created, such as ELIZA, a simple chatbot, and SHAKEN, a problem-solving programme. Despite these early successes, AI research experienced its first setbacks in the 1970s. The initial high expectations could not be met, which led to a sharp decline in funding. This phase is often referred to as the "AI winter" (Cf. *Bohannon*, 2015, p. 252).

With the 1980s came an upswing in the development of expert systems such as MYCIN, which made medical diagnoses. Knowledge-based systems like this were very successful in processing specific tasks in narrow application areas (Cf. *Buchanan and Shortliffe*, 1984, p. 3).

In the 1990s, ML gained in importance, particularly through the further development of neural networks and the introduction of support vector machines. A significant milestone was reached in 1997 when the chess computer Deep Blue by IBM defeated the reigning world chess champion Garry Kasparov (Cf. *Campbell, Hoane, and Hsu*, 2002, p. 57).

With the availability of large amounts of data and more powerful computers, deep learning and neural networks experienced an enormous boom in the 2010s. One notable example is the AlexNet project, which marked a breakthrough in image classification (Cf. *Krizhevsky, Sutskever, and G. E. Hinton*, 2012, p. 84).

Today, AI is used in many areas, from self-driving cars to medical image processing. At the same time, ethical and social issues are at the forefront, such as data protection and job losses. The development towards AGI is a long-term goal that still involves many challenges. The history of AI shows a continuous development characterised by significant milestones and setbacks. From the theoretical foundations laid by Alan Turing in the 1940s, to the coining of the term "Artificial Intelligence" at the Dartmouth Conference in 1956, to the advances in ML and deep learning in recent decades, AI research has had a remarkable journey. The successes and challenges of the past have had a significant impact on current developments and the future of AI. The gradual integration of AI in various areas of life demonstrates the immersive potential of this technology.

The central objectives of AI are diverse and incorporate several key aspects that aim to complement and enhance human capabilities and decision-making processes. One of its main goals is automation, which enables repetitive and time-consuming tasks to be carried out more efficiently and precisely, so humans can focus on non-ordinary tasks. This automation potential ranges from industrial applications, such as the automation of production lines, to everyday applications, such as chatbots and automated customer service systems (Cf. *Brynjolfsson and McAfee*, 2014).

Another important aspect of AI is to improve decision-making. By analysing large quantities of data, AI systems can recognise patterns and correlations that are difficult to access or even invisible to human analysts. This ability is used in areas such as healthcare (Cf. *Obermeyer and Emanuel*, 2016), finance and marketing (Cf. *T. Davenport and Harris*, 2007) to make more informed and accurate decisions based on extensive and detailed data analyses.

The development towards AGI represents one of the greatest challenges and at the same time the most ambitious vision of AI research. AGI aims to create machines that have the same intellectual capabilities as humans, machines that are able to understand, learn and perform a wide range of tasks without being specifically programmed to do so (Cf. *Goertzel*, 2014, pp. 6–7).

Progress in AGI research depends heavily on developments in areas such as ML, neural networks and computing power. Future developments could be accompanied by the combination of deep learning with other approaches such as symbolic AI (Cf. *Lake et al.*, 2016, pp. 1–2). Another important aspect is the ability for autonomous self-improvement, in which AGI systems can continuously expand and improve their own capabilities (Cf. *Bostrom*, 2014).

Despite promising approaches, the development of AGI faces major ethical, technical and safety challenges. These include issues of responsibility and control over autonomous systems, the impact on the labour market and society, and ensuring the ethical use of AGI (Cf. *Yudkowsky*, 2008). Technical challenges include the creation of robust and explainable models and the integration of extensive knowledge databases.

The development of AGI represents a transformative force that could change many areas of society. The continuous progress in AI research reveals that this goal is increasingly within attainable reach, but research and development must be conducted in a rational and interdisciplinary manner.

2.2 Basic technologies of AI

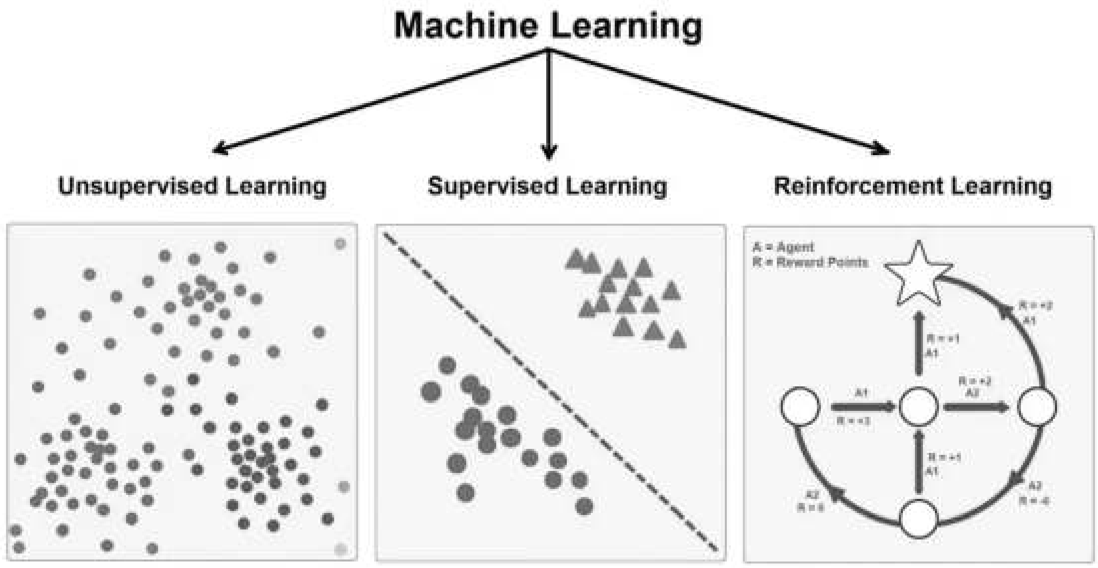
The underlying technologies of AI are based on the ability of machines to learn from supplied data, recognise patterns in that data and make decisions based on the patterns - a process that would traditionally require human intelligence. What these technologies have in common is that they use algorithms and models to analyse large amounts of data and derive predictions or decisions from it. Key technologies include ML, deep learning, NLP, LLMs and CV. These technologies facilitate machines to perform specific tasks ranging from recognising images and voices to processing and generating speech and text.

ML forms the basis of many AI systems by utilising algorithms that enable computers to learn from data and improve their performance over time. Building on this, deep learning is a specialised subcategory of ML that uses deep neural networks to recognise complex patterns in large amounts of data (Cf. *LeCun, Bengio, and G. Hinton*, 2015, p. 436. Cf. *Heaton et al.*, 2018, p. 306). NLP enables machines to understand, interpret and respond to human language. A LLM, such as GPT-3 by OpenAI, is an advanced model of NLP that has been trained with enormous amounts of data to generate human-like text and perform various language-based tasks (Cf. *Brown et al.*, 2020, pp. 8–9). CV is a technology that allows machines to process and interpret visual data, enabling them to perform tasks such as image recognition and classification (Cf. *Pandey*, 2023, p. 510).

While these technologies are based on similar mathematical principles, they have vastly different areas of application and potential utilisations. They are applied in different sectors and have the potential to revolutionise many industries, from automating industrial processes and improving customer service to assisting in medical diagnosis and treatment, each of these technologies offers unique benefits and poses their own challenges. In the following, the basic technologies of ML, deep learning, NLP, LLMs and CV are explained in detail. The purpose is to build an understanding of the differences between these technologies, to know how they work and to identify the potential areas of application in which they can be used profitably.

ML is a sub-discipline of AI that revolves around granting computers the ability to learn and self-improve from data. The basic idea of ML is to recognise patterns and relationships in large quantities of data and make predictions on this basis (Cf. *Alpaydın*, 2020, pp. 5–6). ML algorithms are divided into three main categories: supervised learning, unsupervised learning and reinforcement learning (Cf. *C. M. Bishop*, 2006, p. 3). Figure 1 illustrates the differences between the three main categories of ML, showing examples of typical applications of each method.

Figure 1: Visual representation of types of machine learning



Source: Illustration from ejable.com.

- Unsupervised learning: This algorithm is trained with a data set without explicit output. The aim is to recognise patterns or structures in the data, such as clusters or associations. Examples of this are customer segmentation and market analysis (Cf. *C. M. Bishop*, 2006, p. 3).

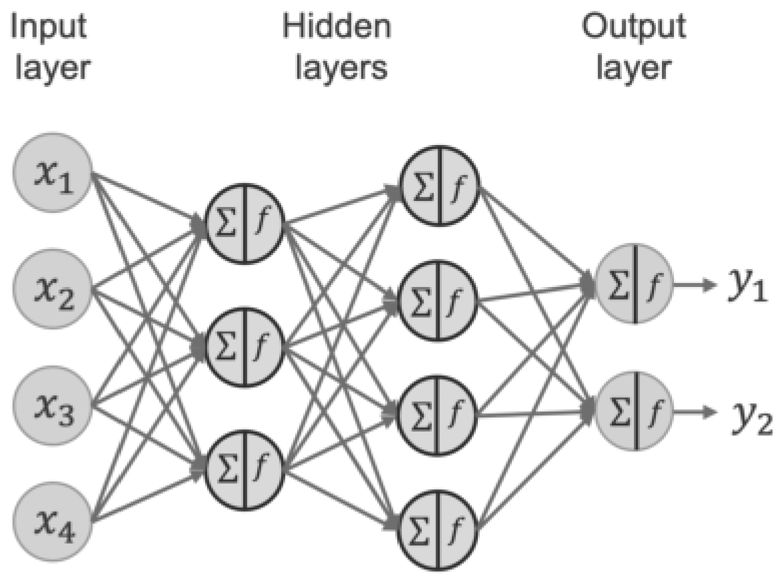
- Supervised learning: In this method of learning, the algorithm is trained with a data set that contains input data and the corresponding output data. The aim is to find a function that maps the inputs to the outputs. Typical applications are classification problems, such as recognising spam emails, and regression problems, such as predicting property prices (Cf. *Russell and Norvig*, 2010, pp. 695–697).

- Reinforcement learning: This method is based on the interaction of the algorithm with an environment. The algorithm learns through trial and error by receiving rewards or punishments for its actions. A well-known example is the development of algorithms for games such as chess or Go, where the algorithm learns by playing against itself or others (Cf. *Russell and Norvig*, 2010, pp. 830–831).

Deep learning is a more specialised form of ML that is based on artificial neural networks and aims to identify complex patterns and correlations in large amounts of data. This technology uses multi-layer networks, also known as deep neural networks, to process and analyse data. Each layer in the network extracts and evaluates increasingly abstract features from the input data, enabling the system to handle highly complex tasks, considering even infinitesimally small features (Cf. *LeCun, Bengio, and G. Hinton*, 2015, p. 436).

Figure 2 shows a typical neural network consisting of an input layer, several hidden layers and an output layer, where each layer is represented by nodes (neurons) and connections.

Figure 2: Example of a fully connected neural network



Source: Illustration from knime.com.

A key aspect of deep learning is the ability to automatically extract features. Traditional ML methods often require manual selection and extraction of relevant features from the data, while in contrast, deep learning can learn and adapt these features automatically, which is particularly advantageous when processing unstructured data such as images, text and audio data (Cf. *Heaton et al.*, 2018, pp. 306–307).

Deep learning enabled significant progress in recent years, because it achieved particularly remarkable results, in the form of specialised networks, in various application areas. For example, convolutional neural networks are often used for image and video analysis, while recurrent neural networks and their further developments, such as long short-term memory networks, are particularly suitable for processing sequential data such as speech and text (Cf. *Krizhevsky, Sutskever, and G. E. Hinton*, 2012, pp. 85–87. Cf. *Hochreiter and Schmidhuber*, 1997, p. 23).

A more recent popular example of the success of deep learning is DeepMind's AlphaGo programme, which defeated the world's best Go player in 2016. Go as a game is about 10^{130} times more complex than chess (Cf. *The Chess Journal*, 2023) and had been dominated by humans up to that point, unlike chess, which was already dominated by computers in 1997 when IBM's Deep Blue beat the then world champion Garry Kasparov. This achievement showed a new milestone in AI research and successfully displayed the ability of deep learning to master complex and strategic games previously considered too difficult for machines (Cf. *Silver et al.*, 2016, p. 14).

Deep learning is already finding increasing use in numerous areas and has, as already showed, the potential to bring about far-reaching changes in many industries. Systems such as IBM Watson Health use deep learning to analyse medical images and support diagnoses (Cf. *Esteva et al.*, 2017, p. 115). Deep learning also plays a key role in the development of self-driving cars by helping to recognise objects and make decisions in real time (Cf. *Bojarski et al.*, 2016, p. 9). These fields of knowledge and application have been fundamentally revolutionised or even made possible in the first place through the use of deep learning.

NLP is a major area of AI that deals with the interaction between computers and human language. The aim of NLP is to give machines the ability to understand, interpret and respond appropriately to human language on all meta levels. The applications of NLP are diverse and range from speech recognition to text analysis.

A primary example of NLP is speech recognition, which enables computers to recognise spoken language and convert it into text or keywords, to then evaluate it. Applications such as Siri, Google Assistant and Amazon Alexa use sophisticated NLP algorithms to understand and respond to voice commands (Cf. *Jurafsky and Martin*, 2008, pp. 14–15).

Another important field of application is text analysis, where NLP techniques are used to extract relevant information from large amounts of unstructured text data. This is often used in market research and social media monitoring to identify trends and sentiment (Cf. *Deepthi and Shanthi*, 2023, p. 1).

Programmes such as Google Translate use NLP techniques to translate texts from one language into another. These systems need to have a deep-rooted understanding of both the source and target language in order to deliver meaningful and grammatically correct translations. This is a significant challenge as it is necessary to comprehend not only the literal meaning but also the context and subtleties of the language (Cf. *Manning and Schütze*, 1999, pp. 463–466).

One of the most significant developments in the field of NLP are LLMs. These models are trained on large text corpuses and are able to handle a variety of complex language tasks with high accuracy. Examples of such models are OpenAI's GPT-3 and GPT-4, which utilise advanced deep learning and NLP techniques to capture contextual meaning and generate high-level human speech. The next section will go into more detail about the functionality and applications of LLMs, which have the potential to significantly extend the capabilities of NLP.

LLMs are a significant advance in the field of NLP and build on decades of research and development. While NLP focuses on the interaction between computers and human language, with the aim of enabling machines to understand, interpret and generate human language, LLMs are a sophisticated application of NLP that utilise large amounts of data and computing power to perform complex language-related tasks, not limited to a specific task like translating (Cf. *Kaswan et al.*, 2023, p. 738).

The breakthrough in NLP research was achieved with the introduction of specialised deep learning techniques. Models such as recurrent neural networks and convolutional neural networks demonstrated the potential of neural architectures in the processing and generation of language. Convolutional neural networks specialise in processing image data by recognising patterns and spatial hierarchies, which makes them irreplaceable for tasks such as image classification (Cf. *Krizhevsky, Sutskever, and G. E. Hinton*, 2012, p. 87). Recurrent neural networks, on the other hand, excel at processing sequential data such as text and time series by preserving context through their memory capabilities, making them crucial for tasks such as language modelling and translation (Cf. *LeCun, Bengio, and G. Hinton*, 2015, pp. 438–440). The pivotal point was the introduction of transformer models that utilise self-attention mechanisms to handle long-range dependencies in text (Cf. *Vaswani et al.*, 2023, pp. 8–10). This led to a significant improvement in language understanding and generation, forming the LLMs.

The first major breakthrough in LLMs came with the development of OpenAI's GPT series. GPT-1, launched in 2018, demonstrated the effectiveness of pre-training a language model on a large corpus and fine-tuning it to specific tasks. This model was trained with unsupervised learning on a variety of web texts and captured a wide range of language patterns and knowledge (Cf. *Radford, Narasimhan, et al.*, 2018, pp. 3–6).

Building on this success, GPT-2 was released in 2019 with 1.5 billion parameters. GPT-2 demonstrated exceptional and unprecedented capabilities in generating coherent and contextually relevant text, leading to a surge of interest in LLMs (Cf. *Radford, Wu, et al.*, 2019, p. 1). The model's ability to perform a variety of tasks without specific training capitalised on the potential of LLMs in the field of NLP.

GPT-3, released in 2020, marked a considerable improvement with 175 billion parameters. This massive model demonstrated remarkable capabilities in language generation, translation, summarisation and even answering complex questions (Cf. *Brown et al.*, 2020, pp. 8–9). GPT-3's ability to generate human-like text with minimal input demonstrated the potency of scaling in LLMs to people worldwide for the first time, and led to a boom in the industry.

The latest iteration of the main series, GPT-4, continues this trend of increasing scale and capability. While specific details about its architecture and parameter count are proprietary, GPT-4 builds on the fundamental principles of its predecessors and incorporates advances in training techniques and data quality. The improvements in GPT-4 are apparent in its improved understanding, generation capabilities, and reduced biases compared to previous models (Cf. *Baktash and Dawodi*, 2023, pp. 3–4).

CV is an area of AI that aims to give machines and computers the ability to interpret and understand visual information. This includes recognising, analysing, and processing images and videos in order to extract relevant information and to perform corresponding actions. The basis of CV is the emulation of human visual perception through algorithms and models that can analyse and interpret images and videos, if necessary in real time (Cf. *Pandey*, 2023, pp. 512–514).

The central techniques of CV include image processing, pattern recognition and ML. Deep learning in particular has enabled enormous progress to be made in this area in recent years. The convolutional neural networks known from this field are the most frequently used models for image processing tasks and have proven to be particularly effective in recognising and classifying objects (Cf. *Krizhevsky, Sutskever, and G. E. Hinton*, 2012, pp. 88–90).

Figure 3 visualises how CV could recognise and classify a set of cars.

CV is used in a variety of areas and has already deeply impacted numerous industries, including:

CV is used in medical diagnostics to recognise and diagnose diseases based on X-ray images, MRI scans and other medical images. This enables more precise diagnoses and early detection of diseases, and can support physicians in analysing large quantities of data (Cf. *Esteva et al.*, 2017, pp. 115–118). Self-driving cars use CV to recognise the environment, identify obstacles and make navigation decisions in real time. This is essential for the development of safe and reliable autonomous vehicles, that can adapt to all real-world scenarios (Cf. *J. Zhang et al.*, 2024, p. 4). Surveillance systems use CV to detect suspicious behaviour, identify people and monitor security threats. This enhances the efficiency and response time of security services, or can considerably simplify the tracing of persons and vehicles (Cf. *Abdulhussein,*

Figure 3: Example of a CV application on cars

Source: Illustration from skywell.software.

Kuba, and Alanssari, 2020, p. 2). In manufacturing, CV is used for quality control and defect detection. Systems can automatically check products for defects and ensure that they meet quality standards (Cf. *J. Liu et al.*, 2019, pp. 10–11). Retailers use CV to analyse customer behaviour, identify products and create personalised shopping experiences. This helps companies to better understand the needs and preferences of their customers (Cf. *X. Liu et al.*, 2007, pp. 4–5).

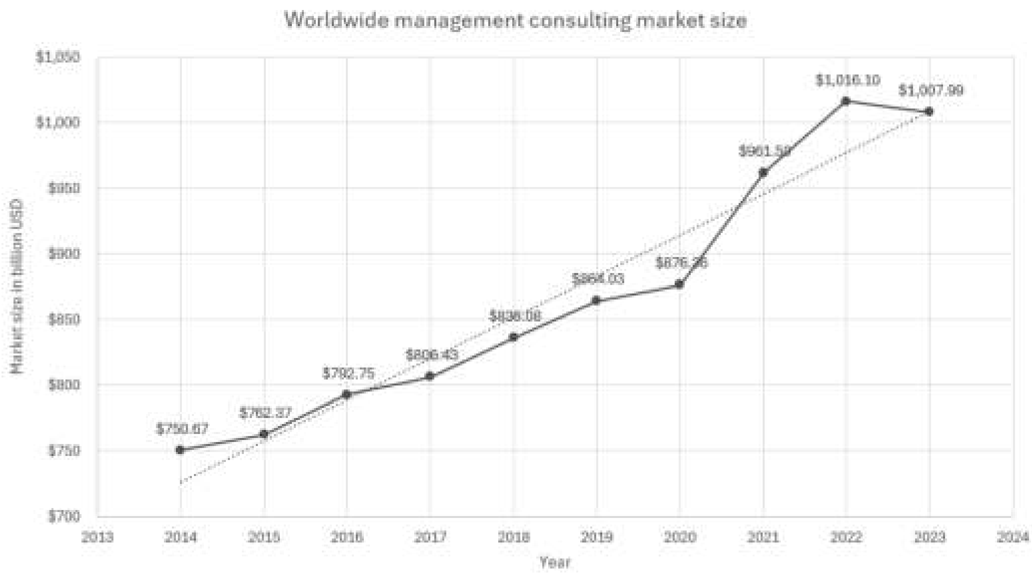
Alongside theoretical advances, CV faces several challenges, including the need for large amounts of data for training, overcoming privacy concerns and ensuring the resilience and accuracy of models in different real-world environments. The future of CV promises developments, particularly in conjunction with other technologies such as augmented reality and virtual reality, which will enable new applications and technological domains. Conversely, the possibility of monitoring people in public places by automated means can be met with considerable resistance, both political and social.

2.3 Introduction to the consulting industry

The consulting industry is comprised of companies and individuals who provide professional services to help organisations solve sophisticated and complex business problems. These services began in the 1960s, and include strategic planning, operational optimisation, technology implementation, risk management, financial advice and much more. Consultants act as external experts who provide objective analyses and make recommendations to improve the performance and efficiency of their clients (Cf. *Armbrüster*, 2006, p. 41). Consulting companies range from large prestigious international firms such as McKinsey & Company, Boston Consulting Group and Deloitte to small, highly specialised consulting firms and one-person companies. The industry is typified by its high level of adaptability and ability to develop customised solutions for unique client requirements.

The consulting industry is an integral part of the global economy and generates significant revenues. According to IBISWorld, the global management consulting market size was approximately one trillion US dollars in 2023, with a forecast for further growth in 2024. The largest markets are North America and Europe, which together account for a significant share of the total market size. Over the past five years, the industry has shown steady growth despite staggering economic fluctuations, reflecting the consistently high demand for consulting services. Figure 4 shows the global market size of the management consulting industry from 2014 until 2023 (Cf. *IBISWorld*, 2024).

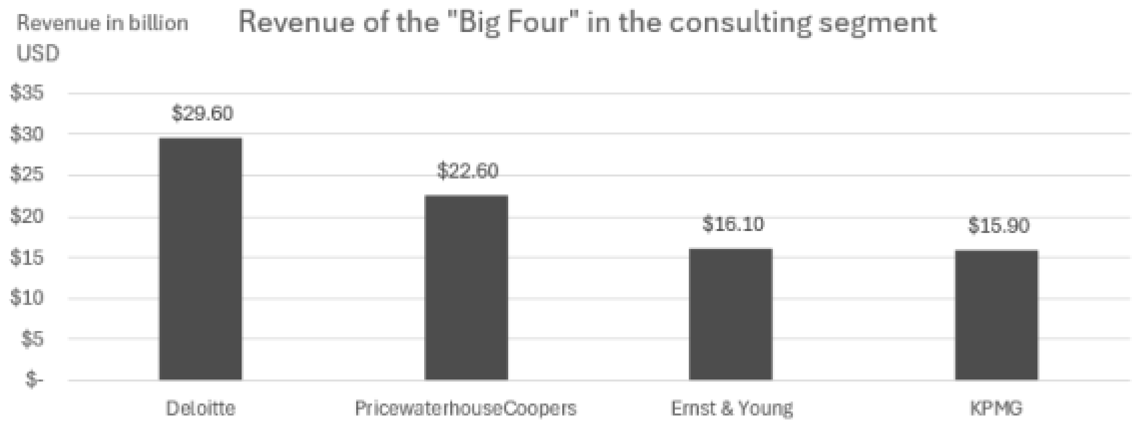
Figure 4: Market size of the global management consulting industry



Source: Own representation based on IBISWorld data via Statista.

A central component of the consulting industry are the so-called “big four”: Deloitte, PricewaterhouseCoopers (PwC), Ernst & Young (EY) and KPMG. These four companies dominate the market and have a significant influence on global consulting activities. The importance of the Big Four lies in their comprehensive expertise and broad range of services, from management and strategy consulting to tax and legal advice, their far-reaching and seminal publications, as well as their long-standing prestige. Figure 5 shows the revenue of the so called “big four” in the consulting industry and illustrates the high turnover of just four companies in the overall market (Cf. *Deloitte, PwC, EY, and KPMG*, 2023).

Figure 5: Revenue in the consulting segment of the “big four”



Source: Own representation based on corporate data via Statista.

Consulting itself can be divided into many different areas:

Strategy consulting includes the development and implementation of long-term corporate strategies that encompass market analyses and competitive strategies or support decision making (Cf. *Buehring and P. C. Bishop*, 2020, p. 423).

Management consulting focuses on the optimisation of internal business processes and structures. This area covers topics such as change management, organisational development and performance management.

IT consulting focuses on the implementation and optimisation of IT systems and infrastructures. Major areas addressed here are enterprise resource planning, cloud computing, cyber security and digitalisation. IT consultants support companies in integrating technological innovations, bringing knowledge in innovation itself (Cf. *Swanson*, 2010, p. 1), and refining their IT strategies.

Financial consultants (more commonly known as financial advisors) support companies with risk management, tax optimisation and financial planning. This also includes services in the area of company valuation and M&A consulting. Other major areas are transaction consulting and financial due diligence.

Human capital consulting advises on topics such as talent management, employee development and organisational culture. The objective is to improve employee retention and motivation and to increase the effectiveness of the HR strategy.

Marketing and sales consultants support companies in the development and implementation of effective marketing strategies and sales channels. Services covered here are market analyses, customer segmentation and the optimisation of sales processes.

The consulting industry is constantly evolving and adapting to new challenges and opportunities. Key current trends include digital transformation, the introduction of digital technologies to improve business processes. Companies are looking for consulting services to help them implement agile working methods and technologies such as big data and Internet of Things technologies, and transform their business models (Cf. *Radov*, 2022, pp. 46–47).

Another significant trend is sustainability and the integration of ESG (Environmental, Social, Governance) criteria into business strategies. Companies are increasingly placing importance on sustainability and consultants are assisting them in developing and implementing strategies to promote environmental and social responsibility and fulfil regulatory requirements. Consultants also provide support with, inter alia, "stakeholder alignment, management, strategic foresight, and scenario planning, as well as the use of digital and internet services throughout the circular economy value chain based on both ESG and carbon information" (*Liao, Pan, and Y. Zhang*, 2023, p. 4).

The use of AI and automation to improve business processes and decision-making is also a growing trend. Consultants help companies integrate these technologies to increase efficiency and gain competitive advantage. The evaluation of potential AI systems is also a part that can be realised by consultants (Cf. *T. Davenport and Ronanki*, 2018).

The COVID-19 pandemic has accelerated remote working in a significant way. Consultants can provide support in implementing remote working strategies and adapting business processes to the new way of working to maximise productivity and employee engagement and commitment (Cf. *B. Wang et al.*, 2021, pp. 35–36).

2.4 Importance of AI for the consulting industry

The consulting industry has undergone significant changes over the years, particularly through the integration of AI, which was first used by consulting firms in the 2000s to support data-based decision-making. These initial successes laid the foundation for the ongoing use and development of AI in the industry. A high-profile and proven example of a breakthrough AI product in consulting is IBM Watson, which was first made public in 2011 and offered complex data analytics and NLP. The use of such systems transformed the way companies interpret and use data, allowing them to gain precious insights by analysing unstructured data, to find information buried within information (Cf. *Chen, Argentinis, and Weber*, 2016, p. 697).

The use of AI in the consulting industry has evolved significantly; initially, efforts focussed on rule-based systems and simple algorithms that could automate specific tasks. But with the advent of more advanced technologies, such as deep learning, consulting companies have been able to tackle more complex problems and gain deeper insights from increasingly large amounts of data (Cf. *Al-Amin et al.*, 2024, pp. 24–25).

The areas of application of AI in the consulting industry are diverse and have so far mainly included the automation of routine tasks, the cataloguing and querying of stored data in databases, the improvement of decision-making and the provision of personalised services. AI systems can analyse large amounts of data and recognise patterns that are difficult for human analysts to access. This enables more precise and faster decision-making, especially in situations where a lot of data needs to be analysed, especially unsorted data. In addition, consulting companies can use AI to develop highly customised solutions for their customers, which can significantly improve customer satisfaction and loyalty (Cf. *Fianto and Dutahatmaja*, 2023, p. 57).

The use of AI gives consulting companies a significant competitive advantage by increasing their innovative strength and efficiency, as the implementation of advanced AI technologies enables companies to develop new services and optimise existing processes. This not only enables differentiation in the market, but also the expansion into new business areas. This can be done by use of AI to develop predictive models that can forecast future market trends and customer needs in key areas. Having a competitive edge, and to offer unrivaled, innovative and data-driven AI, is a decisive factor for the long-term success and competitiveness.

3 Theoretical analysis of AI in the consulting industry

The following subsections deepen the understanding of the theoretical aspects and limitations of AI in the consulting industry and are essential to understanding how AI is shaping this industry and the challenges and opportunities it presents. Insights into the external factors that influence the implementation and use of AI are provided to better understand the strategic considerations that organisations need to make in order to use AI effectively.

As a first step, the theoretical limitations and challenges of AI are discussed. Here, fundamental limitations and the complexity of AI technologies, such as the “black box” problem and the significant data requirements for the development of robust AI systems, are addressed. This knowledge is crucial to effectively integrate AI into consulting practices and address potential roadblocks. This is followed by an analysis of the applications of AI in consulting. The specific tasks and processes that are transformed by AI technologies are presented and the transformative potential of AI to make consulting practice more efficient and insightful is emphasised.

A broad analysis then examines the political, economic, social, technological, environmental and legal factors influencing the implementation of AI in the consulting sector. This analysis provides a framework to understand the external forces shaping the ongoing adoption of AI and the strategic considerations organisations need to make to effectively utilise AI. Finally, the current state of AI in the consulting industry is presented. This chapter provides an overview of the current use of AI in consulting companies, including technological advances and market trends. It discusses the competitive dynamics and how consulting firms are using AI to create value and secure a competitive advantage in a rapidly evolving industry.

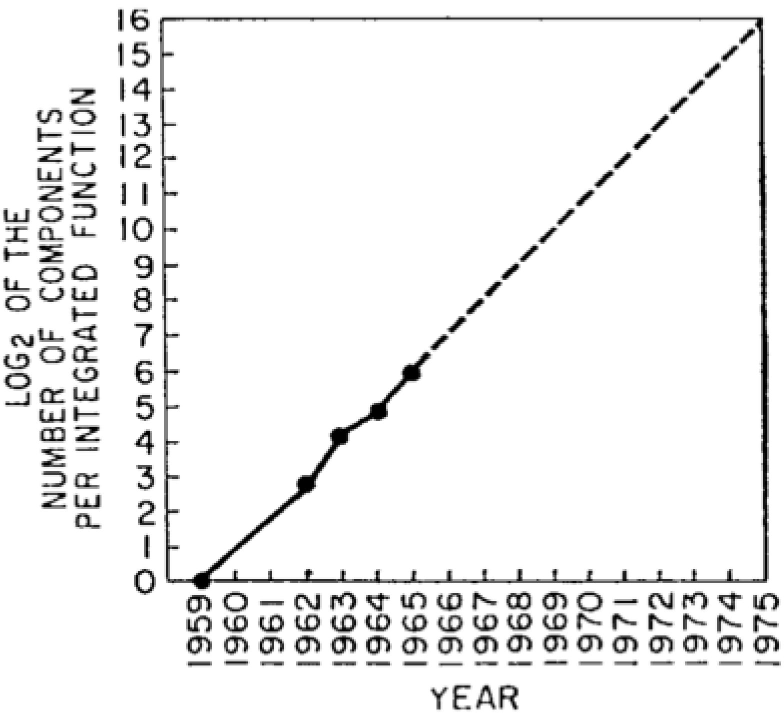
Accordingly, these chapters provide a comprehensive overview of the challenges and opportunities presented by AI in consulting and emphasise the importance of strategic planning and adaptation in the use of AI technologies for predictable, necessary, and sustainable business growth.

3.1 Theory on the limitations of AI

The theoretical limitations of AI are closely tied to the available computing power; the ability of an AI system to perform complex tasks depends directly on the amount of computing resources available to it. This computing power is in turn largely determined by the density of transistors on the microchip on which the computer is based, as transistors are the basic switching elements that process electronic signals and enable calculations. Increasing transistor density increases the computing capacity of a chip, which in turn improves the performance and capabilities of AI systems.

In 1965, Gordon E. Moore, co-founder of Intel, introduced a theory that would later become known as "Moore's law". Moore predicted that the number of transistors on integrated circuits would double approximately every two years, resulting in an exponential increase in computing power. The extrapolation created by Moore as the basis of this theory can be seen in Figure 6 (Cf. *Moore*, 1965, p. 3).

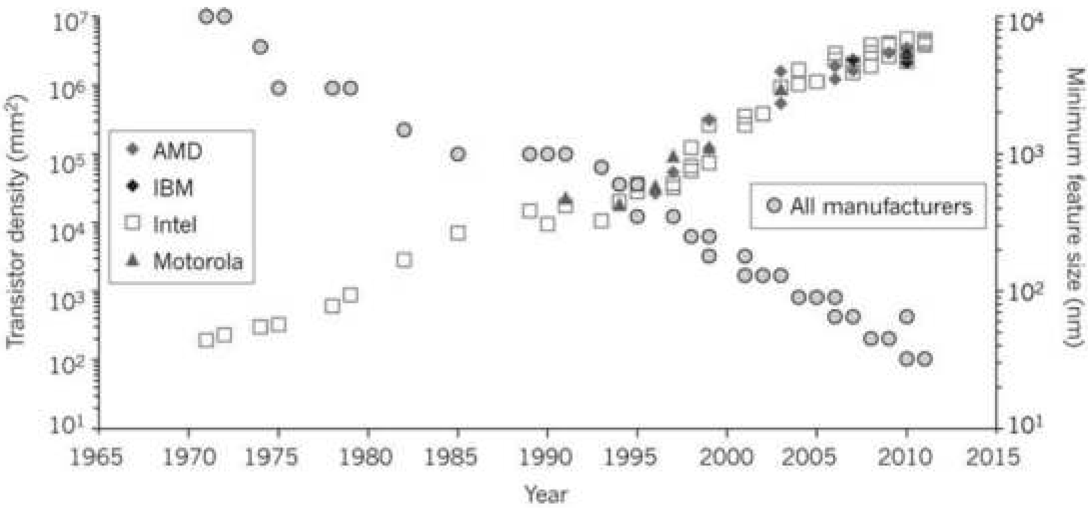
Figure 6: Exponential prediction of growth of components on integrated circuits



Source: *Moore*, 1965.

This law actually proved to be highly accurate for about 50 years, enabling enormous advances in computer technology. The size of the transistors, characterised by the so-called "gate length" or "feature size", halved approximately every two years, thus realising Moore's law. This inverted effect is visible in Figure 7 (Cf. *Ferain, C. A. Colinge, and J.-P. Colinge*, 2011).

Figure 7: Transistor density and gate length over time



Source: *Ferain et al.*, 2011.

In recent years, however, research has gradually come up against physical limits that are significantly restricting the further exponential growth in transistor density and the resulting growth in computing power. The minimum possible size of transistors is currently around 2 nm (Cf. *IBM Research*, 2021). At sizes of less than 3 nm (Cf. *Nawrocki*, 2010, p. 8), quantum mechanical tunnelling effects begin, in which electrons can move through the transistors even if they are "closed", which can lead to miscalculations or, in the worst case, system failure. Even though IBM has already undercut this limit, a slowdown in the decrease in "feature size" is clearly visible.

Three-dimensional chips, also known as 3D chips, could be a possible solution to overcome the limitations of Moore's law and "dramatically enhance chip performance" (*Topol et al.*, 2006). By stacking transistor layers vertically, a higher density and efficiency is achieved, opening a literal new dimension to chip manufacturing. However, these chips require innovative thermal solutions to efficiently dissipate the heat generated by the higher density, as well as new manufacturing processes. This technology has not yet been realised in any commercially available chip.

Quantum computing and superconductors are also seen as potential technologies to overcome the limitations of Moore's law. Quantum computers use the principles of quantum mechanics to perform computational operations that are inaccessible to classical computers, while superconductors use extremely low temperatures to reduce electrical resistance to near zero, maximising efficiency and minimising heat generation. This could make a thermal solution superfluous and significantly simplify the stacking of chips in the manner of a 3D chip.

Unfortunately, the highest known temperature at which a known superconductor can function at ambient pressure is only around 133 K (-140 °C) (Cf. *Drozdov et al.*, 2015, p. 73). This requires expensive and energy-intensive cooling techniques that currently limit their widespread use, whereby the disadvantages of this necessary cooling solution would significantly outweigh the benefits in practical computer applications.

On quantum computing, Arute et al. (2019) determined that quantum processors based on superconducting qubits are already capable of performing calculations that are simply inaccessible to classical supercomputers. This marks the beginning of "quantum supremacy", in which quantum computers solve tasks that are practically impossible for classical (super-)computers. This development could herald a new Moore's law for quantum processors, with computing power growing exponentially, having the potential to even surpass Moore's law in regard to classical computers. Despite these advances, significant improvements in quantum error correction are required to realise the theoretical benefits in practice. Nonetheless, quantum computing offers the potential to enable complex calculations that cannot be handled by conventional computers (Cf. *Arute et al.*, 2019).

Despite these seemingly impossible tasks, both superconductors and quantum computing represent realistic solutions for overcoming the limitations of Moore's law. Advances in materials science and engineering could enable higher operating temperatures for superconductors, while continued research and development in quantum computing could lead to more stable and powerful quantum processors. Both technologies have the potential to increase computing power and efficiency far beyond current limits, making them important areas of future research.

Continuing Moore's law is one of the most important challenges of our time to maintain the momentum of digitalisation, especially AI.

An AI model, be it ML, CV or LLM, is only as good as the data on which it is based. The quality and variety of data are critical to the performance and accuracy of a model. Data is the foundation that determines a models ability to learn and perform tasks, especially in edge cases that do not occur frequently. In order to develop a robust and reliable AI model, the underlying data must be diverse, of high quality and available in sufficient quantity. This ensures that the model not only works well in everyday situations, but also remains reliable in rare or unexpected cases. Data should therefore be representative of all possible scenarios that the model could encounter. The question of where this data originates from is equally important. Data can come from a variety of sources, including publicly available databases, proprietary data from companies or specialised data providers. However, sourcing and integrating this data can be challenging, especially when it comes to data privacy and legal considerations.

In a study, Sambasivan et al. (2021) investigated the immense importance of data quality in high-stakes AI applications. It was found that "data cascades", cumulative negative effects caused by data problems, are common and often avoidable. These problems arise from disregard for data quality in traditional AI and ML practices and lead to significant negative impacts on the development and deployment of AI models. The study shows that data work is often undervalued, while model development receives more recognition, leading to a lack of incentives for ensuring high data quality (Cf. *Sambasivan et al.*, 2021).

Such "data cascades" are, for example, data that lead an AI model to develop prejudices against precisely this data and thereby positively reinforce itself. They cause the AI becoming "blind" to other relevant data. The implications of these data cascades are far-reaching: they lead to limited generalisability of the models, increased distortions, unfair and unreliable predictions as well as costly and time-consuming corrections. In addition, the legal consequences of these data cascades can be severe, as biased or unfair predictions can lead to discrimination and violations of data protection and anti-discrimination laws. Companies could be held liable for the negative impact their flawed AI systems have on individuals or groups, which can lead to severe financial penalties (Cf. *R. A. Maydanyk, N. I. Maydanyk, and Velykanova*, 2021, p. 153).

The ultimate output of AI models, such as the predictions of predictive AI or the text output of NLP and LLM systems, is based on complex internal processes, often referred to as black box processes. The black box issue is one of the most demanding challenges in the field of AI. The term “black box” refers to the opaque nature of many modern AI models, especially deep neural networks, where the internal decision-making processes are difficult for humans to understand. The reason for this is that many algorithms of the learning process, such as the so-called “random forest” algorithm, are based on random numbers. This renders back-calculations impossible.

A major problem with the black box issue is that users and developers simply do not know exactly how an AI model developed a certain decision or prediction. This results in a lack of transparency and explainability, which can be particularly problematic in safety-critical applications such as medical diagnostics, autonomous driving or financial decisions (Cf. *Samek, Wiegand, and Müller*, 2017, p. 2). In addition, the underlying causes of possible systematic biases cannot be found and corrected without major effort. This could possibly require a completely new training of the model, which is accompanied by downtime and high costs.

Another, social, aspect of the black box problem is trust. If the internal processes of an AI system are not comprehensible or even look arbitrary, users struggle to place their trust in the results of the system. People, who are assessed on the basis of automated decisions, cannot find out why a loan was not granted, for example. The missing reason can significantly limit the acceptance and spread of AI technologies (Cf. *Lipton*, 2018, pp. 42–43).

To address this challenge, several approaches have emerged to improve the explainability and transparency of AI models. Explainable AI is a field of research that specialises in the development of methods to better understand and interpret the inner functioning of AI systems. Techniques such as LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations) provide tools to make the decision-making processes of models more transparent (Cf. *Ribeiro, Singh, and Guestrin*, 2016. Cf. *Lundberg and Lee*, 2017). In practice, these techniques have proven useful in various industries, particularly in healthcare for medical diagnosis, in finance for credit scoring and fraud detection, and in marketing for personalised advertising campaigns (Cf. *Lundberg, Erion, et al.*, 2019, p. 3).

3.2 Areas of application of AI in the consulting industry

AI has been an integral part of the services provided by many consulting companies for decades. The use of AI has continuously expanded and gained in importance.

Beyond general advice on predictive AI, Davenport (2018) describes how companies can utilise their existing analytical capabilities to facilitate the transition to AI. AI plays a particularly instrumental role in the area of predictive analysis, which is based on statistical models. ML and deep learning methods, which are fundamental forms of predictive analytics, enable organisations to make accurate predictions and decisions based on large amounts of data. By expanding their analytical expertise to include AI, companies can not only optimise internal processes, but also develop innovative products and services based on advanced predictive models (Cf. *T. H. Davenport*, 2018). Such projects and/or transformations require a great deal of specific and technical knowledge, which is generally sourced externally, for instance from consulting companies.

Devarajan (2019) describes the importance of AI in process automation and the development of Intelligent Process Automation (IPA). IPA, as an evolution of Robotic Process Automation (RPA), integrates AI and cognitive technologies such as ML, NLP and CV to automate complex, unstructured business processes that require human decision making. These advances enable more efficient and accurate automation of business processes. Consulting companies can support companies by helping to select and implement suitable technologies, conducting process analyses and providing training to ensure the effective use of the new systems (Cf. *Devarajan*, 2019).

For Customer Relationship Management (CRM), Ledro et al. (2022) identify three main sub-areas of AI: big data and CRM as a database, AI and ML techniques in CRM activities and the strategic management of AI-CRM integrations. AI is crucial for processing large amounts of data and improving CRM through personalised marketing measures, customer predictions and automation of customer interactions (Cf. *Ledro, Nosella, and Vinelli*, 2022). Consulting companies can provide support by advising companies on the selection and implementation of suitable AI and big data solutions for CRM, supporting the integration of new technologies into existing CRM systems and offering training to ensure that the new systems are used effectively and that the definded strategic goals in the area of CRM are achieved.

In the field of strategy and decision support, Basingab et al. (2024) investigate the optimisation of sensors for e-commerce and consumer electronics using AI. They show how AI-based decision-making systems can significantly improve energy efficiency and network performance. Al-Zubaidy et al. (2022) analyse the perspectives of stakeholders regarding the implementation of AI-supported clinical decision support systems in the healthcare sector. They revealed that the acceptance and utilisation of AI-supported systems are influenced by user needs, perceived usefulness and integration into existing workflows. Both studies were able to emphasise the importance of AI in improving decision-making processes and the ability to adapt to changing environments. Through its ability to analyse and process data, AI delivers deeper insight and optimised decision-making in diverse application areas. Consulting companies can support the implementation of such AI systems in specific areas such as e-commerce and healthcare. They offer expertise in analysing business processes and integrating AI technologies to develop customised solutions that meet companies' individual requirements. This specialised support enables companies to take full advantage of AI and achieve their strategic and operational goals more effectively (Cf. *Basingab et al.*, 2024. Cf. *Al-Zubaidy et al.*, 2022).

Bedi et al. (2020) look at the transformative impact of AI on risk management and compliance in different industries. The authors provide a non-technical overview of key AI strategies that are beneficial for risk management, such as automation of routine processes, advanced data analytics and ML. These strategies are applied in areas such as credit risk, market risk, organisational risk and compliance, and demonstrate AI's ability to increase efficiency, reduce human error and improve decision-making processes through big data processing and pattern recognition. The paper highlights several AI applications in risk management, such as RPA to automate repetitive tasks, NLP to analyse unstructured data and network analysis to identify relationships and potential risks. Despite these advances, the authors point to challenges such as the need for effective data management, accountability and a lack of the necessary skills within organisations. Consulting companies can play a decisive role in supporting companies integrate AI technologies into their risk management and compliance frameworks. They can offer expertise in selecting suitable AI tools, ensuring compliance with regulatory, legal and international standards and developing strategies for effective implementation and monitoring (Cf. *Bedi, Goyal, and Kumar*, 2020).

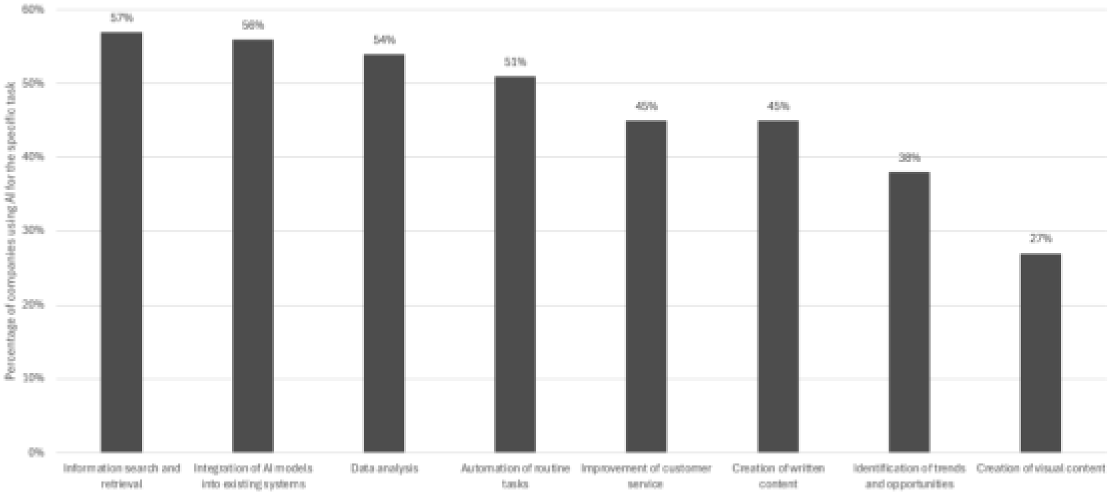
AI is also increasingly prominent in Human Resources (HR) and talent management by supporting and automating processes such as recruitment, compliance, training and onboarding. Achchab and Temsamani (2021) show that AI can help overcome many of the current challenges in HR, such as reducing manual tasks and improving decision-making through data-based analyses. AI technologies such as ML and RPA make it possible to process large amounts of data and recognise patterns, leading to more efficient and accurate HR processes. Consulting companies can play a crucial role here by helping companies to identify and implement suitable AI solutions. They can also ensure that AI applications comply with legal and data protection standards and organise employee training on how to use the new technologies effectively. By integrating AI into HR processes, companies can increase their efficiency, make better HR decisions and ultimately increase their competitiveness (Cf. *Achchab and Temsamani*, 2021).

The research by Wang et al. (2019) analyses the role of AI in product design: The ongoing development and widespread use of AI technologies is creating new opportunities for innovative product design. AI improves efficiency in the design process, fulfilling not only daily needs but also spiritual requirements through humanisation, intellectualisation and interactive experiences. The authors describe the concepts of AI, its application and development trends in the design field and offer theoretical and practical references for product design. The relevance of AI in innovation and product development is evident in several areas: AI is changing productivity and creating new production tools, integrating massive amounts of data to analyse public intentions and enabling real-time optimisation of design processes. AI can unleash creativity, increase design efficiency and humanise products. Consulting companies can assist with this by advising companies on the implementation of suitable AI solutions, providing training on the effective use of these technologies and ensuring that the applications comply with legal and ethical, and copyright standards. By integrating AI into product development, companies can significantly increase their innovative strength and competitiveness (Cf. *L. Wang, H.-C. Zhang, and Q. Wang*, 2019).

Aside from the benefits for the consulting company's clients, AI is also used internally within the consulting firms with great impact. Areas of application include increasing efficiency, improving knowledge management and innovation in consulting practice.

According to a survey by the Management Consultancies Association (2024) in the UK, AI systems are used in a variety of ways: The most common applications include information search and retrieval (57%), integration of AI models into existing systems (56%) and data analysis (54%). Automation of routine tasks is also widespread (51%), as is the improvement of customer service and the creation of written content (45% each). Other important areas of application are the identification of trends and opportunities (38%) and the creation of visual content (27%) (Cf. *Management Consultancies Association*, 2024). This data is shown in figure 8.

Figure 8: Use of AI by UK consulting companies



Source: Own representation based on data by MCA.

A key advantage of using AI is the automation of routine tasks. Technologies such as RPA can automate repetitive and time-consuming tasks, relieving consultants and minimising human error (Cf. *S. Liu*, 2022, p. 26). This allows consultants to focus on more value-adding activities that have a direct impact on the success of projects. The use of AI also leads to an improvement in decision-making. Consulting companies can analyse large amounts of data and gain valuable insights. ML and data mining make it possible to recognise patterns and trends that human analysts might overlook. This leads to more informed and faster decisions based on solid data analysis (Cf. *Rahmaty*, 2023, p. 14).

Another important area is knowledge management and utilisation. AI-supported knowledge management systems can organise and search large amounts of information. Systems based on NLP, or those building on LLM, facilitate access to important information (Cf. *Tharayil et al.*, 2024) and support consultants in answering client questions efficiently. This is proving particularly useful in strategy consulting, where customised solutions need to be developed for specific customer requirements. In addition, AI-supported systems can use the knowledge and experience of previous projects to provide personalised recommendations, which further increases the quality of consulting.

Customer interaction and satisfaction can also be significantly improved through the use of AI. AI-based chatbots and virtual assistants enable consulting companies to process customer inquiries around the clock and answer simple questions, arrange appointments and could even provide initial consulting approaches or provide references on similar projects. This increases customer satisfaction, relieves the burden on human consultants and can improve customer interactions. AI tools can also analyse large amounts of customer feedback and gain valuable insights. Sentiment analysis and text mining techniques can help to measure customer satisfaction and identify potential for improvement (Cf. *E. Kazia and B. Kazia*, 2023, p. 22).

Finally, AI contributes to knowledge generation and innovation. By analysing market data and customer requirements, consulting companies can develop new services and products that better meet customer needs. AI systems also support research and development by searching scientific literature and identifying new fields of research. The integration of AI into the innovation process makes it possible to implement creative ideas more efficiently and increase competitiveness.

This shows that consulting companies can also use the same AI systems that they offer their clients internally to achieve comparable effects. As a result, they benefit twice over: on the one hand, by improving their own efficiency and, on the other, through the added value they offer to their clients. This stresses the importance of technical expertise within consulting companies to ensure both the implementation and effective use of these technologies.

3.3 Potentials and challenges of AI

In order to fully understand the potentials and challenges of AI in the consulting industry, it is useful to conduct a PESTEL analysis. The PESTEL analysis, an extension of the STEP-Analysis, provides a structured approach to analyse the various external factors that influence the implementation and use of AI. This method takes into account political, economic, social, technological, environmental and legal aspects, all of which play an important role in the development and application of AI (Cf. *Aguilar*, 1967).

Political factors cover regulatory requirements and government initiatives to promote AI technologies, which set the framework for the use and development of AI. Economic factors relate to the general economic situation and the willingness of clients to invest in consulting services and how these factors influence the demand for AI solutions. Social factors relate to social acceptance and ethical considerations that play a role in the implementation of AI, particularly in relation to data protection and job security.

Technological factors refer to technological progress and the rate of innovation in the field of AI. The continuous further development of AI technologies is crucial for their possible applications and efficiency in consulting. Environmental factors may encompass sustainability requirements and the environmental impact of the technologies that need to be considered in the development and application of AI. Finally, legal factors consist of laws and regulations that govern the use of AI and the protection of data and ensure that AI technologies are used safely and ethically.

By conducting a PESTEL analysis, one can comprehensively analyse the various external factors. This analysis is necessary in order to make strategic decisions and take into account the challenges and opportunities associated with the application of AI (Cf. *Theodora Issa, Chang, and Tomayess Issa*, 2010, p. 3).

Political factors

Political factors play a key role in the implementation and development of AI in the consulting industry. The political landscape significantly influences the framework conditions under which companies can introduce and utilise AI technologies: Governments around the world are increasingly recognising the importance of AI and have developed various initiatives and strategies to promote the research and application of AI. For example, many countries are investing heavily in national AI strategies and offer financial incentives and support programmes for companies wishing to invest in AI (Cf. *Androshchuk*, 2023, p. 40).

Regulatory requirements and legislation also have a direct impact on the use of AI. Data protection laws such as the European General Data Protection Regulation (GDPR) set strict requirements for the handling of personal data, which plays a significant role in many AI applications. These laws require companies to implement strict security measures and ensure the transparency of their AI models in order to protect the privacy and rights of users (Cf. *European Parliament and Council of the European Union*, 2016).

Another political issue is the ethical dimension of AI. Governments and international organisations are increasingly discussing ethical guidelines and standards to ensure that AI is used fairly, transparently and responsibly. This includes aspects such as avoiding discrimination and ensuring that AI systems make decisions that are comprehensible and fair (Cf. *Ferrer et al.*, 2021, p. 76).

The geopolitical situation influences the development and implementation of AI on another political level. Trade disputes, particularly between major economic powers such as the USA and China, can influence access to important technologies and data. This is an especially relevant issue as semiconductor technologies from the Republic of China (Taiwan) are vital for computationally complex systems such as AI (Cf. *Bown*, 2020, pp. 377–378). Tensions such as these can affect supply chains and international collaboration in AI research and development.

It can therefore be argued that political factors play a fundamental role in influencing the implementation and utilisation of AI in the consulting industry. They determine not only the legal framework and ethical standards, but also the availability of funding and general political support for AI initiatives, as well as the general feasibility of AI.

Economic factors

Economic factors play a central role in the integration of AI in the consulting industry. Economic conditions and trends have a significant influence on companies' willingness to invest in AI technologies and the demand for corresponding consulting services. One important economic aspect is the expected growth of the global AI economy. According to a study by PwC, the contribution of AI to the global economy could increase to up to USD 15.7 trillion by 2030, which serves to emphasise the importance of AI as an economic driver (Cf. *PwC*, 2017, p. 3).

The cost of implementing and maintaining AI systems is another crucial factor.

While initial investments in AI technology and infrastructure can be significant, these investments promise long-term cost savings through automation and efficiency gains. Consulting companies offering AI solutions must therefore demonstrate the long-term economic benefits to their clients to ensure successful implementations.

Market conditions and the competitive situation also influence economic factors. Companies that invest in AI technologies early on and develop innovative solutions experience productivity increases and may even be able to secure competitive advantages and strengthen their market position (Cf. *Babina et al.*, 2023, p. 40). However, this requires careful analysis of market conditions as well as strategic planning and implementation of AI initiatives.

Looking at the bigger picture, the general economic situation also influences the propensity of companies to invest in new technologies. In times of economic uncertainty or recession, companies may reduce their spending, which could have a negative impact on the demand for AI services. On the other hand, in difficult economic times, AI can be seen as a means of reducing labour costs and increasing efficiency, which could boost demand for corresponding consulting services (Cf. *Chui, Manyika, and Miremadi*, 2016, pp. 2–3).

Accordingly, it can be concluded that economic factors have a decisive weight on the implementation and utilisation of AI in the consulting industry. The economic conditions, the cost-benefit analysis, the competitive situation and the general economic situation are crucial elements that influence the willingness of companies to invest in AI technologies.

Social factors

Social factors play a pioneering and decisive role in the implementation and acceptance of AI in the consulting industry. One of the most important social aspects is public perception and trust in AI technologies. In many areas that could be automated by AI, people expect contact with other people, not with machines (Cf. *Chui, Manyika, and Miremadi*, 2016, p. 3). Society's acceptance of AI significantly influences how quickly and to what extent AI solutions can be implemented in various areas, including consulting itself.

A further key social factor is the training and qualification of the workforce. The use of AI requires specialised knowledge and skills, which emphasises the need for further training and retraining of the workforce. Consulting companies must ensure that their employees have the necessary skills to work effectively with the AI technologies implemented (Cf. *Bughin et al.*, 2018, p. 49). This can be achieved through continuous training programmes and collaboration with academic institutions (Cf. *Gehlhaus and Koslosky*, 2022, pp. 30–32).

The impact of AI on employment is also a significant social factor. While AI technologies can automate certain tasks and thus replace jobs, new fields of work and roles requiring specialised skills are emerging at the same time. Consulting companies face the challenge of managing these changes and helping their clients realise the benefits of AI without neglecting the social impact. The elimination of jobs is particularly sensitive in countries with labour-friendly jurisdictions, and therefore needs to be carefully planned with the potential redeployment of workers (Cf. *Autor, Hazell, and Restrepo*, 2022, p. 337).

Social acceptance of data protection and ethical standards also occupies an important part. The broad acceptance of AI technologies depends heavily on how well these technologies respect data protection and adhere to ethical principles. Consulting companies must therefore promote transparent and ethical practices in order to gain the public's trust so that implemented systems are also accepted. Taken as a whole, it can be said that social factors are determining for the success of the integration of AI in the consulting industry. Public perception, the skills of the workforce, the impact on employment and compliance with data protection and ethical standards are all central considerations that need to be taken into account.

Technological factors

Technological factors are important for the introduction and use of AI in the consulting industry in the first place. The rapid development and innovation in the sphere of technology is creating new opportunities and challenges for consulting companies. The most important technological factor is the continuous development of AI algorithms and models. Advances in ML, deep learning and NLP make it possible to automate increasingly complex tasks and perform more precise analyses. These developments increase the efficiency and accuracy of consulting services and also open up completely new fields of application.

The availability and utilisation of big data is another key technological factor. Large amounts of data and powerful analysis tools enable consulting companies to gain detailed insights into market trends, customer behaviour and operational efficiency in the first place. The ability to analyse data in real time and make recommendations based on it gives companies a competitive advantage. In addition, generative AI such as ChatGPT relies on large amounts of data, the so-called "training data".

The availability and quality of such data sets enable the development of ever better models, both for generative and predictive AI.

Technological infrastructure and computing power also play a more enabling role. Advances in cloud computing technology make it possible to process large amounts of data efficiently and train AI models. As a result, consulting companies can offer scalable and cost-effective solutions based on the latest technological standards without having to install hardware on site at their clients' premises. The price stability and scalability of cloud computing is therefore essential for implementation (Cf. *Armbrust et al.*, 2010, pp. 57–58). The integration of AI into existing IT systems and processes represents a further technological challenge (Cf. *Abouelyazid and Xiang*, 2019, p. 16). Consulting companies must ensure that their IT infrastructure is compatible with modern AI technologies and enables seamless integration. This requires investment in IT architecture and continuous adaptation to technological developments.

Since technology in the sense of deep learning as well as computing capacity is the backbone of AI, every AI solution stands and falls with this very technology.

Environmental factors

Environmental factors are becoming increasingly relevant to the consulting industry with the growing relevance of the "E" of ESG criteria, including in the context of AI implementation. These factors include a variety of aspects that can influence both the development and application of AI technologies. One of the most serious environmental factors is the sustainable development and ecological footprint of AI systems. The energy consumption of data centres where AI models are trained and operated is considerable. This can have a significant environmental impact, especially if the underlying power grid is based on fossil fuels. For example, training large AI models such as GPT-3 and GPT-4 requires enormous computing resources, resulting in high energy consumption, estimated at 10 GWh for GPT-3, with an estimated 1 GWh per day for queries (Cf. *McQuate*, 2023). Consulting companies must therefore develop solutions that are both efficient and environmentally friendly in order to meet the increasing demands for sustainability.

Compliance with legal and regulatory requirements in the area of environmental protection poses another important aspect. Companies worldwide are increasingly legally obliged to comply with environmental standards and promote sustainable practices. This also applies to the use of AI, where it is important to implement environmentally friendly technologies and methods in order to fulfil legal requirements. In addition, public perception and awareness of environmental issues plays an important role. Companies that actively strive for sustainable practices and minimise their environmental impact can improve their reputation and competitiveness. This is especially true for consulting companies that pioneer the use of AI and help their clients implement environmentally friendly solutions. Environmental factors influence not only business management and regulatory compliance, but also public perception and the long-term sustainability of consulting companies and their clients.

Legal factors

In addition to political factors, legal factors play a second, external role in the implementation and use of AI in the consulting industry. These factors include legal provisions and regulatory requirements that companies must observe in order to avoid legal consequences and ensure that their business activities comply with the law.

One key aspect is data protection and data security. With the introduction of the GDPR in the European Union in 2018, strict rules on the protection of personal data were introduced (Cf. *European Parliament and Council of the European Union*, 2016). Consulting companies that use AI technologies must ensure that they comply with these regulations in order to avoid significant fines and reputational damage; this applies in particular to the processing and storage of large amounts of data, which is essential for AI models. Another important issue is ethical guidelines and the avoidance of discrimination by AI systems. Regulatory authorities worldwide are increasingly advocating for ethical standards in AI development to ensure that AI systems are fair and unbiased. Companies must ensure that their AI models do not produce discriminatory results and adhere to ethical guidelines (Cf. *Modi*, 2023, p. 31).

There are also industry-specific regulations that may be relevant for consulting companies. In the financial sector, for example, there are specific regulations that govern the use of AI for trading and advisory services. These regulations are designed to ensure that AI systems are transparent and traceable to ensure client confidence (Cf. *Financial Industry Regulatory Authority*, 2020).

Another upcoming significant legal framework is the planned EU AI Act, which aims to create standardised regulations for the development and application of AI in the European Union (Cf. *European Parliament and Council of the European Union*, 2021). This draft law classifies AI systems according to their risk and sets strict requirements for high-risk applications to ensure the safety and protection of fundamental rights. This means that consulting companies using AI solutions in highly regulated areas such as healthcare or transport must adhere to strict regulations to ensure compliance with the EU AI Act. In the United States, stricter guidelines have also been imposed on federal agencies per executive order, which has far-reaching implications for them and any consulting companies that may be advising them (Cf. *Biden*, 2023).

The legal framework for AI is constantly evolving and companies need to stay up to date to ensure that they comply with all relevant laws and regulations. This requires continuous monitoring and adaptation of internal processes to prevent legal risks and maximise the benefits of AI technologies. For consulting service providers, on the other hand, this opens up the opportunity to advise their clients on the constantly changing legal conditions involved.

The PESTEL analysis shows that although AI as an overall field is already well established, it must face new regulations such as the EU AI Act, especially in the current era with the development of high-capacity LLMs. In addition, research into such models is cutting-edge and is expected to continue to make great progress in the coming years. The impact of AI on society in the coming years will also have a huge impact on the adoption of AI-based solutions, just as the sustainability of AI solutions will have an impact on environmental friendliness. Skilfully manoeuvring through these multifaceted, confusing, and sometimes still unknown issues will require a lot of planning, and will make hiring consultants for these services even more attractive.

3.4 Current state of AI in the consulting industry

As already shown, AI has been an integral part of the services offered by numerous consulting firms for a number of years. Its use has continued to expand and grow in importance with technological advances. Knowledge of the current state of AI use in the consulting industry is therefore of key importance in order to understand the latest developments and trends and to better assess future opportunities and challenges.

The global AI consulting market size was USD 5,506.08 million in 2022 and is expected to reach USD 45,632.36 million by 2031, growing at a CAGR of 26.49%. This remarkable growth is driven by the increasing demand for sophisticated AI solutions across various industries. AI consultants play a distinct role in helping organisations increase operational efficiency. At the heart of the development of the AI consulting market is constant investment in research and development, aimed at refining AI algorithms, improving predictive analytics and providing innovative solutions tailored to specific industry needs. The growth of the market is driven by the continuous efforts to realise the full potential of AI and provide companies with strategic insights and practical applications to navigate the complexities of the modern business environment. The COVID-19 pandemic has also had a major impact on the AI consulting market. While the initial phases of the pandemic led to project delays and uncertainty in client investments, the later phase saw an acceleration in the adoption of AI solutions to address evolving business challenges. The increased reliance on digital transformation and the need for data-driven decision making during remote working phases have fueled the demand for AI consulting services. Overall, the impact of the pandemic on the AI consulting market can be considered positive as organisations increasingly relied on AI solutions to address the complexities caused by the pandemic, which ultimately drove growth in the sector (Cf. *Business Research Insights*, 2024).

The key players in the AI-based consulting services market are some of the largest and most renowned consulting firms in the world.

Accenture sees itself as a leader in designing technology-driven solutions that recognise the human element. Accenture realises that technology is becoming increasingly human, opening up new ways to unleash human potential, productivity and creativity. In its "Technology Vision 2024" report, Accenture emphasises that companies that embrace these technologies now will win in the future. The development of AI, which simulates human-like thinking and behaviour, as well as new technologies such as spatial computing, offer far-reaching opportunities to shape digital change and expand access to knowledge. Accenture understands that the future technological landscape is forcing organisations to fundamentally rethink their strategies. Generative AI and other emerging technologies are changing not only how data is used, but also how organisations are structured and operated. The introduction of AI agents that can make decisions and act autonomously is seen as the next stage of digital transformation. Accenture emphasises the need to look at these developments not only from a technological perspective, but also to integrate human values and ethical aspects in order to create a sustainable and trustworthy technological ecosystem (Cf. *Accenture*, 2024).

Deloitte regards itself as a pioneer in the design of human-machine collaborations and underlines the need to go beyond pure automation and develop hybrid systems in which human and machine capabilities complement each other. Deloitte sees that the integration of AI technologies should not only be used to reduce costs, but also to create more value for customers and create more meaningful jobs for employees. Rather than viewing AI simply as a means to automate tasks, Deloitte suggests using the capabilities of computers to augment human skills. This perspective makes it possible to design systems in which humans and machines work collaboratively, complementing each other's strengths and compensating for weaknesses. Deloitte calls these hybrid systems "superminds" and sees them as a way of designing the workplace of the future that creates both economic value and offers employees more fulfilling work (Cf. *Guszcza and Schwartz*, 2020).

McKinsey & Company, and its AI division, QuantumBlack, is a leading consulting company that combines comprehensive research, in-depth analysis and strategic advice with the implementation of best practices to help companies make effective use of AI. McKinsey recognises that a clear vision and strategy for AI, the full support and commitment of senior leadership, and significant investment in talent and technology are critical to generating significant value from AI initiatives. In addition, McKinsey emphasises the importance of a holistic approach where companies build a structured end-to-end platform for data science, data engineering and application development. This includes developing and adapting AI solutions in-house and running training programmes to increase the overall analytical understanding within the organisation. McKinsey stresses that these practices enable organisations to effectively scale AI initiatives and create real business value.

In addition, McKinsey places great focus on mitigating risks associated with AI, in particular by increasing the transparency and traceability of AI models to promote their acceptance and trust. They also place value on partnerships and creating an ecosystem around AI to continuously benefit from new developments and innovations. McKinsey sees itself as a frontrunner in helping companies realise the full potential of AI and achieve sustainable success through a combination of in-depth knowledge, strategic thinking and practical implementation (Cf. *Balakrishnan et al.*, 2020).

IBM also views itself as a field pioneer in AI, continuously driving innovation to facilitate the integration and use of AI in companies. IBM Watson, an AI system that first became known for winning the “Jeopardy!” challenge (Cf. *Best*, 2013), laid the foundation for the research and application of AI in various industries. With the development of watsonx, an advanced generative AI and ML, IBM now offers a comprehensive solution that enables organisations to train, adapt and deploy a broad field of AI models. IBM acknowledges that the evolution of Watson to the watsonx platform is critical to help organisations train, adapt and deploy AI models. This platform includes core components such as watsonx.ai, watsonx.data and watsonx.governance, which together provide a comprehensive solution suite for managing AI workflows. By providing tools such as the watsonx Assistant and the watsonx Code Assistant, IBM empowers companies to use AI-supported virtual agents and programming recommendations without extensive prior knowledge. This will accelerate digital transformation and significantly increase companies’ productivity and ability to innovate (Cf. *IBM Watson*, 2024).

Current trends in the competitive landscape show an increased collaboration between consulting companys and technology companies. These partnerships allow consulting companies to utilise cutting-edge AI technologies and develop customised solutions for their clients. Consulting companies bring their expertise in project management and industry-specific knowledge, while technology companies provide advanced technological capabilities such as AI and ML. This synergy results in an acceleration of implementation through innovative and effective solutions tailored to client needs. The growing demand for AI-driven solutions across various industries is met through these collaborations, ensuring that AI implementations are strategically aligned and deliver tangible business value (Cf. *Vial et al.*, 2023, pp. 670–671).

4 Critical analysis and discussion

This chapter will first present the key literature from recent years to create a theoretical context and to illustrate the current state of research. This the key to contextualise the developments and changes in the consulting industry through the use of AI. The key statements from this literature are then summarised. This summary serves to highlight the most important findings and trends that form the basis for further analyses.

The next segment of the chapter presents the research design, in particular the interviews conducted. These interviews are crucial as they provide direct insights from professionals from leading consulting companies, illuminating the practical implications and challenges of AI integration in the industry. This is followed by the formulation of the research question. This research question serves as the baseline for the detailed analysis that follows.

The key findings from the interviews are subsequently presented to highlight the different perspectives and experiences of the experts. These points provide invaluable information on how AI is used in practice and what changes and challenges are associated with it. The research question is critically analysed in an extended discussion. This discussion is essential to test the validity of the answer to the research question and to comprehensively analyse the various aspects of AI integration in the consulting industry. Ethical and social implications as well as regulatory challenges are also considered here.

Finally, the limitations of the study and recommendations for future research are discussed. This is relevant to place the findings in a broader context and to show what further research is needed to further enhance the understanding of the impact of AI in the consulting industry.

4.1 Current research on AI in the consulting industry

The following pages provide a thorough analysis of the available literature and highlight significant research gaps. The chapter examines how AI can transform the consulting industry, the ethical challenges involved and how human expertise and AI can be optimally integrated. These parts are of great importance to understand how AI will transform the consulting practice and what new business models could emerge. This aids to better anticipate future developments and develop effective strategies for the implementation of AI in consulting. Moreover, it is important to mention publications that cover a broader range of topics to promote a deeper understanding of the diverse aspects and challenges associated with the introduction of AI in the consulting industry. By incorporating research from related fields, valuable insights are gained and it can be ensured that the analysis is built on a broad and sound knowledge base. This aids to make informed decisions, make transferable conclusions and develop best practices for the integration of AI in consulting.

4.1.1 Literature overview and Research gaps

The following literature review will look at multiple selected publications that deal with the effects and applications of AI. The focus is on the objectives, methods and analysed aspects of the respective studies in order to provide an insight into the working methods of each study. The main information is then provided in table 1.

In “Artificial Intelligence’s Impact of the Management Consultancy Sector over the Next Five Years”, Oarue-Itseuwa (2024) examines the impending impact of AI on the consulting sector over the next five years. The article provides a historical overview of technological innovations and their societal impact and highlights the current landscape of management consulting. Oarue-Itseuwa focuses on the potential changes AI could bring to the consulting industry by looking closely at the development and implementation of AI technologies that could revolutionise the sector (Cf. *Oarue-Itseuwa*, 2024).

Gîngută et al. (2023) explore the ethical challenges and risks of AI technologies in business consulting in “Ethical Impacts, Risks and Challenges of Artificial Intelligence Technologies in Business Consulting: A New Modelling Approach Based on Structural Equations”. They use a structural equation model based on data collected through a comprehensive survey of 98 business consultants. This survey aimed to capture and analyse the perceived ethical risks and professional characteristics of the consultants (Cf. *Gînguță et al.*, 2023).

In “The Future of Competitive Intelligence in an AI-enabled World”, Hoffman and Freyn (2019) analyse the impact of big data and AI on the field of competitive intelligence. They examine how these technologies are changing the role of the human analyst and how competitive intelligence can remain relevant through the integration of AI and big data. The authors draw on a detailed analysis of current trends and developments in competitive intelligence and examine the potential benefits and challenges posed by the introduction of AI (Cf. *Hoffman and Freyn*, 2019).

In “Agency and AI in Consulting: Pathways to Prioritise Agency-Enhancing Automations”, Cemaloglu, Chia and Tam (2019) explore how ethnographic methods can be used to improve human agency at work through AI and automation. Through ethnographic studies in three different consulting companies, they isolate the decisions of human agents in different case studies and identify ways in which automations can harness the potential to improve the agency of individuals. Their methodology includes participant observation and unstructured interviews that allow for in-depth analysis of work processes (Cf. *Cemaloglu, Chia, and Tam*, 2019).

Klemmer et al. (2024) explore the use of AI assistants in secure software development in “Using AI Assistants in Software Development: A Qualitative Study on Security Practices and Concerns”. They conducted 27 semi-structured interviews with software experts, including software engineers, team leaders and security testers. Additionally, they analyse 190 relevant Reddit posts and comments to gain insights into the current discussion about AI assistants for software development. This qualitative research aims to capture developers’ security practices and concerns when using AI assistants (Cf. *Klemmer et al.*, 2024).

Vial et al. (2023) explore the challenges and strategies of managing AI projects in “Managing artificial intelligence projects: Key insights from an AI consulting firm”. They conduct a comprehensive case study at a North American AI consulting company and analyse the internal logics and conflicts that drive the work. By conducting detailed interviews and observations, they identify the different approaches of traditional project management, agile methods and AI workflow practices and develop practical strategies to overcome the resulting conflicts (Cf. *Vial et al.*, 2023).

In “Artificial Intelligence (AI) Transformation Leadership Consulting Framework”, F. Murtza and A. Murtza (2023) develop a framework to support companies in the implementation of AI technologies. They examine the technological transformation and the necessary adaptation of business processes, corporate culture and customer experience. Their framework consists of five phases that enable the systematic implementation and continuous improvement of AI solutions. The authors use extensive literature research and practical case studies to develop a structured and practice-orientated framework (Cf. *F. Murtza and A. Murtza*, 2023).

In his publication “AI in Consulting” (2019), Bayati analyses the application of AI in consulting. Based on extensive research and an expert interview with a consultant from Ernst & Young, he analyses the current applications and future prospects of AI in consulting. The work includes a theoretical introduction to the different types of consulting and the specific applications of AI in different consulting contexts. Bayati sheds light on the selective application of AI and the need for further empirical studies on the broader implementation and long-term impact of AI in consulting (Cf. *Bayati*, 2019).

In their paper “AI enabled Business Process Optimisation and Digital Marketing”, Abdulla and Hussain (2024) review the role of AI in optimising business processes and improving digital marketing strategies. They analyse different AI methods to illuminate their advantages and disadvantages in the business context. The focus is on the application of AI to personalise marketing content and improve customer loyalty through AI-supported tools such as chatbots and predictive analytics (Cf. *Abdulla and Hussain*, 2024).

Fern et al. (2024) explore the development of AI solutions for agriculture in the article “AgAID Institute-AI for Agricultural Labor and Decision Support”. TThey identify challenges in the field of special crops and develops methods for optimising agricultural processes through the use of AI. The research focuses on improving work processes, farm operations and water management through the application of advanced AI technologies (Cf. *Fern et al.*, 2024).

In their paper “Personalized Interiors at Scale: Leveraging AI for Efficient and Customizable Design Solutions”, Zhou and Wang (2024) examine the application of AI in the field of interior design. They use AI to generate images in order to optimise and personalise the design process. The authors describe a method for the efficient creation of customised interiors and evaluate its effectiveness through experimental results and case studies (Cf. *Zhou and T. Wang*, 2024).

The paper “Transformative Potential of AI in Healthcare” by Bekbolatova et al. (2024) looks at the use of AI in healthcare. Through extensive research and expert interviews, it analyses current applications and future prospects of AI in medicine (Cf. *Bekbolatova et al.*, 2024).

The publication by Özkan and Sasani (2023) “Discussion on the Artificial Intelligence (AI) Tools Usage in the Scientific World” discusses the role of AI tools in scientific research. They accentuate the benefits of AI in tasks such as literature searches and data analysis, but warn of risks such as false references and misinterpretation. A particular concern is the uncontrolled citation of AI models such as ChatGPT as co-authors, as they cannot fulfil authorship requirements (Cf. *Özkan and Sasani*, 2023).

The paper by Shanmugapriya and Amaleshwari (2024) "Barriers and Enablers in Integrating AI into Human Resource Management Strategies: Maximising Human Capital" analyses the barriers and enablers in integrating AI into HR management. It uses qualitative research with an abductive approach and identifies positive factors such as collaborative employees, strong digital leadership and reliable HR data as well as barriers such as lack of emotional decision-making skills and ineffective digital experts. The aim is to promote the use of AI to maximise human capital (Cf. *R. Shanmugapriya*, 2024).

The publication "Integrating Mental Workload Management in Advanced Human-Machine Interaction: the Development Process of the Proof-Of-Concept to Refine the Concept" by Nenni (2024) explores the impact of automation on workload and develops a proof-of-concept for an AI-based tool for real-time workload assessment and management. The methodology is based on design thinking and involves the collection of subjective and objective data. The aim is to develop strategies for optimising human-machine collaboration in automated environments (Cf. *Nenni*, 2024).

In their paper titled "Artificial Intelligence and Knowledge Management: Impacts, Benefits, and Implementation" Hamed and Madanchian (2023) critically review how AI can support knowledge management in organisations. By analysing studies over ten years, the authors explore how AI technologies can address the gaps in traditional knowledge management processes. The review identifies the benefits of integrating AI into knowledge management, such as enhancing knowledge sharing, capturing, and problem-solving (Cf. *Taherdoost and Madanchian*, 2023).

In "AI and Knowledge Management Orchestration Implementation in Today's Business," Wulansari and Prabandari (2024) also examine how AI and knowledge management are being integrated to optimise operations and enhance competitiveness in modern businesses. Using a theory review method, they analyze existing literature and viewpoints on the implementation of AI and knowledge management (Cf. *Wulansari and Prabandari*, 2024).

Table 1: Overview of literature

Author(s)	Year	Title	Journal	Research method
Oarue-Itseuwa	2024	Artificial Intelligence's Impact of the Management Consultancy Sector over the Next Five Years	Management Consulting Journal	Qualitative
Gîngută et al.	2023	Ethical Impacts, Risks and Challenges of Artificial Intelligence Technologies in Business Consulting: A New Modelling Approach Based on Structural Equations	Electronics	Quantitative
Hoffman and Freyn	2019	The Future of Competitive Intelligence in an AI-enabled World	International Journal of Value Chain Management	Qualitative
Cemaloglu, Chia and Tam	2019	Agency and AI in Consulting: Pathways to Prioritise Agency-Enhancing Automations	Ethnographic Praxis in Industry Conference Proceedings	Qualitative
Klemmer et al.	2024	Using AI Assistants in Software Development: A Qualitative Study on Security Practices and Concerns	-	Qualitative
Viel et al.	2023	Managing artificial intelligence projects: Key insights from an AI consulting firm	Information Systems Journal	Qualitative

F. Murtza and A. Murtza	2023	Artificial Intelligence (AI) Transformation Leadership Consulting Framework	International Journal of Management Studies and Social Science Research	Based on qualitative methods
Bayati	2019	AI in Consulting	-	Qualitative
Abdulla and Hussain	2024	AI enabled Business Process Optimization and Digital Marketing	IATMSI 2024	Quantitative
Fern et al.	2024	AgAID Institute—AI for agricultural labor and decision support	AI Magazine	Quantitative
Zhou and Wang	2024	Personalized Interiors at Scale: Leveraging AI for Efficient and Customizable Design Solutions	-	Quantitative
Bekbolatova et al.	2024	Transformative Potential of AI in Healthcare	Healthcare	Qualitative
Özkan and Sasani	2023	Discussion on the Artificial Intelligence (AI) Tools Usage in the Scientific World	European Journal of Therapeutics	Qualitative
Shanmugapriya and Amaleshwari	2024	Barriers and Enablers in Integrating AI into Human Resource Management Strategies: Maximizing Human Capital	European Economic Letters	Qualitative
Nenni	2024	Integrating Mental Workload Management in Advanced Human-Machine Interaction: the Development Process of the Proof-Of-Concept to Refine the Concept	HORA 2024	Mixed

Hamed and Madanchian	2023	Artificial Intelligence and Knowledge Management: Impacts, Benefits, and Implementation	Computers	Qualitative
Wulansari and Prabandari	2024	AI and Knowledge Management Orchestration Implementation in Today's Business	International Journal of Business Innovation, Economics and Social Science	Qualitative

Source: Own representation

From this broad overview of diverse publications, it is clear that research on AI in consulting covers a wide range of topics, technological transformations to practical applications and methodological innovations. The publications offer multifaceted insights into the complex interactions between AI technologies and the consulting industry, and which research approaches are being utilised. Despite the extensive research, several common and individual research gaps emerge that future research should address:

One of the biggest common research gaps concerns the long-term impact of AI on the consulting sector. Both Oarue-Itseuwa (2024) and Bayati (2019) focus on the immediate impact of AI, but both emphasise the need for further research into the long-term changes and adaptations in the consulting industry. It remains unclear how the consulting landscape will change in the near future and what new roles and business models will emerge as a result of AI (Cf. *Oarue-Itseuwa*, 2024. Cf. *Bayati*, 2019).

Another important area that requires further research is ethical challenges and how to overcome them. Gînguță et al. (2023) identify ethical risks such as discrimination, data protection violations and social isolation. Accurately identifying and mitigating these risks remains a major challenge. There is a need for studies that investigate how consulting firms can effectively implement and monitor ethical standards and policies to minimise these risks (Cf. *Gînguță et al.*, 2023).

The integration of AI and human expertise is also an area that requires further investigation. Hoffman and Freyn (2019) as well as Cemaloglu et al. (2019) address the role of the human analyst and the preservation of employees' ability to act. There is a need for further studies on the optimal integration of AI and human expertise. This raises the question of how hybrid models that utilise both AI and human intelligence can be designed and implemented to achieve the best results (Cf. *Hoffman and Freyn*, 2019. Cf. *Cemaloglu, Chia, and Tam*, 2019).

There are also individual research gaps that relate to specific aspects of AI application in management consulting. Oarue-Itseuwa (2024) addresses the expected emergence of specialised, AI-driven consulting firms, but it remains unclear what this market segmentation will look like in concrete terms and what specific niches might emerge. Further research could investigate which industries and business areas will benefit most from this segmentation (Cf. *Oarue-Itseuwa*, 2024).

Altogether, all the papers analysed show that AI has the potential to profoundly change consulting. Long-term implications, ethical challenges and the integration of AI and human expertise remain key research topics. Specific gaps in market segmentation, methodological innovation and the broader empirical application of AI in consulting require further investigation. Future research ought to address these gaps in order to develop a comprehensive understanding of the role of AI in consulting and provide practice-orientated solutions to the identified challenges.

4.1.2 Key findings from recent studies

The publications analysed provide detailed insights into the diverse effects and applications of AI in the field of consulting. The key findings and main results of these studies are presented and discussed here.

In his paper, Oarue-Itseuwa (2024) predicts significant changes in the consulting indsutry due to the introduction of AI. He emphasises that AI-driven analyses and insights will push consultants into the role of data interpreters and strategists. This requires an upskilling in AI and data-related competences. In addition, Oarue-Itseuwa expects the emergence of specialised, AI-driven consulting companies that focus on niche areas, which will deepen market segmentation. Technology companies specialising in AI could enter the consulting sector and intensify competition. The use of AI could also lead to a change in pricing structures, moving away from time-based models towards success-based or value-based models. Oarue-Itseuwa also points out the importance of ethical considerations and compliance with data protection regulations, as the increasing use of AI brings with it new ethical challenges (Cf. *Oarue-Itseuwa*, 2024).

In their study, Gînguta et al. (2023) identify a positive correlation between the perceived ethical challenges and the negative effects of AI. The ethical risks include discrimination, violation of privacy, denial of individual autonomy, unreliable results and social isolation. These risks have a negative impact on the willingness to implement AI in management consulting in the future. Gînguta et al. emphasise that management consultants are less willing to delegate tasks to AI systems or invest in such technologies if they perceive significant ethical risks. This suggests that successful implementation of AI requires careful consideration and mitigation of ethical risks (Cf. *Gînguță et al.*, 2023).

Hoffman and Freyn (2019) argue in their article that AI and big data will not make the role of the human analyst redundant, but will transform it. AI-supported analyses enable the processing of large amounts of data and offer deeper insights, but the interpretation and strategic application of this data remains a central task of the human analyst. Hoffman and Freyn see the future of competitive intelligence in a hybrid model where AI and human analysts work together to capitalise on the strengths of both approaches (Cf. *Hoffman and Freyn*, 2019).

Abdulla and Hussain (2024) show how important it is to integrate AI into business processes. This is also and especially possible when business partners use automation, e.g. to better organise supply chains and support production planning (Cf. *Abdulla and Hussain*, 2024). Fern et al. (2024) and Zhou and Wang (2024), on the other hand, clearly show how fundamentally different the approaches are to developing AI solutions in different industries. Not only do the products and technologies differ, but also the basic steps in problem identification (Cf. *Fern et al.*, 2024. Cf. *Zhou and T. Wang*, 2024). It is not possible to create and market a universal solution for AI. Instead, the needs of companies must be assessed according to their environment and weighed up with a great deal of professional expertise.

Bekbolatova et al. (2024) and Ozkan and Sasani (2023) show that the automation of trivial and repetitive tasks in various fields makes perfect sense if the results are used responsibly. The fact that these statements come from the fields of medicine and scientific research also makes it clear that AI has established itself in fields that are otherwise highly sceptical about the transfer away from human expertise. Both sources place great value on the benefits of AI in their respective fields (Cf. *Bekbolatova et al.*, 2024. Cf. *Özkan and Sasani*, 2023).

Both Hamed and Madanchian (2023) and Wulansari and Prabandari (2024) highlight the value of knowledge databases. Although there are technical, social, and privacy issues, the benefits exceed the effort required to create such a system. The synergy of LLMs, which excel in the interaction with natural language, and the poorly indexable knowledge that is stored in said natural language, is of great value to companies (Cf. *Taherdoost and Madanchian*, 2023, pp. 4–9. Cf. *Wulansari and Prabandari*, 2024, pp. 55–56).

The publications together provide a bigger picture; the introduction of AI will significantly change the consulting sector. AI will take everyday tasks out of the hands of consultants, allowing them to concentrate on more value-adding tasks. In addition, the introduction of knowledge databases is inevitable. In the relationship with his clients, the consultant of the future will offer highly specialised solutions to give his clients a competitive advantage.

4.2 Methodology and research question

The coming pages offer a detailed consideration of the research design and the formulation of research question for this thesis. The focus is placed on the necessity of a qualitative research method in order to close some of the aforementioned research gaps. In addition, the importance of involving leading consulting companies and their experts is emphasised in order to gain well-founded and practical insights. The chapter on research design explains how qualitative interviews were conducted with experts from the largest consulting companies to gain deeper insights into the practical application and perception of AI in the consulting industry.

In the formulation of the research quest, a central questiom about the transformative power of high-performance generative AI and its impact on the consulting industry is presented. This research question serves as the basis for investigating how AI technologies can not only increase the efficiency and quality of consulting services, but also transform entire industries. These chapters are essential to understand the methodological foundations of the work and to recognise the theoretical questions underlying the study. They provide the framework for the subsequent analysis and discussion of the research findings and help to clarify the relevance and potential impact of AI implementation in the consulting industry.

4.2.1 Research design

The reseach design of this thesis builds on the reseach gap that more empirical, qualitative research methods are needed to draw conclusions about AI in the consulting industry. Bayati (2022) states that a "paper could be more credible if interviews are conducted with at least 2 [from one] more experts to ascertain the findings and eliminate the bias factor from the equation" (*Bayati*, 2019, p. 33). Shahid and Lee (2019) proceed in exactly the same way by inviting exactly ten participants and asking them several open questions, with the possibility of asking follow-up questions based on the answer (Cf. *Shahid and Li*, 2019, p. 29) This results in a framework of two to ten people, whereby the implication of Bayati (2022) is to interview as many different perspectives in different companies.

On this basis, experts were invited for interviews whose curriculum vitae proved them to be capable of providing the overall picture needed for this thesis. Experts from the ten largest and best-known companies were selected and invited:

- McKinsey & Company
- Boston Consulting Group
- Bain & Company
- Deloitte
- PricewaterhouseCoopers
- Ernst & Young
- KPMG
- Accenture
- Capgemini
- IBM

In total, over 50 contact attempts to different experts were made using various methods, including contact with the public relations departments. These contact attempts ultimately resulted in five interviews.

Table 2 shows the participants, their company and their role. For respondents who asked to remain anonymous, their role and company have been redacted and their name pseudonymised.

Table 2: Company, name, and role of the interviewees

Company	Name	Role
KPMG Germany	Tobias Mertes	Manager, head of AI taskforce
Bain & Company	Allan Dieguez	Director, data science
IBM	Wolfgang Hildesheim	Head of IBM Watson
[redacted]	John Doe (pseudonymised)	[redacted]
Capgemini	Mutaz Al Awamleh	Lead of Artificial Intelligence

Source: Own representation

Participants were asked the following main questions, which were designed so that follow-up questions could be asked based on the answer:

1. Can you please briefly describe your professional background and your current role at [company]?
2. What role does artificial intelligence play in your daily work?
3. Can you describe a current project in which AI plays a central role?
4. How has artificial intelligence been perceived in your company or industry in the past?
5. How has the perception and use of AI developed in recent years?
6. What types of AI do you mainly use in your projects?
7. In your opinion, how has the consulting industry changed through the use of AI?
8. What future developments and trends in AI do you see for the consulting industry?
9. What are the biggest challenges when implementing AI in consulting projects?
10. What opportunities do you see for consulting firms and their clients through the use of AI?
11. Is there anything else you would like to add or that we haven't discussed so far?

The interviews were transcribed and can be found in the appendix. The interviews were conducted in English; if requested or pragmatic, the interview was conducted in German and then translated.

4.2.2 Research question formulation

Research question

Is high-performance generative AI leading to a new industrial revolution, enabling consulting companies to transform entire industries and themselves through cost-efficient and value-adding use of AI?

The introduction of LLMs such as GPT-3 and GPT-4 has triggered a paradigmatic shift in the perception and use of AI. While specialised applications such as chess computers have demonstrated the power of AI in the past, they were too specific to illustrate the broad potential of AI (Cf. *Bali and Nayak*, 2020, pp. 1–2). LLMs, on the other hand, have shown that AI systems are capable of solving the problem of accomplishing tasks that require human-like communication and understanding, which has long been the ultimate goal of human-machine interaction (Cf. *Makhoul et al.*, 1989, pp. 463–464). This has led many people and companies to realise the real capabilities and the potential of AI.

Examples such as the AI model "humanornot.ai" by AI21 Labs, and specialised GPT-4 variants can pass almost 50% of Turing tests (Cf. *Jones and Bergen*, 2024), and the ubiquitous use of generative AI for image, sound, video and text production, underline this development. These technologies have proven that AI can perform not only specialised tasks, but also creative and communicative activities. These realisations are acting as a catalyst for a digital revolution that is having a profound impact on the consulting industry in particular. Consulting companies are now challenged to transform entire industries and guide their clients through this revolution, while having to apply the same processes internally to remain competitive in their own industry. Companies that fail to embrace this transformation risk losing profitability and ultimately disappearing from the market (Cf. *Schrettenbrunnner*, 2020).

LLMs therefore have the potential to fundamentally change the way consulting firms work and the services they offer. By using LLMs, the consulting industry can significantly increase its efficiency and quality, develop innovative solutions and better adapt to the needs of clients. Therefore, the reseacrh question can be derived: "Is high-performance generative AI leading to a new industrial revolution, enabling consulting companies to transform entire industries and themselves through cost-efficient and value-adding use of AI?"

4.3 Research results

The results of the interviews are analysed qualitatively in the following. The aim is to present the results objectively so as to reach conclusions. In order to avoid subjective results, a structuring content analysis is used. The implementation is described step by step, and then the results are presented openly and proposals for further action are given.

4.3.1 Presentation and examination of the collected data

Conducting the interviews generated large amounts of data, which must be analysed in more detail using a suitable procedure. Specific answers must be filtered out of the individual answers to the questions and summarised on the basis of agreement with other interviewees. To implement this, a qualitative content analysis according to Mayring was chosen. Mayring describes the rough procedure of a qualitative content analysis with the following steps (Cf. *Mayring*, 2000).

Determination of the material

The first step is to decide on a specific source of information. In this case, these are transcribed interviews. The material was created during interviews via the platform Microsoft Teams, on which the interview was recorded for later evaluation and transcription. The participants consented to these recordings and subsequent processing. The interviews were conducted with the partner alone. The direction of the questions, AI in consulting, was known. The context of this thesis was also made clear. The questions themselves were not made available in advance.

The available video material was then transcribed. The transcription was simplified. Slips of the tongue, stutters and pauses were removed, as they have no influence on the content of the statements. The transcripts and, if necessary, translations can be found in the appendix.

Direction of the analysis

The direction of the analysis describes the specific aim of the analysis. In this case, the aim of the analysis is the text itself, its factual statement. The questions during the interview are designed for precisely this analysis.

Form of the analysis

The form of analysis chosen was the structuring content analysis. Mayring's structuring content analysis is the best choice because it offers a systematic and theoretically sound method for analysing interviews in a targeted way. This method makes it possible to develop and apply clear categories, which ensures a high degree of precision and comparability of the results. The structured approach allows large amounts of data to be analysed efficiently, patterns and correlations to be identified and the central statements to be worked out. This leads to a valid and comprehensible analysis that provides substantiated findings.

Categorisation

The category system is formed inductively, from the material itself. This is done in the following.

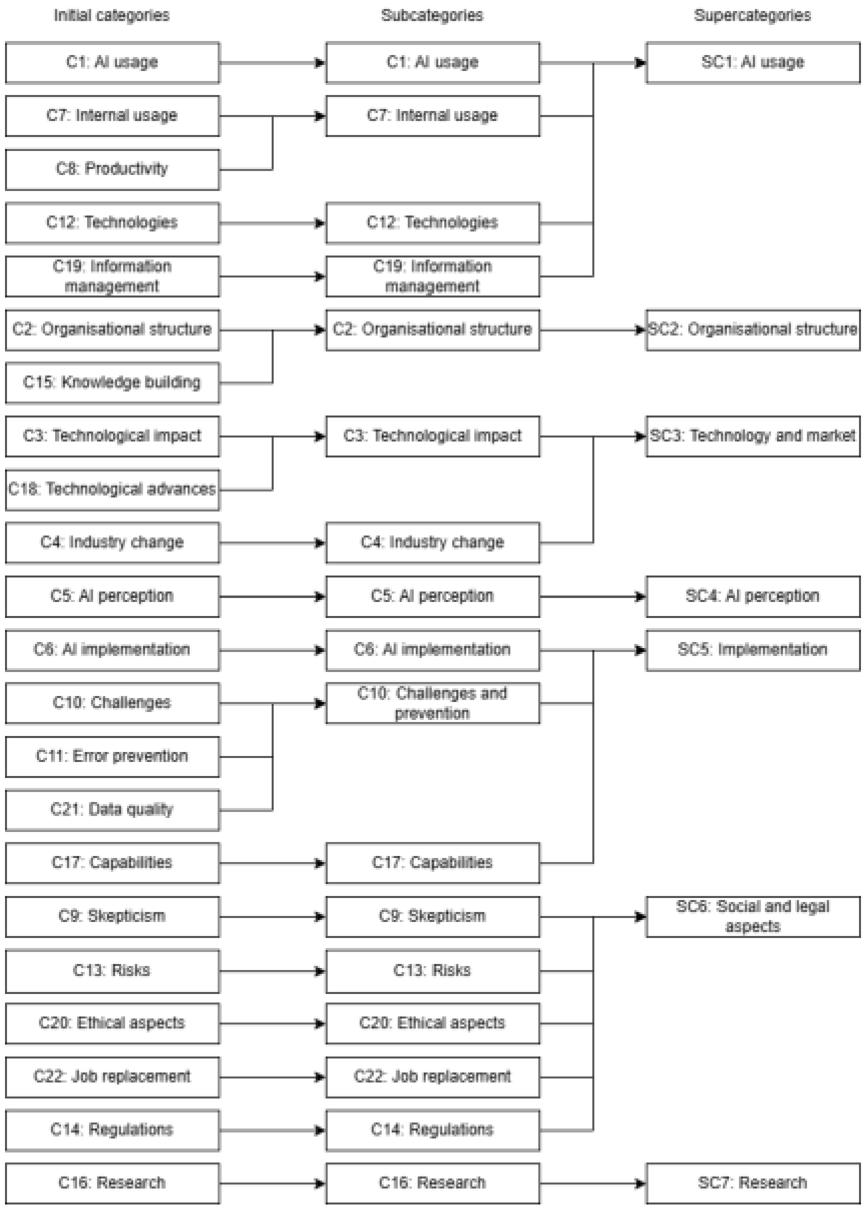
First, the unit of analysis is defined. The unit of analysis is defined as a paragraph of the transcribed interview. This approach is appropriate because logically coherent statements are often expressed in several dependent sentences. This ensures that logical units do not flow into different categories, but can be coded and categorised appropriately. The paragraphs are labelled in the interview material. The number of the paragraph is given in square brackets in front of it.

The first step is paraphrasing. The purpose of is to condense each unit of analysis and eliminate unnecessary information. Paraphrasing is followed by a further level of abstraction, generalisation. Two levels of abstraction are performed if the material is too complex in terms of content, which is the case here. The second level of abstraction is followed by open coding. Here, each paraphrased and generalised unit of analysis is assigned a code that can be used to categorise this statement later.

Once finalised, these codes are first transferred into categories, whereby these are kept concise and non-redundant. These categories are then transferred into a hierarchical category system consisting of supercategories and subcategories. A recombination of similar categories results in the final categorisation, which can be seen in figure 9. The coding of the paraphrased and generalised material is included in the supplementary material.

On the basis of this categorisation, a coding guide was drawn up, which distinguishes categories according to their characteristics, and provides rules and examples for each category. This categorisation guide is also included with the supplementary material.

Figure 9: Result of the inductive categorisation according to Mayring

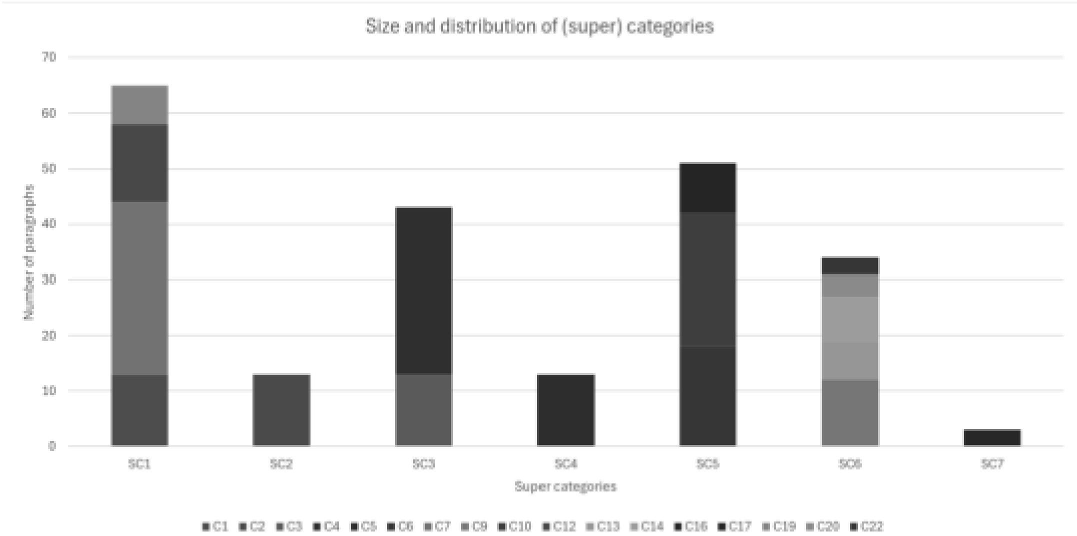


Source: Own representation based on transcripts.

With the help of this guide, the material was recoded, with all relevant text passages now being assigned to one of the categories. The recoding then serves to check the generated categories against the material and ensure that they actually reflect the essential content. Since each paragraph could be assigned to a category, the categorisation guide can be accepted as complete. An overview of the recoding is also included with the supplementary material. Figure 10 visualises the size and composition of the resulting supercategories.

The collected material is now categorised and can be analysed in a structured way in the next step.

Figure 10: Size of supercategories after recoding



Source: Own representation based on transcripts and recoding.

To ensure the quality criteria, all steps and results were documented and made available with full transparency. As further criteria require longer-term observation and repeated execution of the research method by other individuals, further quality criteria cannot be applied. The research methodology cannot be fully applied in the time allotted.

4.3.2 Results analysis

Next is the presentation of the analysed data. For this purpose, each supercategory is analysed, and within the supercategory each subcategory and each characteristic. The purpose is to be able to present the data in a structured way and to show which data was extracted in order to provide an objective picture of the volume of information. After the presentation of the data, recommendations for action are given. The supercategory on research is not dealt with here, as it is outside the scope of the thesis.

AI usage

AI technology has already been used in various areas, including in portfolio management and to support investment decisions. Projects involved the automation of price validations, which led to significant cost savings. This demonstrates that AI has already been used to optimise business processes and increase efficiency. At present, AI is being used in many different areas. One recent case in point is the implementation of a GPT-based AI in a large South American bank, replacing an IBM Watson-based AI. AI is also being used in book publishing for translations and text generation. Another innovative project involves reading out patents using generative models. These applications show the diversity and progress of the current use of AI in various industries.

The future of AI holds the prospect of significant changes. Particularly relevant are conversational robots and chatbots, which will become more intelligent and context-aware thanks to fine-tuned models and specific customer information. This will make interaction with systems easier and more efficient. In addition, the consulting and document industries are predicted to change dramatically over the next five years. These developments point to a future world of work that will be strongly characterised by AI. There are differences in views on the implementation and benefits of AI in different industries. One paragraph emphasises the difficulty of making general statements, as the use of AI depends heavily on the industry in question. This highlights that the actual benefits and challenges of AI can vary depending on the industry.

A key feature of the internal use of AI in consulting is the elimination of trivial tasks by AI. Several quotes point out how AI tools help to take over routine tasks that previously took a lot of time. One example is the shortening and designing of presentation slides, which significantly reduces working time and allows consultants to focus on more challenging tasks. These savings lead to an increase in efficiency and allow consultants to utilise their intellectual and empathetic skills to a greater extent. However, it remains unclear to what extent these tools can be used equally effectively in all areas and for all employees, as the introduction and acceptance of AI tools varies from company to company.

On the other hand, the automation of complex tasks is another feature under discussion. Statements show how advanced AI systems are already able to perform complex analyses, such as tax or balance sheet analyses. This automation allows advisors to move away from performing these tasks directly and instead monitor and interpret the results. However, this change requires consultants to adapt their skills as they increasingly need to be able to use and understand these tools. A common theme is that the quality and reliability of automated systems must be continuously improved in order to realise the full benefits and gain the trust of users.

A further key aspect are the AI tools developed internally. Many consulting companies develop their own solutions to fulfil specific internal requirements. Examples include systems that analyse internal documents and extract relevant information to support decision-making. These internal tools are often better customised to the specific needs and data of companies than generic AI solutions. Nevertheless, there are challenges in implementing and operating these systems, particularly in terms of integrating them into existing workflows and continuously adapting them to meet new demands.

Furthermore, the participants emphasised the importance of collaboration between humans and machines. Rather than viewing AI systems as a replacement for human advisors, it is suggested that these systems serve as a complement to enhance consultants' capabilities and make their work more efficient. This collaboration is seen as key to maximising productivity and improving the quality of consulting services. However, there are also concerns about the control and transparency of AI systems, suggesting that full automation without human oversight is not currently realistic or desirable.

In terms of technologies, ML takes a central role. A wide range ML and AI libraries are used to realise various projects, including IBM's watsonx platform, which combines open source software and tested enterprise software. The diversity and flexibility of the technologies used are emphasised, with no contradictions between the statements. The development of AI is strongly driven by the use of open source libraries, the continuous innovation and integration of new technologies is crucial. As another technology, CV is used in a wide range of applications, from fashion analysis to urban graffiti monitoring. The technology provides more accurate results than text-based methods and increases efficiency through automation. The examples complement each other and illustrate the versatility and effectiveness of CV.

The category of information management was discussed in the context of consulting companies in particular. A recurring issue is the challenge of accessing the immense amount of knowledge within a company and utilising it effectively. It is repeatedly mentioned that companies have an enormous amount of implicit and explicit knowledge that is often decentralised and difficult to access. Modern technologies are depicted as promising solutions to overcome this challenge. These technologies make it possible to ask human questions and get relevant answers from a large amount of data, which can significantly increase the efficiency and effectiveness of knowledge management. There is some contradiction in the perception of the current use and effectiveness of information management tools. Some statements centre on the fact that large consulting firms such as McKinsey or Boston Consulting already have extensive databases and successfully use AI tools to extract relevant information quickly. However, other statements suggest that it is still very difficult to harmonise knowledge within a company and make it accessible, despite considerable effort and energy invested in these processes.

As shown in chapter 4.1, AI is an essential tool for optimising business processes, both internally and externally, for instance with business partners (Cf. *Abdulla and Hussain*, 2024). It also became apparent that it is not possible to create a universal solution for AI and that different industries require different AI solutions, as they have to solve fundamentally different problems (Cf. *Fern et al.*, 2024. Cf. *Zhou and T. Wang*, 2024). Companies must find solutions that are designed for their target sector(s) in order to gain a competitive advantage.

The transfer of trivial and repetitive tasks to AI has also been demonstrated several times and in various areas, such as medicine (Cf. *Bekbolatova et al.*, 2024) or scientific research itself (Cf. *Özkan and Sasani*, 2023). The collaboration between humans and machines was likewise discussed. The harmonious partnership as a precursor to efficient AI integration was shown to be seminal (Cf. *R. Shanmugapriya*, 2024, p. 1862). It is important to note that incorrect integrations of automation can actually worsen the efficiency of human operators (Cf. *Nenni*, 2024, p. 1).

Knowledge management has also been addressed and it has been shown that the automation of knowledge databases using AI offers considerable advantages that go far beyond a standard database (Cf. *Taherdoost and Madanchian*, 2023, pp. 4–9).

Even if a potentially high initial effort can be associated with the deployment, the advantages can clearly outweigh these (Cf. *Wulansari and Prabandari*, 2024, pp. 55–56).

In summary, the following recommendations for action can be derived, which are shown in table 3:

Companies should invest in the further development and adaptation of AI technologies in order to optimise their processes and remain competitive. Industry-specific solutions are necessary to address individual needs. Companies must prepare for the profound changes brought about by AI in the coming years.

Consulting firms should continue to invest in the development and improvement of AI tools to eliminate routine tasks and automate complex analyses. It is important to involve employees in the process of introducing and using these tools and to train them accordingly. At the same time, collaboration between man and machine should be encouraged in order to maximise the benefits for both sides.

A further clear recommendation for action is the implementation and utilisation of internal knowledge databases supported by AI. These databases should allow specific questions to be asked and precise answers to be obtained quickly, significantly improving the efficiency of information searches. Such a database should function like an internal Wikipedia that is easily accessible and searchable.

Table 3: Proposals on the usage of AI

Research result	Recommendation for action
There is no standard solution for all AI problems. These are highly industry-dependent.	Companies must focus on industry-specific AI solutions in order to be competitive in these industries.
Automating routine tasks is essential in order to prioritise tasks that require a higher level of intellectual capacity.	Companies should identify which tasks are repetitive and trivial and can be usefully replaced by AI, and then implement this.
It is important to introduce automation through AI in a targeted manner to the workforce in order to achieve a positive outcome.	Companies should engage with their workforce and introduce AI automation together with them to minimise negative side effects.

Knowledge databases are an important tool for effectively utilising and exploiting company data.	Companies should identify their knowledge resources and develop solutions to be able to query them in a language interface.

Source: Own representation

Organisational structure

In terms of organisational structure, it is clear that companies are increasingly receiving enquiries about AI and therefore need to structure themselves better in order to meet this demand. They need to position themselves better to operate more efficiently both internally and externally. It is clear that it is not just about having technological expertise, but also the ability to apply it quickly and in a structured way. There is a general consensus that AI tools will increasingly contribute to increasing efficiency in various consulting processes.

In the area of outsourcing and nearshoring, it is discussed that many pure consulting companies are more expensive than traditional IT service providers and can only remain competitive if certain services are outsourced. Nearshoring and offshoring are seen as solutions to reduce daily rates and thus remain competitive. This proves that economic considerations play a central role in the decision-making process, especially when it comes to implementing IT solutions.

However, companies are faced with the challenge of attracting highly skilled AI developers who are more likely to go to tech giants such as Google or Facebook than into consulting when raising their own talent. It is noted that the consulting industry increasingly expects technical skills from its employees, with coding skills and an understanding of generative AI emphasised as valuable qualifications. The statements show a clear trend: from few technical experts in consulting firms a few years ago to a higher proportion of technicians today. This suggests a significant change in the requirements profile, with technical knowledge increasingly seen as essential.

The corporate culture is crucial to how successfully new technologies and methods are integrated. It is recognised that employees need to be motivated and empowered to apply new technologies and understand their importance to the business. The shift from providing consulting services to a greater emphasis on technical implementation and integration shows that organisations must not only develop strategies, but also be able to implement them effectively. This requires a culture of continuous learning and adaptation.

It is of importance that companies adapt to new levels of digitalisation with the help of any necessary restructuring (Cf. *Cherednyk*, 2023, pp. 365–367). Bottlenecks and duplicate structures should be avoided. In addition, the implementation of other automation products has shown that a good corporate culture has a positive influence on their acceptance (Cf. *Perkasa and Fardinal*, 2021, pp. 402–403).

As listed in table 4, it is therefore recommended that companies adapt their internal structure for future eras of automation through AI in order to avoid duplicate and parallel structures in which departments work independently on the same AI solutions. Furthermore, companies should orientate their corporate culture towards AI in order to attract better talent and create a culture of innovation and progress.

Table 4: Proposals on organisational structure

Research result	Recommendation for action
The internal structure should adapt to the change in the relevance of AI in order to position the company more efficiently and responsively	Companies must face the new reality of AI through good internal structuring in order to remain competitive and responsive.
Companies that live a culture with AI and in the spirit of progress will attract more and better talent.	Companies should incorporate AI as part of their corporate culture and work together with their organisation to advance it.

Source: Own representation

Technology and market

In terms of technological impact, the introduction of new technologies has triggered significant change in recent years. ChatGPT has brought a high level of dynamism to the AI landscape that was previously barely present. Now there are more and more tenders targeting AI implementations and the demand for natural human-computer interactions is growing. Despite the potential of AI, some experts believe that the promised revolution has not yet fully materialised. There is uncertainty about the long-term social impact, such as the reduction of the labour force through automation.

Technological advances, particularly through faster GPUs, enable efficient and unprecedented training of LLMs. Specialised algorithms offer further increases in performance, while deep neural networks improve data processing. Technological development shows that despite physical limitations, there are still ways to increase the performance of computers, such as through the increased use of parallelisation, and the possible future in quantum computing.

AI projects have evolved from generic and exploratory approaches to more specialised applications as the sector has changed. Enquiries and tenders have become more extensive and more specific, particularly in the field of generative AI. In the past, mainly fundamental techniques were used; today, advanced methods such as neural networks and image processing are common. This development shows a stronger commercialisation and specialisation of AI projects: AI is now a central component of many company strategies. Consulting companies are not only using AI to optimise internal processes, but also as a sales argument. This requires an adaptation of corporate structures and greater integration of AI teams. Employees should work in a more creative and problem-orientated way in order to meet the requirements of the AI-supported working world.

AI is generally recognised as an industrial revolution and is changing the requirements for various industries. Companies must adapt to the new opportunities and increasingly focus on collaboration and knowledge sharing. Traditional consulting companies could shrink or face specialisation. AI allows for more efficient work processes and offers opportunities for higher profits and market share. Nevertheless, there is a risk that some companies and jobs will be lost.

The recommendations for action are that companies must face up to the reality that AI will make up a larger part of the consulting services market in the future. Companies should invest in technology to adapt to the changing market and consult their existing clients in the new facets of the industrial revolution. According to the experts, the progress made in AI technology in recent years will not stop, and companies that do not embrace this progress could see their existence threatened. These recommendations are listed in table 5.

Table 5: Proposals on technology and market

Research result	Recommendation for action
Tenders and requests for AI projects will take up a larger share of the consulting market in the future.	Companies must position themselves in the field of AI in order to protect their share of the market

The new industrial revolution requires consulting companies to be technically well educated in order to be able to advise their clients to the best of their knowledge.	Consulting companies must acquire technical expertise and capitalise on this expertise.
Progress in AI technology is not expected to slow down	Consulting companies must realise this progress and adapt to the new situation in order not to be pushed out of the market.

Source: Own representation

AI perception

The development of access to AI shows a clear change. In the past, the implementation of AI in companies was difficult for decision-makers to conceive of and seemed to have no practical use. This changed with the advent of free online tools such as ChatGPT, which revolutionised accessibility to AI. Today, even non-experts can easily interact with AI, which was previously a significant hurdle. This democratisation of technology has led to companies recognising the benefits of AI, particularly in terms of faster and more accurate information retrieval and closing knowledge gaps.

The perception of AI has changed considerably through the observation and use of AI technologies such as ChatGPT. In the past, AI was often seen as a gimmick or a nice extra feature that had no significant business relevance. Today, companies and society in general recognise the real added value of AI applications. However, there is also a risk of overheating expectations, as a comparison with the Gartner Hype Cycle shows. This hype can lead to unrealistic expectations, which could later result in a phase of disillusionment.

It is clear that in many cases a simplification or abstraction of the technology is necessary to demonstrate its true value. The implementation of AI is often hindered by complex technical requirements and long documentation processes. The transition from older systems to more modern technologies shows the challenges and the enormous effort involved. It is therefore important to make AI more understandable and accessible in the business environment in order to promote its acceptance and application.

Since in the past AI was mostly seen as unnecessary or an expensive gimmick with no real business value, companies felt no urgency to invest large sums in AI as the benefits were not obvious. This previous perception has changed drastically as the practical benefits of AI are now much clearer and more tangible. This shows how much attitudes towards AI have changed, from scepticism of real, measurable benefits to recognition of its importance. The current perception of AI is divided: On the one hand, there are high hopes and positive expectations about the possibilities of AI, while on the other hand there are also fears and uncertainties about its impact. This ambivalent attitude shows that society is still in the process of developing a balanced understanding of the role and potential of AI. The current hype around AI, as with ChatGPT, reflects both the enthusiasm and the caution associated with new technologies.

Even if the democratisation of AI has had far-reaching consequences in terms of the way it is viewed, it is still important to abstract the technology for potential clients in order to be able to demonstrate the actual benefits. Companies should have realistic expectations of the technology, and consultancies should communicate this in exactly the same way. They need to help their clients not to invest in technology on the upswing of a hype that may turn out to be futile before it is even ready for use. These recommendations are shown in table 6.

Table 6: Proposals on AI perception

Research result	Recommendation for action
The democratisation of AI allows far more people to see the benefits of AI.	Consulting companies must help their clients to use this new technology in a way that actually adds value.
AI is presumably at the peak of a hype cycle.	Clients must be advised by their consultants to the best of their knowledge and judgement not to invest in possible soon-to-be-obtuse technology.

Source: Own representation

AI implementation

Several major challenges arise during implementation. Identifying use cases for AI is critical: many companies have difficulty recognising suitable use cases. Often, automation processes rather than real AI applications are identified. Consulting services help companies to find real AI use cases and integrate them into workflows.

One problem is that internally developed use cases often do not progress beyond prototype status and are not utilised in day-to-day business. Strategically, it is recommended to first analyse the available data and manual processes before developing AI applications. This analysis helps to identify areas in which automation and AI make sense. Moreover, the use of AI should not only be embedded as a technical project, but as an integral part of the entire organisation. This requires a rethink and a possible realignment of some aspects of the company as a whole. It is also recommended to combine the use of AI tools to create a more comprehensive system.

While AI technology is often easily available from major players such as Microsoft and OpenAI, implementation fails due to practical hurdles such as integration into workflows and technical difficulties in transferring prototypes into productive systems. Besides the technology of the model itself, the data is most important, the quality of the data is crucial for success, because the quality of the data is decisive for the performance of AI models. It has been emphasised that poor or unfiltered data can lead to inaccurate or inappropriate results. Furthermore, testing AI models is a significant challenge as there are no standardised processes. Since the input of LLMs is natural language, there are virtually an infinite number of test cases. In addition, the dynamic and rapidly changing nature of AI requires flexible and adaptive test methods.

In the category of challenges and error prevention, the difficulty of measuring the success of generative AI was a recurring theme. One statement describes the challenge of quantifying the benefits of generative AI in daily use, for example how often and to what extent it is used. It is clear here that success is often perceived subjectively and concrete metrics are lacking. Some statements emphasise the importance of monitoring and correcting AI outputs. It was described how important it is to humanly check the results of AI systems and correct them if necessary in order to avoid wrong decisions.

Several statements addressed the technical challenges, particularly in conservative sectors such as banks, which often have outdated systems and a complex internal organisation. Switching to more modern technologies is described as necessary but difficult. It is mentioned how these old and sometimes incompatible information processing systems can hinder work. Companies that have neglected their digital infrastructure or have not standardised for new purposes face more hurdles to using AI in a valuable way.

A central conflict can be seen in human interaction. While AI is capable of taking over many technical tasks, interpersonal communication remains an area in which AI cannot currently compete. One statement emphasises that human skills such as reading between the lines, understanding emotions and internal political dynamics remain pivotal. These skills are what make a good consultant and cannot yet be replaced by AI.

It is recommended that AI applications are developed in close coordination with the actual needs and working conditions of users. Consulting companies should support their clients in ensuring that the use cases developed are sustainably integrated into everyday working life. In order to evaluate the effectiveness of models, companies should develop clear KPIs to better assess the benefits and efficiency of generative AI. This allows the benefits of different systems to be evaluated independently. It is also advisable to implement strict data quality standards and ensure that only high-quality, verified data is fed into AI systems. To keep information that should not leave an AI system in check, one recommendation is to implement "ringfencing" techniques to ensure that confidential information can only be viewed by authorised persons. In use cases where AI output touches on critical processes, a multi-level review system should be implemented in which humans cross-check the output. Another recommendation is to establish a dedicated test team that continuously develops and adapts new test strategies to meet changing requirements. An overview of all these recommendations is listed in table 7.

Table 7: Proposals on AI implementation

Research result	Recommendation for action
Use cases are hard to find and develop into actual products.	Consulting companies should set up competence centres that strategically find use cases for their clients.
The success of (generative) AI models is difficult to measure.	The creation of KPIs should be used to compare and evaluate AI models.
Data quality can significantly weaken AI models if the data is of poor quality.	Consulting companies should advise their clients on the acquisition of data, and work with them to develop guidelines to keep data quality high.
It is difficult to suppress unwanted information output from LLMs.	Consulting companies should advise on the use of "ringfencing", among other things, to protect the data of their clients from unauthorised access.

In critical applications, unchecked output from AI could lead to serious effects.	The use of human overview as part of a multi-level review system can prevent this outcome.

Source: Own representation

Social and legal aspects

Points of scepticism include scepticism about the accuracy of the data provided by AI systems, which is frequently encountered. Hallucinations and false outputs are often pointed out, which are particularly problematic in areas such as consulting. The lack of verifiability and traceability of AI decisions reinforces this scepticism, as users are not sure whether information is correct. Many people remain sceptical about the way AI works, which is reinforced by a lack of transparency and traceability. There is also a general reluctance to embrace new technologies. Human habits are a major obstacle to the acceptance and use of AI. Several statements show that people often cling to established ways of working and are reluctant to adopt new technologies. The initial learning process and the slowdown caused by new tools mean that people quickly revert to their usual methods if the AI does not immediately deliver the desired results.

In the area of risk identification, it is clear that internally generated content through AI does not initially have a negative impact as long as potential pitfalls are recognised and eliminated. This minimises the need for proactive risk management that not only identifies potential problems, but also develops strategies to mitigate risks. Several aspects are addressed under the risk of improper use. It is emphasised that when using generative AI systems such as ChatGPT, there is a risk of content being recognised as machine-generated. This can be problematic both internally and externally. It also emphasises the risk of generated content being copied verbatim, which is not in line with professional standards.

Data security is another key concern. The analyses show widespread concern about data protection and information leaks. One participant describes that the biggest challenge at the moment is uncertainty about the handling of data by AI providers such as OpenAI. It is unclear whether the data is used for further AI training, made publicly available or stored securely on the servers. The risk of data leaks is described as particularly unpleasant and frequent, which serves to highlight the importance of strict data protection measures. The analysis shows that all participants have a strong focus on ethical responsibility when dealing with AI. The statements address the need to thoroughly check AI tools before they are released in order to minimise social risks and possible injustices. It is emphasised that AI is a “black box” for many people, which can lead to fear and mistrust. Transparency and understanding are therefore essential to increase acceptance and trust in AI technologies.

The analysed statements on the fear of job losses show that employees fear being replaced by AI, especially for routine tasks such as writing reports. This fear leads to resistance within organisations. At the same time, it is pointed out that AI can complement the skills of skilled workers. Therefore, it is important that employees upskill and use AI as a tool to remain competitive.

The introduction of regulations such as the EU AI Act is seen as an opportunity for consulting companies, as it allows them to tap into new areas of consulting. This creates more points of contact with clients and thus opens up new business opportunities. Regulation also offers the opportunity to achieve competitive advantages through targeted consulting and adjustments to the regulations. The development of regulation is seen as necessary, but there are considerable uncertainties and challenges. It is recognised that the current regulatory landscape is not yet fully developed and that it is difficult to define clear guidelines, particularly in complex areas such as copyright law in connection with AI. The need for technical and precise drafting of laws is emphasised in order to maintain control over AI developments.

Another point that is discussed is the cultural dependency of regulation. Social and cultural values strongly influence how strict or liberal the laws are. This is illustrated in the context of biometric data and its use in the EU compared to China. There is a clear cultural discrepancy in the acceptance and handling of surveillance technologies. The goal of regulation, as formulated in the EU AI Act, is based on European values and aims to find a balance between progress and ethical standards. Protection against misuse, particularly through the manipulation of information and the creation of fake news, is cited as one of the main motivations for regulation. It is recognised that AI technologies have the potential to undermine democratic processes with the creation of realistic-looking fake news, which reinforces the need for clear and effective regulation.

Recommendations for action include improving the transparency and verifiability of AI decisions in order to strengthen user confidence. To this effect, employees who use AI should be trained in how it works and what the wrong outputs of AI might look like. In addition, AI should be presented as a tool to support and improve work and not as a replacement for employees. Employees should be able to use AI in such a way that they have more capacity for tasks that are less trivial. In order to protect the company's data, employees should also be informed that they are not allowed to use freely available AI models for their work, as it cannot be ensured that the employees' input remains confidential. Consultancy firms should also position themselves to benefit from the regulations by selling products and service approaches that are compliant with the new guidelines. All of these recommendations for action are listed in table 8.

Table 8: Proposals on social and legal aspects

Research result	Recommendation for action
Some employees do not trust the results of AI models.	Employees should be trained in how to deal with the results and how they are generated. This makes them less likely to be perceived as random.
Employees with repetitive and trivial tasks resist the introduction of AI as they could be replaced.	These employees should be trained to use AI so that they can take care of automation as experts and at the same time take on more complex tasks. This requires further training, for example.
Employees use external AI models for their work.	It must be ensured that no internal company data is transferred to external tools. This could happen through instructions, training or site blocking.
AI will be the target of complex regulations in the future.	Consulting companies should take advantage of this to consult their clients in the context of new regulations and develop products and services that comply with these regulations.

Source: Own representation

4.4 Critical Discussion of AI in the consulting industry

This section examines the extent to which literature consistent with the interview findings can support or refute the research question. The main points include the transformative power of powerful LLMs, the industrial revolution brought about by AI, the ability of AI to change entire industries and the resulting cost-reducing and value-enhancing effects of AI. The important regulatory and social issues that ground this revolution are then examined in order to create a coherent picture. These points correspond to the fragmented research question as its partial research questions, whereby the research question itself can be better analysed using the principle of “divide and conquer”.

4.4.1 Implications for consulting practices

The interview partners unanimously emphasised the transformative power of powerful LLMs such as GPT-3 and GPT-4. It was described how the introduction of ChatGPT brought a new dynamic to the AI task force and significantly increased the demand for AI-based solutions. Further it was argued, that GPT-based systems enabled the development of complex AI applications that go beyond traditional analysis methods, while it was emphasised that the GPT series have revolutionised the perception of AI by making it accessible to the general public. The momentum of GPT-3 and GPT-4 were identified as both surprising and impressive, as they have made unexpectedly rapid and dramatic advances in language processing. GPT-3 and GPT-4 were a game changer, turning AI from something insignificant to something ubiquitous. The literature observes similarly: Floridi & Chiriatti (2020) confirm that GPT-3 serves as a paradigm shift that accelerates the integration of AI into everyday life by revolutionising text production and enabling numerous applications in daily life (Cf. *Floridi and Chiriatti*, 2020, pp. 684–685, 692–693). Rahaman et al. (2023) argue that the developments of GPT-4 and other advanced LLMs have continuously enhanced this effect by providing even more accurate text processing, multimodality and broader applicability in various areas of daily life (Cf. *Rahaman et al.*, 2023, pp. 3–7).

The expert statements and literature largely agree that the development and introduction of powerful LLMs such as GPT-3 and GPT-4 have brought about a profound change in the perception and use of AI. Both sides favour the improved accessibility and expanded applications of AI, pointing to the transformative power of these technologies. One Statement offers a unique perspective by pointing out that AI was in use for a long time, and constantly improving, before it became immensely popularised by GPT, offering a more nuanced view of the development and implementation of AI: While this emphasises the continuous increase from the capacity of AI, it also highlights the sharp change in perception that all interviewees noted. These slight differences could be due to the different contexts and perspectives of the experts and authors. While the experts report from practice and accentuate the immediate impact of GPT technologies on their work, the literature analyses the technological advances and their broader societal impact, which may be less biased by personal perceptions.

Research shows that GPT models have not only revolutionised the way people look at AI, but also offer the possibility of developing complex applications that go far beyond traditional methods. This positively confirms the partial research question, if powerful generative AI opens up completely new opportunities to transform entire industries profitably and efficiently. Expert statements and the literature consistently show that GPT models such as GPT-3 and GPT-4 have profoundly changed the way AI is used and perceived. The positive confirmation of the partial research question also has far-reaching implications for the further research. It stresses the need for further research into how (consulting) companies can use these technologies effectively in order to achieve maximum benefit. It also opens up new perspectives for the development and implementation of AI-based solutions in various industries.

The interviewees are keen to emphasise that AI is seen as an industrial revolution, talking about the massive innovation in the coming years. Brynjolfsson & McAfee (2017) also describe AI as the most significant thing since the industrial revolution, on a par and combined with the networking of the world through the internet (Cf. *Brynjolfsson and McAfee*, 2014, p. 82). They base this statement on the exponential nature of this technology, amongst other factors.

The expert statements and the literature agree that AI represents a fundamental industrial revolution. While the experts mainly emphasise the immediate impact of AI on their industries and work, Brynjolfsson & McAfee analyse the broader technological and societal implications. The literature's emphasis on the exponential nature of the technology emphasises the long-term and extensive impact of AI, which goes beyond short-term innovations. The research shows that AI is not only perceived as an industrial revolution, but also as a technology with enormous potential to bring about long-term and profound changes in various industries and society as a whole.

The results support the positive answer to the partial research question, if powerful generative AI will lead to a new industrial revolution. The expert statements and the literature consistently show that AI has a transformative power that can bring about profound changes. This allows consulting companies to use AI not only to optimise their own processes, but also to transform entire industries. The positive confirmation emphasises the importance of further research into how all business sectors need to explore every opportunity to embrace this revolution in order to achieve maximum benefit, and not perish from the consequences of neglected innovation. The findings confirm that powerful generative AI is heralding a new industrial revolution. This opens up opportunities for consulting companies to transform and revolutionise entire industries through the cost-effective and value-adding use of AI.

The ability of AI to change entire industries was mentioned several times in the interviews. It was reported on the automation of simple processes and the associated increase in efficiency. It was further reported about more sophisticated use cases in which generative AI replaced existing systems and significantly increased efficiency. The experts argued that AI will fundamentally change the way people work and the need for human labour in various industries. Companies whose main product is text in particular will experience dramatic changes over the next five years. Krishnababu et al. (2023) back up this assertion by stating that AI is revolutionising the way drugs are developed and brought to market by analyzing large amounts of data, speeding up processes and improving results, thus enabling significant advances in the pharmaceutical industry (Cf. *Krishnababu et al.*, 2023, pp. 26–27). Mungoli (2023) takes this argument further and shows that the revolutionary impact of AI technologies is not limited to the pharmaceutical industry, but is also bringing about significant changes in the healthcare, financial services, manufacturing and retail sectors (Cf. *Mungoli*, 2023, pp. 206–207).

Here once again, expert statements and the literature agree that AI has the potential to fundamentally change entire industries by increasing efficiency through automation and profound changes in the way people work. The literature supports these views and extends their scope. This expansion could be explained by the different focuses and perspectives of the experts and the literature: While the experts give specific examples from their professional practice, the literature covers a broader range of industries and application areas.

The results of the research show that AI can not only optimise existing processes, but also enable fundamentally new methods and approaches that can bring about profound changes in diverse environments. This supports the positive answer to the partial research question, if powerful generative AI is ushering in a new industrial revolution in which consulting firms can transform entire industries through the cost-efficient and value-adding use of AI. The confirmation of the partial research question signifies the importance of further research into how consultancies can effectively harness the transformative power of AI to maximise value.

The interview partners also placed value on the importance of AI for increasing efficiency in consulting itself. Experts described the use of internal AI tools to process information more efficiently and support everyday tasks. Further mentioned was the use of AI tools for text recognition and generation. The experts agreed that AI increases efficiency internally in consulting by taking over less demanding tasks and allowing consultants to focus on more complex, intellectual and empathetic activities, and that AI can increase the internal efficiency of consultancies by automating routine tasks and freeing employees from less value-adding tasks. This gives employees more time to focus on value-adding work instead of dealing with simple tasks. Trabelsi (2024) recognises that AI increases productivity through automation and the improvement of decision-making processes, for example by optimising data analysis and risk assessment; these efficiency gains can be directly transferred to consulting companies, as they can particularly benefit from automated, data-driven decision-making processes and risk management due to their large amounts of data (Cf. *Trabelsi*, 2024, pp. 142–143). In addition, Reznikov (2024) shows that generative AI can be used in consultancies to improve marketing strategies, product designs, automate routine tasks and create content and documentation, which further increases efficiency (Cf. *Reznikov*, 2024, pp. 378–382).

Both sides recognise that AI can significantly increase efficiency in consulting companies. While the experts cite specific examples from their professional practice, the literature covers a broader spectrum of efficiency increases and areas of application. Reznikov (2024) specifically highlights the improvement of marketing strategies and product designs through generative AI, which is discussed in less detail in the expert statements. The research shows that AI can not only optimise existing processes, but also enable new methods and approaches that can profoundly increase efficiency in management consulting. This supports the confirmation of the partial research question, that powerful generative AI can optimise internal processes and increase the competitiveness of the consulting companies using it through cost-efficient and value-adding use of AI.

In the context of the research, the answer to the partial research question has less impact on the research field. It does, however, emphasise the importance of further research into how consulting firms can effectively harness the transformative power of AI to maximise value. However, these processes are likely to be well protected, and at best their effectiveness, but not their efficiency, can be assessed.

These four points, in which the interview participants, in agreement with the literature, support the individual and overall points of the partial research questions, allow only one conclusion; The research question in total is answered in positive.

4.4.2 Ethical and social considerations

The experts highlighted the role of data protection in the implementation of AI in companies. It was explained that customers often have concerns about data security and how this data is used. Further underlined were security issues and the need for specific instances for the operation of AI to prevent data leaks. The importance of keeping AI within certain security fences to control its behavior and protect sensitive data was highlighted, followed by emphasis on the importance of data protection when using generative AI and not to be light-handed when generating training data. The interviewees stressed the importance of data protection by pointing out that companies may use internal AI solutions to ensure that sensitive data remains secure and is not made available to external providers. Data protection is the biggest problem when dealing with AI: It was emphasised that neither customers nor companies know exactly what is happening with their data, when using free online models like Chat-GPT. Sebastian (2023) agrees that protecting sensitive information is extremely relevant as user interactions often involve personal or confidential information and breaches of privacy and data security can not only significantly affect user trust, but can also lead to identity theft, financial loss or reputational damage, significantly damaging the reputation and usefulness of these technologies (Cf. *Sebastian*, 2023, pp. 1–4). For training data, Konidena et al. (2024) agree that it is of paramount importance that AI systems are trained with diverse and representative data sets and are regularly checked for bias to ensure that the systems do not amplify existing biases or produce unfair results (Cf. *Konidena, Malaiyappan, and Tadimarri*, 2024, p. 49).

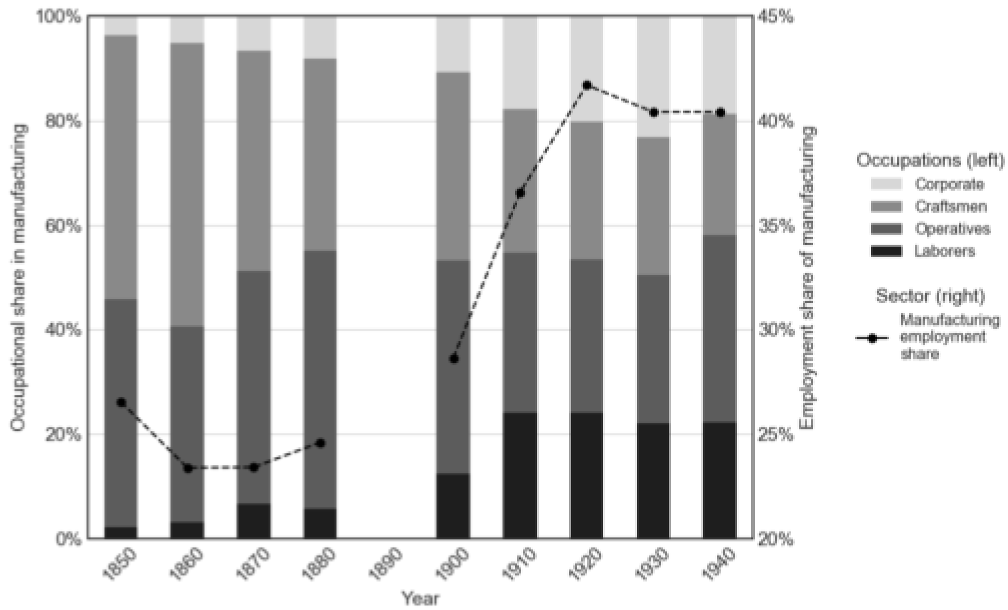
Data protection and security are significant factors in the implementation of AI in companies, according to both groups. While the experts address specific security measures and challenges in their organisations, the literature places a stronger focus on the theoretical and broader societal implications of privacy and bias in AI systems, as well as the legal framework resulting from complications in this domain. It is shown that privacy and security are crucial not only for protecting sensitive information, but also for maintaining user trust in AI technologies in order to realise the full potential of AI. This makes it possible for consulting companies to not only optimise their own processes by using AI, but also to ensure that sensitive data is protected and legal requirements are met.

The experts explained that care is taken to ensure that AI implementations are transparent and understandable for customers. They rely on human oversight to ensure that AI decisions are correct and understandable. They emphasised the challenges of making AI transparent to customers, especially when it comes to complex systems. They argued about the need to educate customers so that they can understand and comprehend how AI works. The experts further mentioned the importance of transparency in the use of AI, especially with regard to the traceability of decisions made by AI. Expanding on this, examples were given that they ensure the transparency of AI decisions by footnoting and sourcing all AI statements so that it is clear where each piece of information comes from. Duarte et al. (2023) claims that the transparency of AI models is crucial for users to better understand their decision-making processes, which in turn increases trust in these systems, especially when explanations of the importance of features are provided (Cf. *Brito Duarte et al.*, 2023, pp. 1–2).

In agreement, experts and literature assert that transparency and traceability are important to increasing trust in AI systems. The two groups examine slightly different perspectives: while the experts address specific measures and challenges in their companies, the literature places a stronger focus on the theoretical foundations and the importance of transparency for user trust. This not only allows consulting companies to optimise their own processes through the use of AI, but also to ensure that the decisions made by AI are transparent and comprehensible. To ensure this, it is important to understand how consulting firms can effectively integrate transparency and traceability to maximise benefits. It also opens up new perspectives for the development and implementation of AI-based solutions that meet the highest standards of transparency and traceability.

The experts also spoke about the initial skepticism towards AI in the industry and how this has changed with the introduction of technologies such as ChatGPT. They discussed the importance of trust in AI and the need to engage customers through transparent communication. They discussed the social challenges of integrating AI into companies, particularly employees' fear of losing their jobs. It was emphasised that education and awareness are crucial to building trust in AI. The experts also predict that the future will be man-with-machine, as opposed to man-against-machine. While jobs will be lost to AI, this can be countered by employees learning to use AI effectively and becoming a better version of themselves. The implementation of AI can lead to social insecurity, as many people fear losing their jobs. One of the biggest challenges is resistance from employees who are afraid of being replaced by AI. Zhang (2023) agrees that the future of AI requires human-with-machine collaboration, where new skills must be learned to alleviate the fear of unemployment (Cf. *X. Zhang*, 2023, pp. 252–253). For the creation of trust, Alekseev and Garbuk (2022) state that trust in AI systems can be fostered by applying a comprehensive evaluation approach that takes into account objective parameters such as measurable and verifiable properties of the algorithms, subjective parameters such as individual experiences and assessments of users and experts, and intersubjective parameters such as consensual assessments and standards within the scientific and regulatory communities (Cf. *Alekseev and Garbuk*, 2022, pp. 1–2). The observation of data from the second industrial revolution in figure 11 results in a similar picture: Even if one might assume that employees were laid off in droves in favour of more favourable innovation, a pattern emerges that literature and experts also expect for AI: The jobs that were lost were created in larger numbers where more intellectual or non-physical work was needed. A symbiosis of man-with-machine arose (Cf. *Hobijn and Kaplan*, 2024).

Figure 11: Structural and occupational transformation in U.S. manufacturing from 1850 to 1940



Source: *Hobijn and Kaplan*, 2024 via the Federal Reserve Bank of Chicago.

The most common scepticism, the social factor, is also addressed in a similar way by experts and literature: They agree that trust and overcoming social challenges are crucial for the successful implementation of AI. The approach differs here too: While the experts address specific social challenges and measures in their companies, the literature places a stronger focus on theoretical foundations and comprehensive evaluation approaches to promote trust in AI.

It effectively shows that trust and social acceptance are of decisive relevance for the successful implementation of AI. This supports the idea that powerful generative AI must have trust and social challenges as important elements for the successful implementation and use of AI in organisations. It reinforces the importance of further examination of how consultancies can effectively promote trust and social acceptance to maximise benefits.

Furthermore, the impact of the EU AI Act on AI consulting as a whole was mentioned. The experts spoke about the challenges posed by regulations such as the EU AI Act. They pointed out that such regulations are necessary to ensure that AI is used ethically and that sensitive data is not misused. It is argued on the importance of regulation as a societal guide to the future of AI in Europe. Crețu (2022) argues that regulation is essential for AI, as it ensures that the development and implementation of AI technologies is in line with societal values and norms, minimises risks and protects public interests in order to avoid social and economic inequalities (Cf. *Crețu*, 2022, pp. 21–23).

Regulations should reflect societal values as the ground rules, which both groups agree on. Regulations such as the EU AI Act have an essential impact on the development and implementation of AI and are essential to ensure that AI technologies are developed and implemented in line with societal values and norms, minimising risks and protecting public interests to avoid social and economic inequalities. This pushes consulting companies and their clients to ensure their AI applications meet the ethical and legal standards. Thus, consulting companies must be able to effectively manage the requirements and challenges of regulations in order to maximise benefits. It also opens up new perspectives for the development and implementation of AI-based solutions that meet the highest ethical and legal standards.

It is clear that the foundation, social aspects and regulation are vital for the successful use of AI in consulting companies. Data protection, transparency and trust are key elements that must be supported by clear regulations in order to ensure acceptance and security. The comparison of the interview results with the literature underlines the need for a responsible approach to AI in order to overcome both ethical and regulatory challenges and exploit the full potential of the technology.

4.5 Research limitations and recommendations

This chapter highlights the limitations of the current study as well as recommendations for future research and practice. Identifying the study limitations is important to assess the reliability of the results, while the proposed recommendations help to improve future research approaches.

4.5.1 Limitations of the study

Despite the valuable insights offered by this study, there are some limitations that need to be considered. To begin with, the number of interviews conducted was limited to a few leading consulting firms. Although these companies can be seen as representative of the industry, additional interviews with other companies or industry experts could lead to more comprehensive insights. In particular, the practices of smaller consulting companies and sole practitioners could be of interest, as they may use different methods and approaches that are not used in larger companies.

Furthermore, the study focused mainly on leading consulting firms that already have an advanced implementation of AI. This could mean that the results cannot be generalised to smaller or less technologically advanced companies. In addition, the analysis is based on the data and insights available at the time of the study. As AI technology and its use in the consulting industry is evolving rapidly, more recent developments and trends may not have been sufficiently taken into account.

In spite of the attempt to interview people from many regions, blindspots to regions such as the People's Republic of China or Japan could emerge. These markets are large and important, and should definitely be investigated. Another issue is that the information is based on the interviewees' self-reports, which may lead to a bias as the answers could be subjective and possibly influenced by personal or company-specific interests. Finally, the study is mainly based on qualitative data from interviews. Supplementing this with quantitative data, e.g. through surveys or statistical analysis, could further support and validate the results. The hypothesis resulting from the positively answered research question should be verified with quantitative data.

4.5.2 Recommendations for future research

Based on the results and the identified limitations of this study, several recommendations for future research can be derived:

1. The sample should be expanded in future studies to gain a broader perspective. This should be achieved by including more companies, different sizes and different geographical regions.
2. Quantitative methods should be included in future research to validate and complement the qualitative findings. This way could be through surveys, statistical analysis or the use of big data.
3. Long-term studies would be helpful to observe the impact of AI implementations over a longer period of time and to better understand trends and changes.
4. In addition, future research should also consider new and emerging AI technologies such as Explainable AI to get a more comprehensive picture of the opportunities and challenges.
5. The ethical and social implications of AI use should be investigated in greater depth in future studies. This could include the development of frameworks and guidelines for the responsible use of AI.
6. Best practices and practical applications should be investigated to find out how companies can successfully implement and use AI. Case studies and success stories could provide valuable insights.
7. Collaboration between academic research and practice should be strengthened to ensure that research findings can be put into practice and that practice-relevant issues are considered in research.

On the basis of these points, the emerging field of AI in the consulting industry can be examined and understood in more detail.

5 Conclusion and outlook

In this final section, the results and their implications are presented. It is intended to provide a well-rounded conclusion to the overall picture that has emerged in this thesis.

5.1 Summary of key findings

The interviewees, together with the literature, have provided a clear picture: Humanity is only at the beginning of perhaps the biggest revolution in our everyday lives. Decades of AI research and the underlying research in ML are now forming models that can perform everyday tasks, from text generation and knowledge collection to speech, image and text generation. These technologies have already been profitably integrated in the past and have only become more powerful, faster and more accurate since then. Companies that do not adapt to this trend of the future will sooner or later be driven out of the market by their competitors who do.

5.2 Implications and outlook

This puts consulting firms in a strong but also precarious position: On the one hand, they have to implement these changes themselves; they have large amounts of data at their disposal, which it is their job to master in order to advise their clients to the best of their knowledge. At the same time, however, they must also be able to advise companies on how they can use AI profitably. Consulting companies that fail to do this will lose out twice over. This industrial revolution will who can adapt quickly, and profit in the long term, and who will be displaced by the former because they cannot. Even if there are regulations, social acceptance problems and possible technical hurdles, all parties involved have already recognised how important AI is. The European Union is showing initiative with the EU AI Act to give the market a legal basis as quickly as possible, solutions for the transparency of AI decisions are intended to increase acceptance, and technology companies are building the computing units on which this revolution will take place. This accord between all parties lays the foundation for the industry of the future.

References

Print Resources

Abdulhussein, Ansam A., Hasanien Kariem Kuba, and Alaa Neamah Azeez Alanssari (2020). Computer Vision to Improve Security Surveillance through the Identification of Digital Patterns. In: 2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), pp. 1–5. DOI: 10.1109/ICIEAM48468.2020.9112022.

Abdulla, Aysha and Omer Bin Hussain (2024). AI enabled Business Process Optimization and Digital Marketing. In: 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI). Vol. 2, pp. 1–5. DOI: 10.1109/IATMSI60426.2024.10502481.

Abdüsselam, Mustafa Serkan (2023). Qualitative Data Analysis in the Age of Artificial General Intelligence. In: International Journal of Advanced Natural Sciences and Engineering Researches 7.4, pp. 1–5. DOI: 10.59287/ijanser.454.

Abouelyazid, Mahmoud and Chen Xiang (Nov. 2019). Architectures for AI Integration in Next-Generation Cloud Infrastructure, Development, Security, and Management. In: International Journal of Information and Cybersecurity 3.1.

Achchab, Said and Yassine Khallouk Temsamani (2021). Artificial Intelligence Use in Human Resources Management: Strategy and Operation's Impact. In: 2021 IEEE 2nd International Conference on Pattern Recognition and Machine Learning (PRML), pp. 311–315. DOI: 10.1109/PRML52754.2021.9520719.

Aguilar, Francis J. (1967). Scanning the Business Environment. New York: Macmillan.

Alekseev, Andrey and Sergey Garbuk (2022). How can you trust Artificial Intelligence Systems? Objective, Subjective and Intersubjective parameters of Trust. In: Artificial Societies 17.2. DOI: 10.18254/S207751800020550-4.

Alpaydın, Ethem (2020). Introduction to Machine Learning. 4th. Cambridge, MA: MIT Press. ISBN: 9780262043793.

Al-Amin, Md. et al. (2024). History of generative Artificial Intelligence (AI) chatbots: past, present, and future development. DOI: 10.48550/arXiv.2402.05122. arXiv: 2402.05122.

Androshchuk, H. (2023). Policies and strategies for the development of artificial intelligence in the countries of the world: quo vadis? (part 2). In: Science, Technologies, Innovations 2.26, pp. 40–47. DOI: 10.35668/2520-6524-2023-2-05.

Armbrust, Michael et al. (Apr. 2010). A view of cloud computing. In: ommunications of the ACM 53.4, pp. 50–58. DOI: 10.1145/1721654.1721672.

Armbrüster, Thomas (2006). The Economics and Sociology of Management Consulting. Cambridge University Press. ISBN: 9780511488467. DOI: 10.1017/CBO9780511488467.

Arute, F. et al. (2019). Quantum supremacy using a programmable superconducting processor. In: Nature 574, pp. 505–510. DOI: 10.1038/s41586-019-1666-5.

Autor, David, J. Hazell, and P. Restrepo (Apr. 2022). Artificial Intelligence and Jobs: Evidence from Online Vacancies. In: Journal of Labor Economics 40.S1, pp. 293–340. DOI: 10.1086/718327.

Babina, Tania et al. (Dec. 2023). Artificial Intelligence, Firm Growth, and Product Innovation. In: Journal of Financial Economics (JFE). DOI: 10.2139/ssrn.3651052.

Baktash, Jawid Ahmad and Mursal Dawodi (2023). Gpt-4: A Review on Advancements and Opportunities in Natural Language Processing. DOI: 10.48550/arXiv.2305.03195. arXiv: 2305.03195.

Bali, Jatinder and Shivam Nayak (Jan. 2020). Artificial Intelligence. In: Journal of Clinical Ophthalmology and Research 8.1, pp. 1–4. DOI: 10.4103/jcor.jcor_18_20.

Basingab, Mohammed Salem et al. (2024). AI-Based Decision Support System Optimizing Wireless Sensor Networks for Consumer Electronics in E-Commerce. In: Applied Sciences 14.12. DOI: 10.3390/app14124960.

Bedi, Pradeep, S B Goyal, and Jugnesh Kumar (2020). Basic Structure on Artificial Intelligence: A Revolution in Risk Management and Compliance. In: 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), pp. 570–576. DOI: 10.1109/ICISS49785.2020.9315986.

Bein, Adrian Sean and Alexander Williams (Aug. 2023). Development of Deep Learning Algorithms for Improved Facial Recognition in Security Applications. In: IAIC Transactions on Sustainable Digital Innovation (ITSDI) 5.1, pp. 19–23. DOI: 10.34306/itsdi.v5i1.605.

Bekbolatova, Molly et al. (2024). Transformative Potential of AI in Healthcare: Definitions, Applications, and Navigating the Ethical Landscape and Public Perspectives. In: Healthcare 12.2. ISSN: 2227-9032. DOI: 10.3390/healthcare12020125.

Bishop, Christopher M. (2006). Pattern Recognition and Machine Learning. New York: Springer. ISBN: 978-0-387-31073-2. DOI: 10.1007/978-0-387-45528-0.

Bohannon, John (2015). Fears of an AI pioneer. In: Science 349.6245, pp. 252–252. DOI: 10.1126/science.349.6245.252.

Bojarski, Mariusz et al. (2016). End to End Learning for Self-Driving Cars. DOI: 10.48550/arXiv.1604.07316. arXiv: 1604.07316.

Bostrom, N. (2014). Superintelligence: Paths, Dangers, Strategies. Oxford University Press. ISBN: 9780199678112.

Bown, Chad P. (2020). How the United States Marched the Semiconductor Industry into Its Trade War with China. In: East Asian Economic Review 24.4, pp. 349–388. DOI: 10.11644/KIEP.EAER.2020.24.4.384.

Brito Duarte, Regina de et al. (2023). AI Trust: Can Explainable AI Enhance Warranted Trust? In: Human Behavior and Emerging Technologies 2023.1, p. 4637678. DOI: 10.1155/2023/4637678.

Brown, Tom B. et al. (2020). Language Models are Few-Shot Learners. DOI: 10.48550/arXiv.2005.14165. arXiv: 2005.14165.

Brynjolfsson, Erik and Andrew McAfee (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. 1st. W. W. Norton & Company. ISBN: 0393239357.

Buchanan, Bruce G. and Edward H. Shortliffe (1984). Rule Based Expert Systems: The Mycin Experiments of the Stanford Heuristic Programming Project (The Addison-Wesley series in artificial intelligence). Addison-Wesley Longman Publishing Co., Inc. DOI: https://dl.acm.org/doi/10.5555/1096485.

Buehring, Joern and Peter C. Bishop (2020). Foresight and Design: New Support for Strategic Decision Making. In: She Ji: The Journal of Design, Economics, and Innovation 6.3, pp. 408–432. DOI: 10.1016/j.sheji.2020.07.002.

Campbell, Murray, A.Joseph Hoane, and Feng-hsiung Hsu (2002). Deep Blue. In: Artificial Intelligence 134.1, pp. 57–83. DOI: 10.1016/S0004-3702(01)00129-1.

Cemaloglu, Cengiz, Jasmine Chia, and Joshua Tam (2019). Agency and AI in Consulting: Pathways to Prioritize Agency-Enhancing Automations. In: Ethnographic Praxis in Industry Conference Proceedings 2019.1, pp. 533–553. DOI: 10.1111/1559-8918.2019.01306.

Chen, Ying, Elenee Argentinis, and Griff Weber (2016). IBM Watson: How Cognitive Computing Can Be Applied to Big Data Challenges in Life Sciences Research. In: Clinical Therapeutics 38.4, pp. 688–701. DOI: 10.1016/j.clinthera.2015.12.001.

Cherednyk, Anna (2023). Theoretical Principles of Enterprise's Restructuring in the Conditions of Digitalization of the Economy. In: Ukrainian Journal of Applied Economics and Technology 8.3, pp. 365–370. DOI: 10.36887/2415-8453-2023-3-57.

Crețu, Valentin Bogdan (Dec. 2022). Data, governance and tackling the "tragedy of the commons". In: International Journal of Advanced Statistics and IT&C for Economics and Life Sciences 12.2, pp. 17–23. DOI: 10.2478/ijasitels-2022-0003.

Davenport, Thomas and Jeanne Harris (Mar. 2007). Competing on Analytics: The New Science of Winning. Harvard. ISBN: 1422103323.

Davenport, Thomas H. (2018). From analytics to artificial intelligence. In: Journal of Business Analytics 1.2, pp. 73–80. DOI: 10.1080/2573234X.2018.1543535.

Deepthi, B and S Shanthi (2023). A Systematic Analysis of Deep Learning Based Twitter Sentiment Analysis: Emerging Trends and Challenges. In: 2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), pp. 1–9. DOI: 10.1109/ICSES60034.2023.10465567.

Deloitte, PwC, EY, and KPMG (Apr. 2023). Umsatz der größten Wirtschaftsprüfungs- und Beratungsunternehmen weltweit (Big Four) im Geschäftsjahr 2023 nach Geschäftss- egmenten (in Milliarden US-Dollar). Statista. Accessed on 06.08.2024, 14:47 CEST. In supplementary data as BigFourStat.pdf. URL: https://de.statista.com/statistik/daten/studie/445528/umfrage/umsatz-der-groessten-pruefungs-und-beratungsunternehmen-weltweit-nach-segmenten/.

Devarajan, Yuvaraja (2019). A Review on Intelligent Process Automation. In: International Journal of Computer Applications 182.36, pp. 40–44. DOI: 10.5120/ijca2019918374.

Drozdov, A. et al. (2015). Conventional superconductivity at 203 kelvin at high pressures in the sulfur hydride system. In: Nature 525, pp. 73–76. DOI: 10.1038/nature14964.

Esteva, Andre et al. (Jan. 2017). Dermatologist-level classification of skin cancer with deep neural networks. In: Nature 542, pp. 115–118. DOI: 10.1038/nature21056.

Ferain, Isabelle, Cynthia A. Colinge, and Jean-Pierre Colinge (2011). Multigate transistors as the future of classical metal–oxide–semiconductor field-effect transistors. In: Nature 479, pp. 310–316. DOI: 10.1038/nature10676.

Fern, Alan et al. (2024). AgAID Institute—AI for agricultural labor and decision support. In: AI Magazine 45.1, pp. 99–104. DOI: 10.1002/aaai.12156.

Ferrer, Xavier et al. (June 2021). Bias and Discrimination in AI: A Cross-Disciplinary Perspective. In: IEEE Technology and Society Magazine 40, pp. 72–80. DOI: 10.1109/MTS.2021.3056293.

Fianto, Achmad Yanu Alif and Angga Dutahatmaja (July 2023). Artificial Intelligence and Novel Services: Exploring Opportunities in the Marketing Landscape. In: Journal of Applied Management and Business 4.1. DOI: 10.37802/jamb.v4i1.399.

Floridi, Luciano and Massimo Chiriatti (2020). GPT-3: Its Nature, Scope, Limits, and Consequences. In: Minds and Machines 30, pp. 681–694. DOI: 10.1007/s11023-020-09548-1.

Garg, Tilak, Sahil Shekhar, and Prof. Renu Narwal (2024). An Evaluation of Machine Learning Algorithms Used for Recommender Systems in Streaming Services. In: International Journal of Advanced Research in Science, Communication and Technology 6.4, pp. 340–346. DOI: 10.48175/ijarsct-17652.

Gehlhaus, Diana and Luke Koslosky (Apr. 2022). Training Tomorrow's AI Workforce: The Latent Potential of Community and Technical Colleges. In: CSET. DOI: 10.51593/20210022.

Gînguță, Andrea et al. (2023). Ethical Impacts, Risks and Challenges of Artificial Intelligence Technologies in Business Consulting: A New Modelling Approach Based on Structural Equations. In: Electronics 12.6. DOI: 10.3390/electronics12061462.

Goertzel, Ben (Dec. 2014). Artificial General Intelligence: Concept, State of the Art, and Future Prospects. In: Journal of Artificial General Intelligence 5, pp. 1–48. DOI: 10.2478/jagi-2014-0001.

Heaton, J. et al. (2018). Deep learning. In: Genetic Programming and Evolvable Machines 19, pp. 305–307. DOI: 10.1007/s10710-017-9314-z.

Hobijn, Bart and Robert S. Kaplan (2024). Occupational Switching During the Second Industrial Revolution. DOI: 10.21033/wp-2024-01.

Hochreiter, Sepp and Jürgen Schmidhuber (Dec. 1997). Long Short-term Memory. In: Neural computation 9, pp. 1735–1780. DOI: 10.1162/neco.1997.9.8.1735.

Hoffman, Fred P. and Shelly L. Freyn (2019). The future of competitive intelligence in an AI-enabled world. In: International Journal of Value Chain Management 10.4, pp. 275–289. DOI: 10.1504/IJVCM.2019.103268.

Issa, Theodora, Vanessa Chang, and Tomayess Issa (Aug. 2010). Sustainable business strategies and PESTEL framework. In: GSTF Journal on Computing (JoC) 1. DOI: 10.5176/2010-2283_1.1.13.

Jones, Cameron R. and Benjamin K. Bergen (2024). Does GPT-4 pass the Turing test? DOI: 10.48550/arXiv.2310.20216. arXiv: 2310.20216.

Jurafsky, Daniel and James Martin (2008). Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition. Vol. 2. Prentice Hall.

Kaswan, Kuldeep Singh et al. (2023). ChatGPT: A Comprehensive Review of a Large Language Model. In: 2023 International Conference on Communication, Security and Artificial Intelligence (ICCSAI), pp. 738–743. DOI: 10.1109/ICCSAI59793.2023.10421090.

Kazia, Esmeralda and Bledar Kazia (Mar. 2023). Enhancing Customer Relationship Management through Sentiment Analysis and Social Media Data Mining. In: American Journal of Business and Operations Research 10.1, pp. 16–24. DOI: 10.54216/AJBOR.100102.

Klemmer, Jan H. et al. (2024). Using AI Assistants in Software Development: A Qualitative Study on Security Practices and Concerns. DOI: 10.48550/arXiv.2405.06371. arXiv: 2405.06371.

Konidena, Bhargav Kumar, Jesu Narkarunai Arasu Malaiyappan, and Anish Tadimarri (Mar. 2024). Ethical Considerations in the Development and Deployment of AI Systems. In: European Journal of Technology 8.2, pp. 41–53. DOI: 10.47672/ejt.1890.

Krishnababu, Krishnagiri et al. (June 2023). Revolutionizing the Pharmaceutical Industry with Artificial Intelligence. In: Journal of Artificial Intelligence, Machine Learning and Neural Network 3.4, pp. 26–37. DOI: 10.55529/jaimlnn.34.26.37.

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton (2012). ImageNet classification with deep convolutional neural networks. In: Communications of the ACM 60, pp. 84–90.

Lake, Brenden M. et al. (2016). Building Machines That Learn and Think Like People. DOI: 10.48550/arXiv.1604.00289. arXiv: 1604.00289.

LeCun, Yann, Y. Bengio, and Geoffrey Hinton (May 2015). Deep Learning. In: Nature 521, pp. 436–44. DOI: 10.1038/nature14539.

Ledro, Cristina, Anna Nosella, and Andrea Vinelli (2022). Artificial intelligence in customer relationship management: literature review and future research directions. In: Journal of Business & Industrial Marketing 37.13, pp. 48–63. DOI: 10.1108/JBIM-07-2021-0332.

Liao, Han-Teng, Chung-Lien Pan, and Yuan Zhang (Mar. 2023). Collaborating on ESG consulting, reporting, and communicating education: Using partner maps for capability building design. In: Frontiers in Environmental Science 11.

Lipton, Zachary C. (Sept. 2018). The mythos of model interpretability. In: Commun. ACM 61.10, pp. 36–43. DOI: 10.1145/3233231.

Liu, Jiange et al. (2019). An Intelligent Vision System for Detecting Defects in Micro-Armatures for Smartphones. In: Applied Sciences 9.11. DOI: 10.3390/app9112185.

Liu, Shaoyu (2022). Robotic Process Automation (RPA) in Auditing: A Commentary. In: International Journal of Computer Auditing 4.1, pp. 23–28. DOI: 10.53106/256299802022120401003.

Liu, Xiaoming et al. (2007). What are customers looking at? In: 2007 IEEE Conference on Advanced Video and Signal Based Surveillance, pp. 405–410. DOI: 10.1109/AVSS.2007.4425345.

Lundberg, Scott M., Gabriel Erion, et al. (2019). Explainable AI for Trees: From Local Explanations to Global Understanding. DOI: 10.48550/arXiv.1905.04610. arXiv: 1905.04610.

Lundberg, Scott M. and Su-In Lee (2017). A unified approach to interpreting model predictions. In: Advances In Neural Information Processing Systems. Red Hook, NY, USA: Curran Associates Inc., pp. 4768–4777. ISBN: 9781510860964.

Makhoul, John et al. (1989). White paper on spoken language systems. In: Proceedings of the Workshop on Speech and Natural Language. Cape Cod, Massachusetts: Association for Computational Linguistics, pp. 463–479. ISBN: 1558601120. DOI: 10.3115/1075434.1075525.

Management Consultancies Association (Jan. 2024). Current uses of artificial intelligence (AI) within consulting firms in the United Kingdom (UK) in 2023. Accessed on 06.08.2024, 14:48 CEST. In supplementary data as ConsUK.pdf. URL: https://www.statista.com/statistics/1461010/consulting-firms-current-ai-use-uk/.

Manning, Christopher D. and Hinrich Schütze (1999). Foundations of Statistical Natural Language Processing. Cambridge, MA: MIT Press. ISBN: 9780262133609.

Maydanyk, Roman A., Nataliia I. Maydanyk, and Maryna M. Velykanova (2021). Liability for Damage Caused Using Artificial Intelligence Technologies. In: Journal of the National Academy of Legal Sciences of Ukraine 2, pp. 150–159. DOI: 10.37635/jnalsu.28(2).2021.150-159.

Mayring, Philipp (June 2000). Qualitative Inhaltsanalyse. In: Forum: Qualitative Social Research 1.

McCarthy, John et al. (2006). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. In: AI Mag. 27, pp. 12–14.

Modi, Tejaskumar B. (June 2023). Artificial Intelligence Ethics and Fairness: A study to address bias and fairness issues in AI systems, and the ethical implications of AI applications. In: Revista Review Index Journal of Multidisciplinary 3.2, pp. 24–35. DOI: 10.31305/rrijm2023.v03.n02.004.

Moore, Gordon E. (1965). Cramming More Components Onto Integrated Circuits. In: Electronics 38.8.

Mungoli, Neelesh (July 2023). Revolutionizing Industries: The Impact of Artificial Intelligence Technologies. In: Journal of Electrical Electronics Engineering 2.3, pp. 206–210. DOI: 10.33140/jeee.02.03.03.

Murtza, Farhan and Alia Murtza (2023). Artificial Intelligence (AI) Transformation Leadership Consulting Framework. In: International Journal of Management Studies and Social Science Research 5.5. DOI: 10.56293/IJMSSSR.2022.4701.

Nawrocki, Waldemar (2010). Physical limits for scaling of integrated circuits. In: Journal of Physics: Conference Series 248. DOI: 10.1088/1742-6596/248/1/012059.

Nenni, Maria Elena (2024). Integrating Mental Workload Management in advanced Human-Machine Interaction: the development process of the Proof-Of-Concept to refine the concept. In: 2024 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), pp. 1–6. DOI: 10.1109/HORA61326.2024.10550724.

Oarue-Itseuwa, Esioze (2024). Artificial Intelligence's Impact of the Management Consultancy Sector over the Next Five Years. In: Management Consulting Journal 7.1, pp. 49–58. DOI: doi:10.2478/mcj-2024-0005.

Obermeyer, Ziad and Ezekiel J. Emanuel (2016). Predicting the Future — Big Data, Machine Learning, and Clinical Medicine. In: New England Journal of Medicine 375.13, pp. 1216–1219. DOI: 10.1056/NEJMp1606181.

Özkan, Mazhar and Hadi Sasani (2023). Discussion on the Artificial Intelligence (AI) Tools Usage in the Scientific World. In: European Journal of Therapeutics 29.4, pp. 996–997. DOI: 10.58600/eurjther1837. URL: https://eurjther.com/index.php/home/article/view/1837.

Pandey, Arjoo (2023). Computer Vision. In: International Journal of Recent Advances in Science, Engineering and Technology 11.7, pp. 510–514. DOI: 10.22214/ijraset.2023.54701.

Perkasa, Yanka and Fardinal (2021). The Influence of Organizational Culture, Internal Control on the Implementation of Good Corporate Governance through the Integration of Accounting Information Systems (Research at Dr. Chasbullah Abdulmadjid General Hospital, Bekasi City). In: Saudi Journal of Business and Management Studies 6.10, pp. 394–404. ISSN: 2415-6663. DOI: 10.36348/sjbms.2021.v06i10.001.

R. Shanmugapriya, U. Amaleshwari (2024). Barriers and Enablers in Integrating AI into Human Resource Management Strategies: Maximizing Human Capital. In: European Economic Letters (EEL) 14.1, pp. 1862–1869. DOI: 10.52783/eel.v14i1.1295.

Radov, Mariana (Dec. 2022). Emerging trends in business and management consulting. In: Eastern European Journal for Regional Studies 8, pp. 30–49. DOI: 10.53486/2537-6179.8-2.03.

Rahaman, Md. Saidur et al. (May 2023). From ChatGPT-3 to GPT-4: A Significant Advancement in AI-Driven NLP Tools. In: Journal of Engineering and Emerging Technologies 2.1, pp. 1–11. DOI: 10.52631/jeet.v2i1.188.

Rahmaty, Maryam (2023). Machine learning with big data to solve real-world problems. In: Journal of Data Analysis 2.1, pp. 9–16. DOI: 10.59615/jda.2.1.9.

Raj, Mayank, Ashish Devang, and Satya Chanchal (2023). Virtual assistant using artificial intelligence. In: International Journal of Engineering Applied Sciences and Technology 2.8, pp. 348–352. DOI: 10.33564/ijeast.2023.v08i02.053.

Reznikov, Roman (June 2024). PRACTICAL RECOMMENDATION OF USING GENERATIVE AI IN BUSINESS. In: Bulletin of Khmelnytskyi National University 2, pp. 378–384. DOI: 10.47535/1991auoes32(1)007.

Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin (2016). ”Why Should I Trust You?”: Explaining the Predictions of Any Classifier. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1135–1144. ISBN: 9781450342322. DOI: 10.1145/2939672.2939778.

Russell, Stuart and Peter Norvig (2010). Artificial Intelligence: A Modern Approach. 3rd. Pearson.

Sambasivan, Nithya et al. (May 2021). “Everyone wants to do the model work, not the data work”: Data Cascades in High-Stakes AI. In: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, pp. 1–15. DOI: 10.1145/3411764.3445518.

Samek, Wojciech, Thomas Wiegand, and Klaus-Robert Müller (2017). Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models. DOI: 10.48550/arXiv.1708.08296. arXiv: 1708.08296.

Schrettenbrunnner, Manfred B. (2020). Artificial-Intelligence-Driven Management. In: IEEE Engineering Management Review 48.2, pp. 15–19. DOI: 10.1109/EMR.2020.2990933.

Searle, John R. (1980). Minds, brains, and programs. In: Behavioral and Brain Sciences 3.3, pp. 417–424. DOI: 10.1017/S0140525X00005756.

Sebastian, Glorin (2023). Privacy and Data Protection in ChatGPT and Other AI Chatbots: Strategies for Securing User Information. DOI: 10.2139/ssrn.4454761.

Shahid, Muhammad Zafeer and Gang Li (2019). Impact of Artificial Intelligence in Marketing: A Perspective of Marketing Professionals of Pakistan. In: Global Journal of Management and Business Research: E Marketing 19.2, pp. 27–33.

Silver, David et al. (Jan. 2016). Mastering the game of Go with deep neural networks and tree search. In: Nature 529, pp. 484–489. DOI: 10.1038/nature16961.

Swanson, E. Burton (2010). Consultancies and capabilities in innovating with IT. In: The Journal of Strategic Information Systems 19.1, pp. 17–27. DOI: 10.1016/j.jsis.2009.12.001.

Taherdoost, Hamed and Mitra Madanchian (2023). Artificial Intelligence and Knowledge Management: Impacts, Benefits, and Implementation. In: Computers 12.4. DOI: 10.3390/computers12040072.

Transforming Knowledge Management System with AI Technology for Document Archives (May 2024). Vol. Day 3 Thu, May 09, 2024. SPE Gas, D022S006R001. DOI: 10.2118/219313-MS.

Topol, A. W. et al. (July 2006). Three-dimensional integrated circuits. In: IBM J. Res. Dev. 50.4/5, pp. 491–506.

Trabelsi, Mohamed Ali (June 2024). The impact of artificial intelligence on economic development. In: Journal of Electronic Business & Digital Economics 3.2, pp. 142–155. DOI: 10.1108/JEBDE-10-2023-0022.

Turing, A. M. (1950). COMPUTING MACHINERY AND INTELLIGENCE. In: Mind LIX.236, pp. 433–460. DOI: 10.1093/mind/LIX.236.433.

Vaswani, Ashish et al. (2023). Attention Is All You Need. DOI: 10.48550/arXiv.1706.03762. arXiv: 1706.03762.

Vial, Gregory et al. (2023). Managing artificial intelligence projects: Key insights from an AI consulting firm. In: Information Systems Journal 33.3, pp. 669–691. DOI: 10.1111/isj.12420.

Wang, Bin et al. (Feb. 2021). Achieving Effective Remote Working During the COVID-19 Pandemic: A Work Design Perspective. In: Applied Psychology 70, pp. 16–59. DOI: 10.1111/apps.12290.

Wang, Li, Hai-Chao Zhang, and Qiang Wang (July 2019). On the Concepts of Artificial Intelligence and Innovative Design in Product Design. In: IOP Conference Series: Materials Science and Engineering 573.1. DOI: 10.1088/1757-899X/573/1/012095.

Wulansari, Retno and Sri Palupi Prabandari (2024). AI and Knowledge Management Orchestration Implementation in Today's Business. In: International Journal of Business Innovation, Economics and Social Science 1.1, pp. 55–59. DOI: 10.11594/ijbiess.v11p55-59.

Yudkowsky, Eliezer (July 2008). Artificial Intelligence as a positive and negative factor in global risk. Oxford University Press. ISBN: 9780198570509. DOI: 10.1093/oso/9780198570509.003.0021.

Zhang, Jingyu et al. (2024). Research on the Application of Computer Vision Based on Deep Learning in Autonomous Driving Technology. DOI: 10.48550/arXiv.2406.00490. arXiv: 2406.00490.

Zhang, XinNing (Dec. 2023). Research on the Impact of Artificial Intelligence on the Labor Market. In: Advances in Economics and Management Research 8.1. DOI: 10.56028/aemr.8.1.252.2023.

Zhou, Kaiwen and Tianyu Wang (2024). Personalized Interiors at Scale: Leveraging AI for Efficient and Customizable Design Solutions. DOI: 10.48550/arXiv.2405.19188. arXiv: 2405.19188.

Al-Zubaidy, Mohaimen et al. (Apr. 2022). Stakeholder Perspectives on Clinical Decision Support Tools to Inform Clinical Artificial Intelligence Implementation:

Protocol for a Framework Synthesis for Qualitative Evidence". In: JMIR Res Protoc 11.4. DOI: 10.2196/33145.

Online Resources

Accenture (2024). Technology Vision 2024. Accessed on 17.07.2024, 18:26 CEST. In supplementary data as Accenture2024.pdf. URL: https://www.accenture.com/us-en/insights/technology/technology-trends-2024.

Balakrishnan, Tara et al. (2020). Global Survey: The State of AI in 2020. Accessed on 17.07.2024, 18:32 CEST. In supplementary data as Balakrishnan2020.jpeg. URL: https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2020.

Bayati, Mutasim (Nov. 2019). AI in Consulting. Accessed on 17.07.2024, 18:36 CEST. In supplementary data as Bayati2019.pdf. URL: https://www.theseus.fi/handle/10024/266319.

Best, Jo (2013). IBM Watson: The inside story of how the Jeopardy-winning supercomputer was born, and what it wants to do next. Accessed on 17.07.2024, 18:25 CEST. In supplementary data as Best2013.pdf. URL: https://www.techrepublic.com/article/ibm-watson-the-inside-story-of-how-the-jeopardy-winning-supercomputer-was-born-and-what-it-wants-to-do-next/.

Biden, Joseph R. (Oct. 2023). Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence. Accessed on 17.07.2024, 18:08 CEST. In supplementary data as Biden2023.pdf. URL: https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/.

Bughin, Jacques et al. (May 2018). Skill Shift: Automation and the Future of the Workforce. Accessed on 17.07.2024, 18:10 CEST. In supplementary data as Bughin2018.pdf. URL: https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce.

Business Research Insights (2024). Artificial Intelligence (AI) Consulting Market. Accessed on 17.07.2024, 18:38 CEST. In supplementary data as BusinessResearchInsights2024.pdf. URL: https://www.businessresearchinsights.com/market-reports/artificial-intelligence-ai-consulting-market-109569.

Chui, Michael, James Manyika, and Mehdi Miremadi (2016). Where machines could replace humans—and where they can't (yet). Accessed on 17.07.2024, 18:07 CEST. In supplementary data as Chui2016.pdf. URL: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet.

Davenport, Thomas and Rajeev Ronanki (2018). Artificial intelligence for the real world. Accessed on 17.07.2024, 18:02 CEST. In supplementary data as Davenport2018.pdf. URL: https://hbr.org/2018/01/artificial-intelligence-for-the-real-world.

European Parliament and Council of the European Union (Apr. 2016). Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data (General Data Protection Regulation). Accessed on 17.07.2024, 18:07 CEST. In supplementary data as GDPR2016.pdf.

— (Apr. 2021). Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828. Accessed on 17.07.2024, 18:08 CEST. In supplementary data as AIAct2021.pdf.

Financial Industry Regulatory Authority (2020). Artificial Intelligence (AI) in the Securities Industry. Accessed on 17.07.2024, 18:12 CEST. In supplementary data as FINRA2020.pdf. URL: https://www.finra.org/rules-guidance/key-topics/fintech/report/artificial-intelligence-in-the-securities-industry.

Guszcza, Jim and Jeff Schwartz (July 2020). Superminds, not substitutes: Designing human-machine collaboration for a better future of work. Accessed on 17.07.2024, 18:26 CEST. In supplementary data as Guszcza2020.pdf. URL: https://www2.deloitte.com/us/en/insights/focus/technology-and-the-future-of-work/ai-in-the-workplace.html.

Heaven, Will Douglas (2023). Google DeepMind wants to define what counts as artificial general intelligence. Accessed on 17.07.2024, 17:46 CEST. In supplementary data as GoogleDeepMind2023.pdf. URL: https://www.technologyreview.com/2023/11/16/1083498/google-deepmind-what-is-artificial-general-intelligence-agi/.

IBISWorld (Mar. 2024). Market size of the management consulting industry worldwide from 2014 to 2023, with a forecast for 2024 (in billion U.S. dollars). Accessed on 06.08.2024, 14:46 CEST. In supplementary data as ConsMarketSize.pdf. URL: https://www.statista.com/statistics/1234833/global-management-consulting-services-market-size/.

IBM Research (2021). Introducing the world's first 2 nm node chip. Accessed on 17.07.2024, 18:15 CEST. In supplementary data as IBM2021.pdf. URL: https://research.ibm.com/blog/2-nm-chip.

IBM Watson (2024). IBM Watson: Business. Accessed on 17.07.2024, 18:25 CEST. In supplementary data as IBM2024.pdf. URL: https://www.ibm.com/watson/business.

McQuate, Sarah (2023). Q&A: UW researcher discusses just how much energy ChatGPT uses. Accessed on 17.07.2024, 18:11 CEST. In supplementary data as McQuate2023.pdf. URL: https://www.washington.edu/news/2023/07/27/how-much-energy-does-chatgpt-use.

PwC (2017). Sizing the prize: What's the real value of AI for your business and how can you capitalise? Accessed on 17.07.2024, 18:08 CEST. In supplementary data as PwC2017.pdf. URL: https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf.

Radford, Alec, Karthik Narasimhan, et al. (2018). Improving Language Understanding by Generative Pre-Training. Accessed on 17.07.2024, 17:59 CEST. In supplementary data as Radford2018.pdf. URL: https://cdn.openai.com/research-covers/language-unsupervised/language_understanding_paper.pdf.

Radford, Alec, Jeffrey Wu, et al. (2019). Language Models are Unsupervised Multitask Learners. Accessed on 17.07.2024, 18:00 CEST. In supplementary data as Radford2019.pdf. URL: https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf.

The Chess Journal (2023). Chess vs Go: A Deep Dive Comparing Two of the World's Oldest Strategy Games. Accessed on 17.07.2024, 17:42 CEST. In supplementary data as ChessJournal2023.pdf. URL: https://www.chessjournal.com/chess-vs-go/#Complexity_and_Decision_Making.