STRATEGIC APPROACH TO AI IN ORGANISATIONS

Lappeenranta–Lahti University of Technology LUT

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ABSTRACT

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Strategic approach to AI in organisations

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Keywords: AI strategy, AI implementation, Strategy development, AI maturity, Artificial Intelligence

The use of AI in organisations has increased substantially, however, the evidence on the strategic implementation of AI is limited. Organisations develop AI solutions but lack a strategic vision for them. There are a variety of factors to be considered when planning to implement AI into operations and processes. Finding optimal ways to maximise the value of AI is a challenge to organisations. This study aimed to increase understanding on organisations' strategic utilisation of AI. The objective was to identify factors organisations should consider when implementing AI to generate the most value.

This study used a qualitative case study method by interviewing AI professionals globally from the finance sector. The data was collected through four semi-structured interviews. The study found that organisations have taken diverse approaches with implementing AI, but the lack of a strategic view is evident. Creating a roadmap for AI processes is important for scaling the use of AI. Organisations are aiming to develop their internal capabilities to remain competitive in the future. These include upskilling employees, improving data maturity and innovative culture.

The study provided a practical perspective on AI in organisations from the higher strategic level. Additionally it contributed to the existing literature by validating the need for a strategic vision and approach to AI in organisations.

TIIVISTELMÄ

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Organisaatioiden strateginen lähestymistapa tekoälyyn

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Tekoälyn käyttö on lisääntynyt merkittävästi, kuitenkin tutkimukset tekoälyn strategisesta käyttöönotosta ovat rajallisia. Organisaatiot kehittävät tekoäly ratkaisuja mutta heiltä puuttuu strateginen visio sen käytöstä. On olemassa monia tekijöitä jotka tulee ottaa huomioon kun suunnittelee tekoälyn käyttöönottoa organisaation toimintaan ja prosesseihin. Organisaatioilla on haasteita maksimoida tekoälyn tuottama arvo. Tämän tutkimuksen tavoitteena on lisätä ymmärrystä tekoälyn strategisesta hyödyntämisestä organisaatioissa. Tarkoituksena on identifioida tekijöitä joita organisaatioiden tulisi huomioida kun ottaa tekoälyä käyttöön, jotta siitä voidaan tuottaa eniten arvoa.

Tämä tutkimus hyödynsi kvalitatiivista tapaustutkimusta haastattelemalla tekoälyn asiantuntijoita kansainvälisesti finanssialalta. Tutkimuksen data kerättiin neljällä puolistrukturoidulla haastattelulla. Tutkimuksen mukaan organisaatioilla on monipuolisia lähestymistapoja tekoälyn käyttöönottamiseksi, mutta strategisen lähestymisen puuttuminen on selvää. Suunnitelman tekeminen tekoäly prosesseihin on tärkeää, jotta sen käyttöä voidaan skaalata. Organisaatiot pyrkivät kasvattamaan sisäisiä kykyjä pysyäkseen kilpailukykyisinä tulevaisuudessa. Näihin kykyihin sisältyy työntekijöiden kouluttaminen, data maturiteetin parantaminen ja innovatiivisen kulttuurin luominen.

Tämä tutkimus tarjoaa käytännöllisen näkökulman tekoälyyn organisaatioissa ottaen ylemmän strategisen lähestymisen. Lisäksi tämä tutkimus antaa panoksen olemassa olevaan kirjallisuuteen validoimalla tarpeen strategiseen visioon ja lähestymiseen tekoälyyn liittyen organisaatioissa

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Writing this thesis has been a long road but it has put together my entire academic path. Although determining to research on this specific topic was fairly easy choice, the entire process has been quite a learning path with some challenges on the way. First of all, I'm my proud of myself for accomplishing this.

I am grateful for everyone that has been part of this journey. I would like to thank all of the interviewees that participated in this research and shared their valuable thoughts and ideas about this topic. Then I would like to thank my thesis supervisor Juha Väätänen who has been guiding me throughout this journey. I am grateful for his guidance and feedback as well as his confidence towards my abilities.

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ABBREVIATIONS

AI	Artificial Intelligence
IT	Information Technology
R&D	Research & Development
BFSI	Banking, Financial services and Insurance sector

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1 Introduction

This study focused on the fast-phased development of AI in organisations and how organisations can create AI strategies to optimize its usage and application. The emphasis of this study is on the financial sector where the data is collected. The first chapter introduces the topic and gives reasoning on why this study is relevant as well as presents the research questions and overall structure of the study.

1.1 Background and relevance of the study

Currently, AI technologies are used regularly in daily life and for many companies it's an essential element in their business model and not an area of the futurologists anymore (Dwivedi et al., 2021). The development of generative AI will evolve around the existential questions about what it means to be a professional in some field such as a doctor or lawyer (Dhamani 2024, p.137). AI has the potential to free humanity from repetitive tasks and greatly increase the goods and services production. The ability to accelerate scientific research can lead to solutions for resource shortages and climate change. (Russel et al., 2022, p.49) Lack of commitment to AI technologies might result in falling behind other competitors in the market regarding productivity and quality (Barro & Davenport 2019). Although most companies are investing in AI implementation technologies, their strategies for utilizing AI are lacking. As Schuler et al. (2021) mentioned, companies' approach is opportunistic rather than strategic and according to Khanfar et al. (2025), AI strategy is a key factor for AI adoption in the organisation. Many organisations can create a successful AI strategy but at the same time, endless number of organisations fail to do so (Vomberg et al., 2023).

Organisations should in fact make AI as central to modifying their corporate strategies since it can provide a high strategic payoff (Bughin & Hazan, 2017). The revolutionary impact of AI to strategy and operations is essential to understand whether the organisation is a leading digital start-up or a traditional company revamping its operations (Iansiti & Lakhani, 2020). It has been estimated that AI will increase the global economy by $13 trillion over the following decade. (Fountaine et al., 2019)

There is a growing misconception related to the implementation of AI. Many companies are trying to implement AI by thinking it can solve every issue in their business model and offerings, and replace the absence of business vision, however that is not the case. (Kruhse-Lehtonen & Hofmann, 2020) AI can provide great opportunities for organisations but on the other hand, it can pose severe challenges (Holmström, 2022). AI's challenges and benefits are significant topics for organisations across industries. There are many issues organisations are facing when applying AI, such as finding and employing the right talent who has the skills to apply and formulate AI algorithms and systems, or not knowing the extent to which AI can be used. (Alsheibani et al., 2020) Another issue comes if the organisation expects immediate returns and base their view on AI on those. AI requires more than excellent technology and the right talent. It's as important to align the structure and the culture, and the way of working that supports adoption of AI. (Fountaine et al., 2019) These are all part of the strategic approach to AI in organisations.

As the global economy is reshaped by AI, and many companies want to start building their AI capabilities to stay ahead, but they might not know the in-depth consequences that AI can have on the organization. (Herremans, 2021) Additionally, leaders might lack the knowledge of addressing challenges related to AI even though they recognize its key role for organisational performance. (Holmström, 2022) The organisations that are able to tackle the barriers for AI adoption, can effectively secure the opportunities AI can offer (Fountaine et al., 2019). AI and data can help in decision making, automation and obtaining information (Kruhse-Lehtonen & Hofmann 2020) and overall boost the economy though productivity and efficiency increase (Dhamani 2024, p.159).

The AI adoption and strategic implementation process can differ within the size of the organisation and the industry, thus formulating the context for this study is important. This study takes a smaller context of the finance sector that occupies mostly large organisations and has specific challenges related to regulations. The finance sector brings an interesting perspective to the study, as most organisations are mature and not new companies.

1.2 Statement of the problem

As Radhakrishnan et al. (2022) studied, there is a lack of research on the currently used AI strategies of organisations and the benefits of such strategies to those companies. Although

AI is not a new technology, its application systems have faced a surge in recent years and organisations currently lack viable strategies for its use. (Radhakrishnan et al., 2022) Many organisations are struggling to find optimal ways to utilize AI (Vomberg et al., 2023) and no unified frameworks for the implementation of AI have been developed.

If organisations fail to understand the importance of AI to their operations or they underestimate the need for implement it in a way that aligns with the overall strategy of the organisation, they might suffer from lack of competitiveness (Barro & Davenport, 2019). The quick emergence of new AI tools and technologies shows the relevance of this topic to the field. Additionally the strategic approach to utilization of AI is not heavily studied, thus the research focuses on identifying factors that might affect on the AI use in organisations.

1.3 Research aims and question

To build an improved understanding of the approaches organisations are using, this study aims to learn about corporate strategies for AI adoption and implementation from a practical perspective. The theoretical perspective of the study aims to deepen the understanding of formulating an AI strategy. As the research on AI strategy is still in its early stages, the purpose of this study is to connect existing literature and see how organisations are implementing AI and what should be considered when doing so. The idea of this study occurred from an actual organisational need for developing guidelines for beneficial AI implementation. Thus hopefully, this study brings important insights into this relevant topic to real-world organisations.

The implementation of different AI tools as a research topic is overly wide, therefore this study does not focus on the operational level implementation of a diverse range of AI tools but on the strategic approach to implementing AI. This study is not limited by the size of the organisation, and therefore the findings can be applied to a large scale of different organisations.

The primary research question for this study aims to address the problem that was identified above and was developed as follows:

How are organisations strategically implementing AI?

To further address the primary research question, the … following sub-questions were developed as follows:

Sub-question 1: What challenges have emerged when implementing AI?

Sub-question 2: What organisations should consider when adopting AI?

1.4 Research Methodology

An exploratory qualitative research method is applied in this study. This approach allows to produce of new knowledge on topics discussed in real-life contexts. It provides a critical and reflexive perspective on business and the different processes. The major interest of qualitative research is the socially constructed reality, which is then produced and interpreted by cultural context. Qualitative research can be separated into many different approaches that have a variety of features. Thus, the definition of qualitative research is complex. It commonly concerns the understanding and interpretation of a topic. As the approach is sensitive to context, it aims for a holistic understanding of the topic discussed. This is opposed to quantitative research, which is commonly more standardised and structured. (Eriksson & Kovalainen, 2008, p.4-6) Qualitative study was chosen due to the research question types. Additionally it gives more thorough understanding about what is studied. As the topic is quite new, the data is interpretative and requires high expertise on the topic, qualitative research was seen as the most suitable option for the research method.

This study applies a qualitative case study approach to collecting the data. The case study research approach is appropriate for investigating new topics (Eisenhardt, 1989). In the collection of the empirical data, this study conducts four semi-structured interviews. Case study is chosen for the data collection method for its ability to introduce complex business issues in an easy-to-grasp format. While addressing diverse and complex topics. (Eriksson & Kovalainen, 2008, p.117) The cases take a global reach with organisations across Europe to gain more understanding of the topic from international perspective. Multiple-case study approach was taken to be able to identify any differences and additionally compare the results. The interviewees are all from the finance sector which is the context of this research and another reason the results can be compared to each case.

First the key concepts and the existing literature is reviewed and then empirical part of the study is done by conducting the interviews with global experts of AI implementation from the finance sector. After the data is collected, it is systematically analysed to identify relevant themes and possibly new emerging findings. The data is then analysed with Gioia method to ensure qualitative rigor. Gioia method is beneficial for identifying new concepts and advancing knowledge. (Gioia et al., 2013) The choice of research methods is further justified in this research.

1.5 Theoretical framework

The theoretical framework of this study (*Figure 1*) consists of general strategy development, and implementation of new technologies and AI. The general strategy development and new technology implementation are applicable to take into consideration in this study since no formal theory and frameworks have been presented on the topic as it is quite new from an academic perspective. There is a limited amount of research on AI strategies, thus the implications towards formulating an AI strategy are largely based on previous technology strategies. In more detail, the theoretical part focuses on the trajectories of AI, adopting AI and different elements of AI strategy.

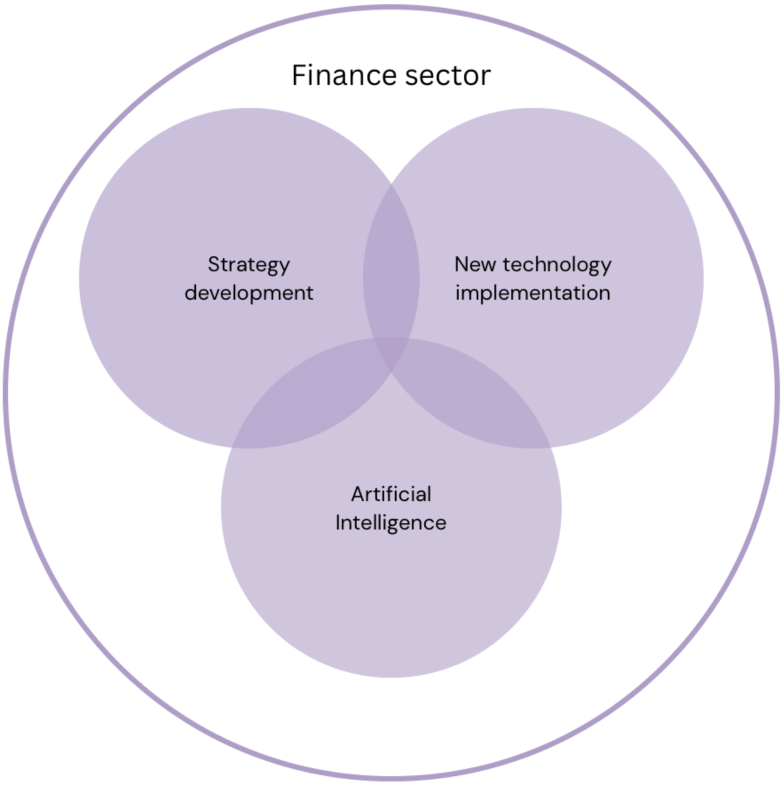

Figure 1 AI strategy development framework

Key theories

The key theories used in this study are discussed and they are presented in the *Table 1*. As the research topic is quite new, the theory background focuses on general strategy development, and technology implementations. Additionally key theories from AI-specific factors are researched. The structure of theoretical framework focuses first on general strategy development, where the resource-based view (Barney, 1991), and dynamic capabilities (Teece & Pisano, 1998) are introduced and their relevance to this study elaborated more. Then the theoretical framework moves towards implementation of new technology, where the Technology acceptance model (TAM) (Venkatesh & Davis, 2000) is presented. The final theoretical frameworks discussed in the literature part are focused AI Trust and the Intention to use AI Systems (ATIAS) (Faruqe et al., 2023), the Trajectories of Technology framework (ToT) (Berthon et al., 2005), and AI strategy framework (Herremans, 2021).

Table 1 Key theories

Theory	From	Relevance to this study
Resource-based view	Barney (1991)	Developing the key resources for an organisation
Dynamic capabilities	Teece & Pisano (1998)	The importance of adapting to changing markets
Technology acceptance model (TAM)	Venkatesh & Davis (2000)	How attitudes affect on accepting or rejecting the adoption of technologies
AI Trust and the Intention to use AI Systems (ATIAS)	Faruqe et al. (2023)	The trust between humans and AI and the intention to use it.
Trajectories of Technology framework (ToT)	Berthon et al. (2005)	Understanding to constant change of technologies
AI strategy framework	Herremans (2021)	Identifying different factors for creating an AI strategy

Key terms:

Artificial Intelligence: According to Duan et al. (2019), no generally accepted definition of Artificial Intelligence (AI) has been formed. However, it is commonly referred to as the machine's ability to perform human-like functions by learning from experience and being able to adjust according to new inputs. The lack of an accepted definition of AI is connected to the rapid evolution of the technology, making it hard to define. (Duan et al., 2019) AI machines can figure out an effective and safe way to act in a variety of situations. There is a wide range of subfields under the term AI as it is relevant to any field of intellectual tasks from learning and reasoning to specific tasks as playing chess. (Russel et al., 2022, p.19)

Digital transformation: The process of responding to changes in the environment by utilising digital technologies to transform the process of value creation. This requires taking into account to several hindering factors to ensure successful outcomes. (Vial, 2019)

Strategy: The Organisation's plan that combines the goals and policies as well as actions as a whole and provides the principles for accomplishing the objectives. (Lynch 2018, p.18; Hunger & Wheelen, 2011, p.23)

Trajectory: Berthon et al (2005) established the Trajectories of Technology (ToT) framework which refers to technology not being static but active in a way that it evolves and changes over time.

AI readiness: Adopting AI creates opportunities and challenges that are different from other technologies thus AI readiness is a good foundation for adopting AI successfully. AI readiness considers 18 measures under five themes, these themes include strategic alignment, resources, knowledge, culture, and data. (Jöhnk et al., 2021)

1.6 Delimitations

The limitations of this study are highlighted in the following part. As presented previously, this study is relevant from academic and business perspective, however, the topic is quite new and constantly evolving. Thus, there can be multiple aspects that are not yet known from the existing literature and the empirical part. The lack of a defined AI strategic framework is another limitation to the study. The AI technologies and differences between used AI systems are not considered in this study as it focuses on a higher-level approach to AI in organisations.

The interviews as a data collection method can create limitations since they can be interpreted differently. Additionally, the native language of some interviewees is not English, meaning there is a possibility for misinterpretation. The data collected is from the finance field, thus different industries are not presented in the study. The limited number of case companies bring additional limitation since the data might not bring all the different approaches financial organisations have utilised in the AI strategy. The size of the case companies are large organisations and their approaches and resources towards AI are vastly different than start-ups or SMEs. Smaller companies or new ventures don't necessarily have the same challenges for approaching AI in strategic manner than large organisations have.

1.7 Structure of the study

The structure of the study progresses with the following concept (*Figure 2*). After the study has been introduced, the study focuses on reviewing the existing literature. The existing literature formulates the theoretical background for this study. As discussed previously, the theoretical background introduces basics of strategy development and then moves towards implementing new technologies and finally takes a look at AI from multiple perspectives. The third chapter of this study introduces the research design and methodology. Additionally, the third part coves the data collection method and data analysis method. The following part presents the findings from the data. The fifth chapter then connects the findings from the interviews to the existing literature and discusses the similarities and differences. In this chapter, the research questions are answered. The final chapter presents the key results, managerial implications, limitations and future research directions.

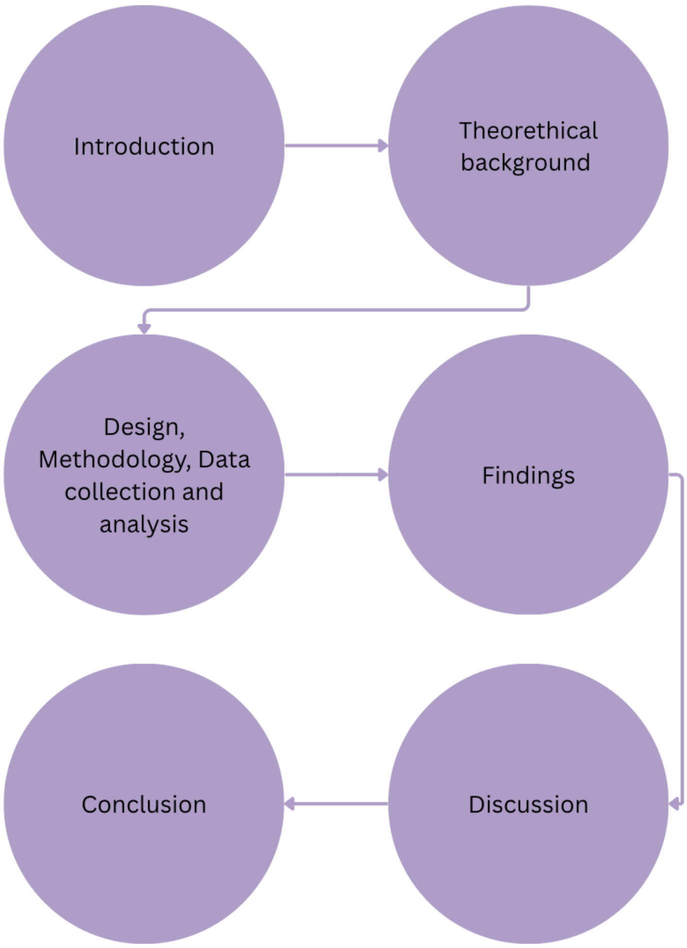

Figure 2 Study structure

2 AI strategy development

This part of the study focuses on the existing literature on the topic. First, the rationale for creating an AI strategy is explained. After this, the general strategy development and strategic implementation of new technology are discussed. Followed with the AI as a new technology and its trajectory. Finally, this literature review further looks at AI in organisations and its implementation. The first step for the literature review was to search documents from the database Scopus with the keyword “AI strategy” or “Artificial Intelligence strategy” in the article title, abstract, and keywords this search only brought 583 documents by limiting the subject area to computer science, engineering, business, and social sciences. 531 of these articles were published between 2018 and 2025. These articles were screened, and majority were not firmly related to this study topic. The number of articles in this topic was limited which is an indication of a relatively new topic since academic articles are emerging. Additionally, as most of the articles were published during a seven-year period, it showcases how emerging the topic is to study further.

2.1 Strategy development

The basic strategic development process is researched, to understand the connections between business and corporate strategy and AI strategy. Strategy acts as a organisation’s long-term direction including the organisational activities. Strategic decision-making addresses the changes happening in the business environment while meeting the values and expectations of the stakeholders. Even though strategic decisions are complex, their purpose is to aid in uncertain situations. Strategic decision-making affects operational decisions, and it should be looked at inside and outside of the organisation. (Johnson et al., 2007, p.6-7) Commonly, strategic formation revolves around the basic forces of a constantly changing environment, the operating system of the organisation seeking to stabilise actions, and leadership as the mediator between the two forces. Organisations’ consistent behaviours to establish their place in the environment for a certain time. Strategic changes are not steady due to environmental inconsistencies and rapid changes. Sometimes, the need for reassessing the current strategy can be irrelevant even for longer periods but sudden environmental turbulence can create a need for re-evaluation. (Mintzberg, 1979)

Building an organisational strategy is crucial to preserve a competitive advantage to be able to face an uncertain and complex future (Sinnaiah et al., 2023). Strategic-decision making can be divided into two categories: content research and process research. Content research handles strategy content issues such as diversification and environmental character alignment with firm strategies. Process research handles strategic decision-making processes on how it is made and implemented. (Elbanna, 2006)

There are four basic elements in the process of strategic management (*Figure 3*): environmental scanning, strategy formulation, strategy implementation, evaluation and control. Each of these elements is important when thinking of strategic management. Environmental scanning consists of the external and internal environment of the organisation. The external environment is the variables of opportunities and threats, the internal environment is the strengths and weaknesses. Strategy formulation is about developing a long-term plan for effectively managing the organisation's external and internal environment. Implementation of the strategy is the process where the strategies are taken into action, and it can involve cultural, structural or managerial changes. (Hunger & Wheelen, 2011, p.21-25)

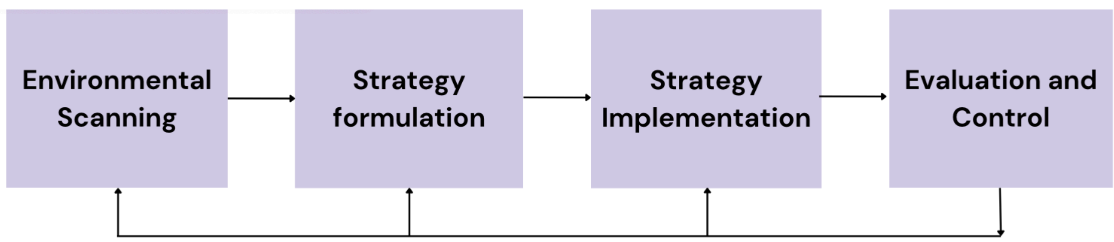

Figure 3 Elements of strategic management process (After Hunger & Wheelen, 2011, p.21)

Strategies can be looked at three different levels corporate, business, and operational (*Figure 4*). Corporate-level strategy is the top level which concerns the purpose and scope of the organisation and the value generation of different parts in the organisation. Commonly the corporate-level strategy is concerned with expectations of shareholders and its crucial part in strategy formation. Business-level strategy is the second level in strategy which includes how the organisation can successfully compete in their market. Even though the corporate and business-level strategies are both quite identical, the corporate-level strategy can include several businesses and still there should be a link between both strategies. Operational strategy is the third level, which concerns the components of the effective resource, process, and people delivery for corporate and business level strategies. (Johnson et al., 2007, p.6-7) This thesis focuses on the corporate and business level AI strategies instead of operational level, due to the diversity of different operational applications. The limited research on corporate AI strategies is another key factor for choosing the higher-level approach.

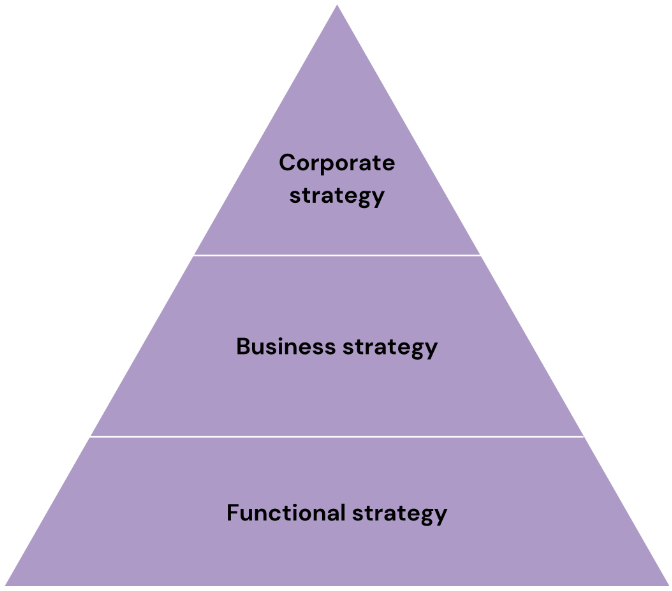

Figure 4 Three levels of strategy (After Johnson et al. 2007)

According to Bharadwaj et al. (2013), it is not enough to align organisations' IT strategy to the operational-level strategy but to generate an interconnection between these terms into a digital business strategy. They define digital business strategy as the organisational strategy that leverages digital resources in order to gain differential value. Generally, technology has sped up the decision-making process for organisations (Bharadwaj et al., 2013), and AI is likely even to generate faster decision-making.

Barney (1991) developed a resource-based view theory to describe the development of sustained competitive advantage by internal resources of the organisation. Resource based view comprises firms' resources, competitive advantage and sustained competitive advantage to for the theory. Resources of the organisation can include human capital, physical capital and organisational capital. Competitive advantage is a strategic approach that competitors are not implementing and sustained competitive advantage is achieved when the same strategy can't be duplicated by another organisation to achieve the benefits. In a industry where the first firm to implement a specific strategy can achieve sustained competitive advantage. There are four attributes that the firms resources have to comply in order to gain sustained competitive advantage. These attributes are valuable, rare, inimitable, non-substitutable. (Barney, 1991) Understanding the first is important regarding the implementation of AI strategy in the financial field.

Managing the set strategies requires the output from managers of implementing the strategy. Strategic management evolves around comprehending the strategic position, forming the strategic choices, and managing the strategy. Organisations should acquire strategic capabilities which are the resources and competencies that the organisations need to prosper and survive. For an organization to be able to compete in their market by meeting the requirements is referred to as threshold capabilities. (Johnson et al, 2007, p.12, 97) The shift in the environment requires a strategic response by leveraging existing capabilities of the organisation. This is referred as dynamic capabilities. The internal and external skills, competences and resources are the capabilities of an organisation and they must be adaptable to the market changes. (Teece & Pisano, 1998, p. 193-210) As AI is being embedded into the markets, organisations have pressure to keep up with the threshold capabilities in order to meet the requirements of customers and the changing landscape. An important question lies in whether AI implementation will become a threshold capability in the near future or is there a possibility to implement it to gain competitive advantages.

When making strategic decisions in the organisation, the aspect of innovation need to be accounted for. Innovation is highly important to the topic since adopting new technologies in organisations requires a level of innovation within the organisation. The reasons behind innovation, are discussed now. Innovation driven by technology push or market pull. With technology push, the new knowledge of a technology is the driving force for innovation where as with market pull the innovation comes from the market demands. Only focusing on existing customers of the organisation, they might be left vulnerable with disruptive technologies where the new needs are being discovered. However only pursuing technological advancements without taking into account the market needs can be damaging. Commonly organisations compromise within the two options. (Johnson et al., 2007, p. 326)

2.2 Strategic implementation of new technology

For this study, it is beneficial to start looking at the historical research regarding technology implementation to understand the basics of applying new technologies to organisations and thus, it can be utilised in the case of AI implementation as it shares similarities. Additionally, this chapter considers different theoretical models for creating a suitable AI strategy for an organisation. These models include the technology acceptance model (TAM) and the technology–organisation–environment (TOE) framework. Taking an approach towards digital transformation reflects the process where an organisation responds to environmental changes by taking advantage on digital technologies to change their process of value creation for remaining competitive. (Vial, 2019) Currently, the key driver of digital transformation in organisations is AI. (Hölmström, 2022).

The technology acceptance model is based on two factors that determine individuals' use of a system and it aims to understand the reasons for rejecting or adopting a new technology. The two factors are perceived usefulness and perceived ease of use. The particular theory has been recognised widely across the research field with different technological systems and thus the applicability of that model for AI strategy should be taken into account. (Venkatesh & Davis, 2000) Khanfar et al. (2025) challenged the previous studies where the determinants of technology adoption as firm and the individual level are independent and created a interrelated holistic model that divided the determinants as social, individual, organisational, and environmental.

The TOE framework aims to explain three elements that influence adoption decisions within a firm context. The elements are technological, organisational, and environmental contexts. Each element influences organisations' technological innovations. Beginning with the technological context, it includes the current technologies the organisation is using and those that are available in the market but which the organisation is not currently using. Technological innovations producing discontinuous change requires organisations to generate quick and decisive adoption in order to be competitive. Some technological innovations that cause discontinuous change can enable gradual change in the organisation when building expertise, while other technological innovations can make existing technologies and expertise obsolete. These latter technological innovations can create extensive transformations in the industry. Carefully considering the organisational changes from new innovations is important, since some have a more dramatic impact on the organisation and the whole industry. Moving to the second factor, which is the organisational context. The organisational context indicates the resources and characteristics of the organisation as well as links between employees and processes. Organisational structure can be used to identify the relationship to the process of adopting innovation. In the environmental context, there are the industry structure, the existence of technology providers or lack of them, and the regulatory environment. The regulatory environment can possess beneficial or disturbing effects on organisational innovation. Governmental regulations in the finance sector can prevent organisation in that industry from introducing specific innovations. All of these elements have an influence on organisations technological innovation. (Baker, 2012)

Digital technologies have drastically influenced organisational operations (Al Aqeel et al., 2024. p.3-19). Fitzgerald et al. (2014) studied how organisations embrace digital technologies and found that introducing new technologies to organization aims to transform the business, however gaining results from new technologies can be challenging. During a digital transformation, most companies lacked the experience with new digital technologies and most saw their digital maturity level as a beginner where their approach and view towards more advanced technologies is slow or skeptical. Some companies hold back from new technologies in purpose and in some cases companies approach is even aggressive towards adopting new technologies but their coordination in different departments and vision is missing. There are always the digital leader companies where the management has strong vision for technological adaptation and area able to manage it whilst gaining value from the transformation. These companies will benefit from more profitability compared to their competitors, which indicates that the digital transformation failure is harmful for the competitiveness of the company. Effective and quick respondence of new technologies affects on the outcome and in the end, the business survival. (Fitzgerald et al., 2014)

Digital technology adoption has created multiple benefits to companies such as customer experience increase through launching new products or enhancing existing services, operational improvements for example automating processes, and change of the business model. (Fitzgerald et al., 2014) There are several obstacles the organization must overcome such as opposition to change, security concerns, and cost (Al Aqeel et al., 2024. p.3-19). Although companies and management are acknowledging the need for transformation towards digital technologies, their challenges arise with reaching the business benefits. This often relates to lack of management temperament and experience for effective transformation with technology. (Fitzgerald et al., 2014)

During digital transformation, some companies experienced a lack of urgency to achieve the transformation which might have been due to no motivation as there were only a few leaders with a vision and road map for it. Choosing the direction for the company to pursue regarding digital transformation is challenging and developing a road map brings difficulties since there are many areas to consider. In some cases, there needs to be structural changes within the organization to transform the process for value creation. These changes can be related to organisational structure, organizational culture, leadership or employee roles and skills. (Fitzgerald et al., 2014)

Employees can create institutional challenges for digital transformation for example if the older generation of employees are reluctant for technological change and thus affect the adoption of new technologies (Fitzgerald et al., 2014). This can occur if the new technology is introduced in a way or pace that is not accustomed (Vial, 2019). Another institutional challenge is the legitimate of existing systems and the complexity of updating those to fit into new technologies. (Fitzgerald et al., 2014) According to Al Aqeel et al. (2024. p.3-19), the existing technological capabilities as means and the know-how affect the adoption of new technologies. If an organisation has more sophisticated capabilities related to technology, they are more likely to be the early adopters and receive a competitive advantage (Al Aqeel et al., 2024. p.3-19) Sometimes, the existing tangible and intangible components of the organisation are heavily correlated to the practices, thus making barriers for innovative and disruptive digital technologies (Vial, 2019).

Embedded attitudes in the company culture can increase the fear and lower adoption of digital transformation whether it is related to lack of familiarity with the technology, resistance to new technologies or threat of losing power structures. Cultural and organizational resistance creates risks for employees to pursue towards digital transformation if there are no clear structure to it. Setting the key performance indicators to measure the digital transformation is key for getting clarity about the expected benefits from such a process. (Fitzgerald et al., 2014)

2.3 AI new technology and trajectories

Previously, this study discussed the strategic implementation of technologies. This chapter looks at the history of AI in brief and then takes another theoretical model that is based on the TAM model discussed previously to understand its reach to AI and then discusses the trajectories of AI.

AI shares the same issues and challenges of implementation as many digital technologies, however, with AI there are additional challenges such as the uncertainty of the capabilities of AI and its future development (Alsheibani et al., 2020. The evolution of AI can be divided into three phases: (1961-1980) initial phase, (1980-200) industrialisation phase, and (2000-) explosion phase. The first summit of the development of AI was in 1985 to 1995 and the second started in the explosion phase in 2006, and it's still growing. The explosive growth of AI has emerged in applications as well as techniques. There are three technological perspectives; platforms, algorithms, and interfaces, where breakthroughs will even further increase the development of AI. Humans are able to dedicate a much more energy to unknown areas when the adoption of AI becomes widespread. (Lu, 2019) According to Dhamani (2024, p.227), during the near future, generative AI will be integrated into other applications and it will become even more efficient and personalized. As advancements in AI are rapidly progressing, companies are compelled to integrate it to their operational frameworks to gain competitiveness (Hölmström, 2022).

Trust is the key factor for using a system. It's a challenge to create an AI system that acts accurately and fairly, but another challenge is to convince others that. The key to using AI is that people can trust it. For an AI system to earn trust, it must go through a verification and validation process. (Russel et al., 2022, p.1047) An extent of the TAM model includes the aspect of trust towards the AI systems for the user. Building trust among humans and AI evolves around transparency about AI's perceived explainability, fairness and privacy. As the TAM model does not include AI ethics as a factor, another model called AI Trust and the Intention to use AI Systems (ATIAS) was composed. (Faruqe et al., 2023) This model takes into consideration the understanding of the adoption of AI and its usage, which is needed to understand the organisation's willingness to generate AI strategy and understand its value, as well as the individual employee's perception of AI, which is important in the implementation of such strategy. (Faruqe et al., 2023) Few researchers have also connected the TAM and TOE models in the case of AI adoption (Chatterjee et al., 2021; Khanfar et al., 2025).

Usually, technologies are developed to fulfil some need and once that is released to the world, it is subject to forces and processes that can alter the trajectory of that technology towards new or even surprising directions. The processes of technology evolving can be either intentional where the technology is changed by the people, or unintentional where people are changed because of the technology. Intentional processes can be about improving existing technology to make it superior, or when a third party adapts the technology for use which it wasn't primarily intended. Another intentional process occurs when a third party aims to affect the adjustments in the technology or initiate restrictions to use it for example governmental restrictions. Regarding unintentional processes, one is when the technology has a changing effect to people either through a positive feedback loop or a negative. The positive feedback loop occurs when the behaviour of consumers and society changes through technology for example with the Internet or mobile phone. The negative feedback loop refers to unintended consequences for the environment, society and consumers which usually are unintended side-effects. All of these intentional and unintentional processes are interrelated. (Berthon et al., 2005) These Trajectories of Technology are intriguing for the development of AI in the society and what directions will the trajectories of AI develop and at what speed.

Developing and shaping technology to fulfil constantly evolving needs and wants, will ultimately shape the society. The trajectories of AI are shifting between advance growth through the unintended process where technology changes society and the demand for safety regulations. As happened with the Internet, AI will likely form to be and behave quite different than what was expected, thus organisations and leaders should expect the unexpected and not take too many assumptions from the past. Anticipating effects of AI while planning for various different scenarios makes a step futher from only seeing AI as an tool for strategic decisions. (Berthon et al., 2024)

Previously the conventional approach to strategy was centred around traditional industry analysis, however, this approach will be less effective in the future. Organisations need to think outside traditional industry boundaries and not only stick to the business they know in a familiar industry. The new era of industries is shaped through data and analytics and algorithms are transforming across usual boundaries. A strategy that is focused on connections across industries and data flow through networks is important. (Iansiti & Lakhani 2020). The strategic alignment of a company is about the potential functions of AI in the business and how it fits into processes. Additionally, strategic alignment relates to how ready the customers are for AI integration and whether there is support from the top management for strategic AI implementation. (Jöhnk et al. 2021) Radhakrishnan et al. (2022) composed a themed summary of the key factors to understand the AI journey in organisations, which included the themes of facilitators and barriers of AI adoption, AI trends and AI capability-building strategy.

2.4 AI readiness

After understanding the reasons for an organisation to develop an AI strategy, the organisation's readiness for AI is discussed and the basics of adopting AI. The different sources of value that are beneficial for the organization can vary and Borges et al. (2021) discovered value creation methods with AI. The decision support that AI can provide to human decision making is one of the sources of value, however some individuals might show persistence to utilize AI information due to fear of elimination of ones job. This requires alignment of AI and human opportunities for successful implementation. Another source of value which might be the most common is automation of processes, which can be achieved with a certain level of easy implementation and create fast return on investment. To achieve the benefits of automation with AI, it is necessary to generate digital business strategy while developing organisational capabilities. Organisations can also create value by developing new products and services that are based with AI, but again, the strategies have to align to successfully implement innovative solutions. (Borges et al., 2021) Creating partnerships with AI and humans can develop beneficial opportunities. In uncertain decision-making processes, AI can assist humans with predictive analytics to enable effective decision-making for humans. (Jarrahi, 2018) However, humans must have trust to the suggestions the algorithm makes and feel empowered form decisions with the help of AI (Fountaine et al., 2019).

Jöhnk et al. (2021) studied the different factors that affect on the organisational readiness within AI adoption and found five themes that should be considered (*Figure 5*). Understanding and managing these themes will generate a higher chance of successful AI adoption, which is important in the research regarding AI strategies. According to Polisetty et al. (2024), organizational AI readiness is dependent on the perceived benefits of AI, such as improved efficiency or cost-savings. Being aware of the benefits of AI, organizations can drive their strategic development which will ultimately support the AI readiness of an organization. There is a potential for adopting AI to gain a competitive advantage. (Polisetty et al., 2024)

Figure 5 AI readiness (After Jöhnk 2021)

AI adoption is related to organisational creativity and productivity increase and ultimately can have a positive impact on the dynamics and capabilities of the organization. There are specific opportunities found in the implementation of AI and these can be divided into several categories. In the organisational environment, implementing AI can increase the understanding of data and from an operational perspective, AI offers predictions and improvements in efficiency. (Dwivedi et al., 2021) A compatible infrastructure that is already existing in the organization is another facilitator. Another key facilitator is the availability of appropriate training data. On the other hand, the complexity of data or its unavailability or poor quality are the barriers of AI adoption. (Radhakrishnan et al. (2022). However successful AI adoption requires not only technological investment but significand organizational and cultural transformation. Thus organisational culture should foster change and innovation as well as encourage experimentation. (Ali et al., 2024)

Jöhnk et al. (2021) saw the resources of an organization as a factor for AI readiness and this includes the financial budget, personnel and IT infrastructure. Third factor relates to the personnel factor, and it is the knowledge of the organisation. There should be awareness of AI, which in itself creates higher results, and if current employees don't have adequate knowledge, they should ensure upskilling the employees with AI-related skills. The culture in the organisation is another key factor for AI readiness. Organisations should promote innovativess and utilise collaborative work to create favorable culture. The final factor is data and its availability, quality, accessibility and flow. (Jöhnk et al. 2021) For managers, the cost of AI system and return on investment are important factors in AI adoption, however these factors are not relevant for employees. Factors influencing the AI adoption of both managers and employees are the complexity of the systems and security. (Khanfar et al. 2025)

Radhakrishnan et al. (2022) and Khanfar et al. (2025) found that organizational culture that encourages and rewards innovation with support from top management and skilled resources can be all seen as facilitators of AI adoption. To ensure that the organisational culture is suitable, there needs to be visionary leaders behind the organisation who have the understanding of implementing technologies as a part of their strategy to make sure they are ready for the future and prepared (Chishti et al., 2020, p.63). Continuing with the organizational culture that resists change or has infrastructure issues or misalignments between their technology and the business are seen as barriers to adopting AI. Organisations also see security and privacy laws and regulations as a barrier. (Radhakrishnan et al., 2022)

The efforts of AI implementation are dependent on the use case and even if some processes generate quick results, their results might contain more minor outcomes as opposed to processes where implementation of AI requires more investment but the outcomes are vastly impactful. (Kruhse-Lehtonen & Hofmann, 2020) Long-term prioritisation for example three-year period with several initiatives where each has different time lines, can be a way to maximise value (Fountaine et al., 2019). Thus AI implementation should be considered in different business areas in the organisation (Kruhse-Lehtonen & Hofmann, 2020). As the AI opportunities for organisations have rapidly grown, organisations might face difficulties determining the starting point. A more straightforward starting point is optimising current processes where existing data is leveraged to enhance organisations services for example. (Kruhse-Lehtonen & Hofmann, 2020)

Radhakrishnan et al. (2022) studied different trends in AI implementation that companies might have followed. The first trend related to the transition from exploratory phase of experimenting which AI tools should be used to implementation phase where those tools have been narrowed. The following trend is focused on the transition to intelligent automation from the previous robotic process automation. The final trend that organizations can follow is the move from collecting data to obtaining knowledge from the data. (Radhakrishnan et al., 2022) Once the organisation has proper data understanding, they can investigate the possibilities of new data-driven business opportunities such as selling data (Kruhse-Lehtonen & Hofmann, 2020).

2.5 AI in organisations

To come up with a corporate AI strategy, all parts related to building such a strategy should be aligned and thought out. The *Table 2* indicates existing research related to the key elements of AI in organisations. Although not all research has used the term "AI strategy", their topics are aligned with this research, and the key elements were quite similar. Thus they could be applied to this study. From the *Table 2*, it can be identified that Herremans's (2021) framework for AI strategy and Kruhse-Lehtonen & Hofmann's (2020) framework for data and AI strategy include the most variety of elements. Those frameworks were combined and brought to this study to implement.

According to Herremans (2021) the corporate AI strategy should be composed by thoroughly considering the following factors: Goals, data, AI team, AI in the company, Technologies, KPIs, Risk level, and Cultural shift. Kruhse-Lehtonen & Hofmann (2020) defined the framework of data and AI strategy through four main areas: DNA, enablers, assets and ambition. The ambition of the organisation is the foundation for the framework and it includes the vision and overall strategy. Assets that the organisation can adopt are the use case business integration, AI portfolio and data assets. Enables for the strategy are human skills, privacy & ethics, architecture & technology. Governance, leadership and culture belong to the dna of data and AI strategy in an organisation. Schuler and Schlegel (2021) addressed the corporate AI strategy through a conceptual framework that consisted of technical questions, corporate culture and HR, which a firm should analyse when making their strategy. Alsheibani et al. (2020) formulated six steps of possible challenges organisations can face with AI and developed a framework to support organisations by asking the right questions. That study highlighted AI business cases, top management support, relative benefits of AI, AI talent, AI compatibility, and effective use of data for organisations to leverage their capabilities to deploy AI and create business value. Jöhnk et al. (2021) research about companies AI readiness is directly linked with the elements of AI strategy.

Table 2 AI Strategy frameworks

Element/ Source	**Objectives**	**Data**	**People**	**AI maturity/ technologies**	**Culture**	**Ethics and risk management**	**Measurements**
Herremans, D. (2021)	Identifying opportunities (problem and goal)	Data strategy	AI team	Technological capacities	Enabling adoption	Weighing risks and benefits	Quantifying value
Schuler, K. & Schlegel, D. (2021)	Strategic alignment, decision processes	Data storage, management, and governance	Organizational capacities, human resources	Infrastructure, sourcing	Organizational structure, leadership, corporate culture, communication	Legal conditions, Ethical conditions	
Kim, J.-S. & Seo, D.	Strategic priority (strategic direction)	Availability of data		Technological capability (core competency), computing power			
Polyviou, A. & Zamani, E. D. (2023)		Data availability, sufficiency and protection	Digital literacy on AI (education and upskilling)		Ecosystem collaboration	Liability and accountability	Continuous monitoring and assessment of AI usage

Ashri, R. (2020)	Business process modelling	Data availability 1-5 stars		Necessary preconditions and processes (AI capabilities)	Organisational motives		
Alsheibani, S., Cheung, Y., Messom, C. & Alhosni, M.	AI business case, AI relative benefits	Effective use of data	AI talent	AI compatibility	To management support		
Kruhse-Lehtonen & Hofmann (2020)	Vision & strategy	Data asset, AI portfolio	Human skills,	Architecture, technology, use case business integration	Organization, governance, leadership, culture	Privacy, ethics	Monitoring performance

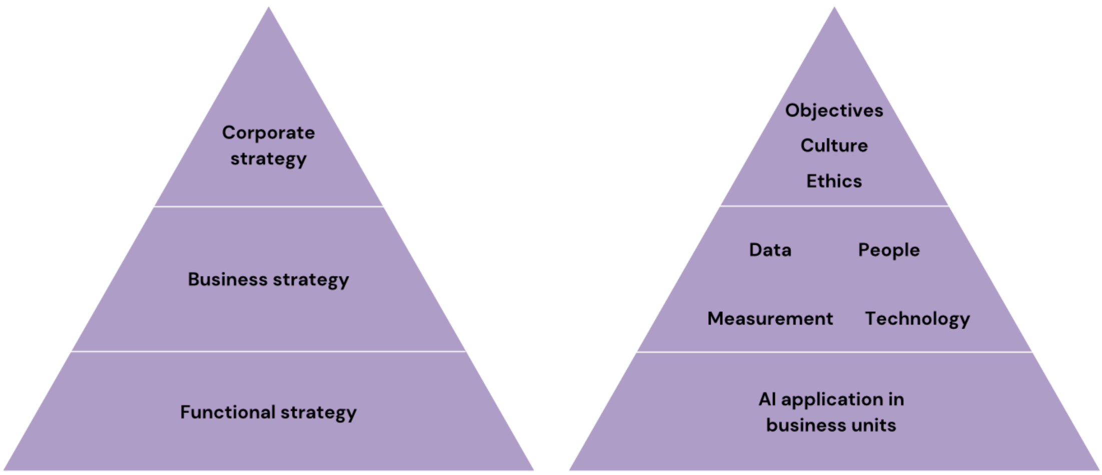

Figure 6 Strategic levels and AI strategy

Figure 6 shows the link between the three strategic levels discussed previously and the AI strategic framework elements that are implemented in this research. As there is a link between the corporate and business strategy, the elements of AI strategy are connected to both levels. The following part of the literature introduces elements of the AI strategy to further understand its importance. Objectives of the organisation is the first factor that is considered important to understand and thus taken to further study. The following factor is the culture and leadership, almost most of the existing literature highlights the importance of those factors. Ethics and risk management is then the third factor to study in the AI strategy. One of the key factors then presented is the data and technology. People in the organisation is the following factor and finally the measuring of the strategy is taken into consideration.

2.5.1 Objectives

AI strategy should be aligned with the general business strategy. (Schuler & Schlegel, 2021; Borges et. al, 2021) Clear goals are an important step for any IT strategy (Herremans, 2021). AI implementation requires clear objectives of what the company wants to achieve rather than abstract agendas (Chishti et al., 2020, p.41) and the organisation's ability to predict areas where value can be added with AI or where it can address certain pain points is important (Akerkar, 2019. p71). However, organisations shouldn't only look at AI as a cost-cutting tool but rather see it as the potential to grow with it by creating new products or achieving larger market share or increasing overall productivity. It is more common to see AI as a cost-cutting tool if the organisation has less experience with AI compared to an organisation where they are more familiar with it. (Bughin & Hazan, 2017)

According to Herremans (2021), organisations should generate ideas of goals and problems in the operations where AI could be leveraged. This would provide possible projects for the organisation to implement where each project has a different risk level and requirements. Finding internal gaps of efficiency where AI could provide benefits to operations can be beneficial. Additionally, this study advises looking for existing AI technologies that could be beneficial and make competitor analysis of their AI tactics. (Herremans 2021) However, as Iansiti & Lakhani (2020) mentioned, only concentrating on industry-specific competition can become ineffective.

2.5.2 Culture and leadership

Effective implementation of AI technologies requires an organisational culture that promotes support and encouragement of utilising AI as well as overall innovativeness. (Heo et al., 2022; Radhakrishnan et al., 2022; Khanfar et al., 2025) Leaders must provide vision that indicates that everyone works for the same goal, this includes the people understanding the importance of AI to the organization and their role in the new culture with AI orientation. The traditional approach from the top down, where employees must consult higher-level management for decision-making, inhibits AI use. (Fountaine et al., 2019)

Business leaders are the key to creating an environment that is effective for implementing AI even though they might focus on the statistics or the coding part. Such an environment includes developing the business goals and employing the best people for the job as well as providing education for the existing workforce. In addition, it's important to implement an operating model that follows goals and incentives for the organisation. (Kruhse-Lehtonen & Hofmann, 2020)

Managing AI technologies includes introducing new leadership skills. The management is committed to the change and participates in transformation programs. (Bughin & Hazan, 2017) Educating and preparing the leaders for making decisions in the future about AI and what could be the best strategy to manage it is a good starting point. Underestimating or even overestimating can lead to missing opportunities or wasting valuable resources. (Barro & Davenport, 2019).

2.5.3 Ethics and risk management

AI implementation has the potential of presenting vast challenges for organizations such as legal and ethical (Dwivedi et al. 2021) Organisations that operate using digital models such as AI can generate value as well as harm even if their intentions are positive (Iansiti & Lakhani 2020). Machine learning can be a powerful instrument in cybersecurity from the attackers side and the defender's side (Russel et al., 2022, p.1041). Mistakes can lead to destructive cyberattacks for large networks and unchecked algorithms can lead to bias and misinformation. Many risks face a large magnification if occurred. (Iansiti & Lakhani, 2020).

Finding the balance between the considerable advantages of AI and basic privacy rights will be an ethical dilemma in the future. It is not enough for AI to perform accurate and high results, it needs to fill the privacy concerns and regulatory requirements. The regulatory and social pressure from data processing will become more demanding for organisations. (Akerkar, 2019. p13) At the same time, the institutions keeping an eye of businesses are struggling to maintain control with the rapid change of technology (Iansiti & Lakhani, 2020).

Jobin et al. (2019) gathered global guidelines for AI ethics and highlighted five ethical principles in AI policies. These principles are transparency, justice, privacy, responsibility, and non-maleficence. However, there are differences in priorities of those principles, which can create challenges for creating global ethical AI agendas. Those described principles should be translated into practice with AI ethics codes and legislation. (Jobin et al., 2019) A large ethical dilemma is the possible societal biases that can occur if the machine picks up gender or racial prejudices from the training set. The developers of such machine learning systems must have a moral responsibility to ensure fairness from the system. (Russel & Norvig, 2022, p.1043)

Lu (2019) raised an important aspect regarding the ethical questions related to the development of AI. AI development can affect regulations and rules of society, and it can lead to ethical issues. If prejudice and errors impact the machine systems, and the AI machine comes up with ideas that differ from human beliefs. The question lies in what humans should do in such a scenario. (Lu, 2019) Since AI don't have true expertise or knowledge, the deployment of such technologies should occur in a human-in-the-loop context. Additionally, it requires stakeholders to develop AI literacy to know how the models work before utilizing them. (Dhamani 2024, p.227) Managing the opportunities and threats is going to be a legitimate test for organisations and their leaders (Iansiti & Lakhani, 2020).

2.5.4 Data and technology

Research suggest that data is the cruzial element in building AI strategies (Herremans, 2021; Schuler & Schlegel, 2021; Polyviou & Zamani, 2023; Ashri 2020; Chishti et al. 2020; Polisetty et al. 2024). AI systems' prerequisites for intelligence are largely based on the availability of relevant data (Akerkar, 2019. p13) and creating a solid digital foundation is needed (Bughin, & Hazan 2017). However, as there are different factors and perspectives of data, it should be thoroughly analysed and then implemented into the strategy. A critical factor when building the data asset is, to begin with use cases or business opportunities that are prioritized since many companies can create a large disconnection between the engineering team and the end business functions teams if the solutions created are not needed. Thus, sustainable results will arise with close collaboration with both teams. (Kruhse-Lehtonen & Hofmann, 2020)

As data is critical in AI, the organizational systems should be designed or have features that support the data availability (Chishti et al., 2020, p.44). According to Radhakrishnan et al. (2022), many firms struggle with not having adequate data that can be used to train the AI system, or if the data is available, it might be biased. In many cases, the sample size disparity, which is the lack of training data, can ultimately lead to results that are biased. This problem of the lack of data can be referred to as a cold-start problem. There, the initial challenge occurs when launching a digital product with no existing users, data or customers that can be leveraged. The cold-start problem must be overcome for AI-led value creation through network effects, where the acquisition of an increased amount of data is the key. (Vomberg et al., 2023) A key practice with data collection is the elimination of personal information, which is referred to de-identification (Russel et al., 2022, p.1042). The problem of de-identification of data, especially in highly regulated industries, is evident. The process of de-identification of data is costly and can even damage the data features that are crucial. Another issue is failing to correctly secure it. (Chishti et al., 2020, p.44)

Regarding the availability of data, an organisation should asses whether they possess necessary data and if not, they should start collecting it. Commonly the more data is integrated into the algorithm, the better the results are, but this is not always applicable. Another challenge in data collection is the pace of acquiring data which in some situations can be lengthy. Legal requirements to keep the data private and safe is a crucial element to consider. (Herremans, 2021)

An organisation should thoroughly analyse the compatibility of existing software used and the possible AI integration. Incompatibility with current software will delay or even refrain from effective AI adoption. Thus, effective implementation of AI in organisations requires compatibility with current technologies (Heo et al., 2022; Radhakrishnan et al., 2022; Polisetty et al., 2024)

2.5.5 People

According to Iansiti & Lakhani (2020), AI will have a significant effect on organisations and employees since possibly half of the activities at work will be replaced by AI, on the contrary Fountaine et al. (2019) found that rather people being replaced by AI, they need to adapt using it. Both can mean the enrichment of many jobs and new interesting opportunities but additionally an extensive dislocation for many occupations. (Iansiti & Lakhani, 2020). Generative AI possibly leads to redundancies of employees with lower skill levels and the increasing need for highly skilled employees (Brühl, 2024). Successful AI strategy does not only include taking new AI technologies into business processes but to recruit and train employees for specific roles or to redesign their roles (Barro & Davenport, 2019). Bughin & Hazan (2017) highlighted the need for equal investment to bot technical and talent capabilities. Integrating employees in the strategic decision-making in AI encourages excitement towards AI instead of intimidation. Additionally, it gives them the opportunity for redesigning their work towards higher-value work. (IBM, 2024) The available AI talent is limited and organisations must attract and keep experts of AI both with technical skills such as software engineering and the experts with domain-knowledge (Herremans, 2021).

Organisations should pay attention to the need for new technical jobs to develop their AI systems as opposed to only considering the loss of old jobs (Bughin & Hazan, 2017). According to Barro & Davenport (2019), organisations should consider developing the skills of current employees or hiring new ones instead of using consulting firms or other vendors to build the knowledge around AI systems that are used. This was reasoned around the existing knowledge of the employees around the business and customer requirements. Still the need for aquiring new talents is present since organisations might not have enough skilled professionals for the job and this should be anticipated. (Barro & Davenport, 2019)

Employees and managers need to know how to interact with AI instead of humans for many repetitive tasks that will be performed by AI. This refers to AI literacy, which helps people to interpret decisions that are AI-based and can challenge the outputs. (Jarrahi et al., 2023) The capabilities of AI literacy can be divided into technology-related, work-related, learning-related, and human-machine-related. Technology-related capabilities is one of the critical dimensions and it covers for example, the collection of data and analysis, as well as the wide range of technologies and how they are interconnected in the world. Even though a statistical background and knowledge of programming are useful, they might not be required from all of the workforce, however the distribution of skills needs to be addressed more thoroughly. Work-related capabilities refer to the understanding of the general use of AI or other integral skills to deploy AI effectively. Learning-related capabilities include the adaptiveness that is required in life-long learning, this is due to technological developments. Finally the human-machine-related capabilities indicates the ability. (Cetindamar et al., 2024)

After the AI talent has been acquired, the organisation must decide the position of those talents in the departments. Successful integration in the organisation is best to avoid any delays and with a short line of reporting, the development pace is faster. (Herremans, 2021) Developing and scaling the AI requires interdisciplinary collaboration istead of siloed work. AI teams should include cross-functional people that pose a mix set of perspectives and skills. This way promotes the largest impact AI can create. (Fountaine et al., 2019) Jarrahi (2018) highlighted the partnership of humans and AI. To come up with an effective AI strategy, organisations should look at the current strategic strengths and build an AI strategy from it and recognise ways in in which both AI and humans complements each other.

2.5.6 Measuring

To be able to track the performance of each AI projects, there needs to be correct success measures defined. Those will aid with navigating threats and providing tools for reporting to the management, which is important in justifying the investments to the projects. Success measures are highly related to the strategic goals of the organisations and often revisited. (Herremans, 2021) After the creation of the AI strategy, the company should assess the implementation of the AI strategy. The AI strategy is not useful if it only works on paper and not in practice, and so the basics of formulating the strategy include evaluating the organisation’s objectives, technical capabilities, and management. (IBM, 2024)

According to Lee et al. (2022), the adoption is usually unrelated to the growth of revenue if the adoption level is low in the organisation. When increasing the adoption level of AI, the revenue growth also increases significantly. Additionally, the AI adoption benefits occur notably when investments are made in complementary technologies such as cloud computing and database systems, as well as R&D.

2.6 AI in the regulatory field

One of the key factors influencing organisations' adoption and implementation of AI is the regulatory side and this is especially evident in the financial services industry. The BFSI sector faces the regulatory and compliance uncertainties that adds another dimension of complexity with adopting AI. The BFSI sector (Banking, Financial services and Insurance) has presented large transformation within recent years where emerging technology has played central role. These technologies such as AI, machine learning and blockchain have transformed the BFSI industry. Analytics and big data have contributed to deeper understanding for example into customer behavior. The future of the BFSI sector is linked to the organisation's ability to adapt to technological advancements and traditionally for example insurance industry has been seen as resistant and cautious to change. The complex and constantly changing regulatory environment for the BFSI sector creates challenges for the organisations. (Saxena et al., 2024, 57-81) The fast development of AI has brought organisations innovation and efficiency, however increasing amount of threats and vulnerabilities has been brought up. The threats of AI in financial services are diverse and unique, it possesses challenges with mitigation and detection. Advancements with AI has created a need for re-evaluating strategies for security within the financial systems and data. (Deshpande, 2024)

This part only concentrates on the European regulations. AI Act is the first legal framework regarding AI. It aims to address risks with AI and enable trustworthy AI. In the AI Act, there are risk-based rules for AI deployers and developers in spesific use cases. Although there are many beneficial possibilities with AI such as a contribution to solve societal challenges, in certain AI systems, there are higher risks that need to be addressed to avoid negative outcomes. Existing legislation currently lacks sufficient protections against challenges from AI systems. In the AI Act, there are 4 levels of risks for the systems including minimal, limited, high, and unacceptable, where unacceptable risks are prohibited such as social scoring. In come cases transparency has to be provided to humans if they are interacting with AI machine. The AI Act reassures that majority of AI systems that are used in EU pose minimal or no risk. Deployers of the AI systems are in charge of ensuring oversight of humans and monitoring of the AI system and additionally report malfunctions or serious incidents. (European Commission, 2025)

3 Research design and methodology

This chapter introduces the research design and methodology including the research philosophy, data collection method, and the reliability and validity of the research. The study follows a qualitative approach which will be described and justified in this chapter. After conducting the literature review the suitable data collection method and research design was decided. *Figure 7* presents the chosen research design, which will be described in this chapter.

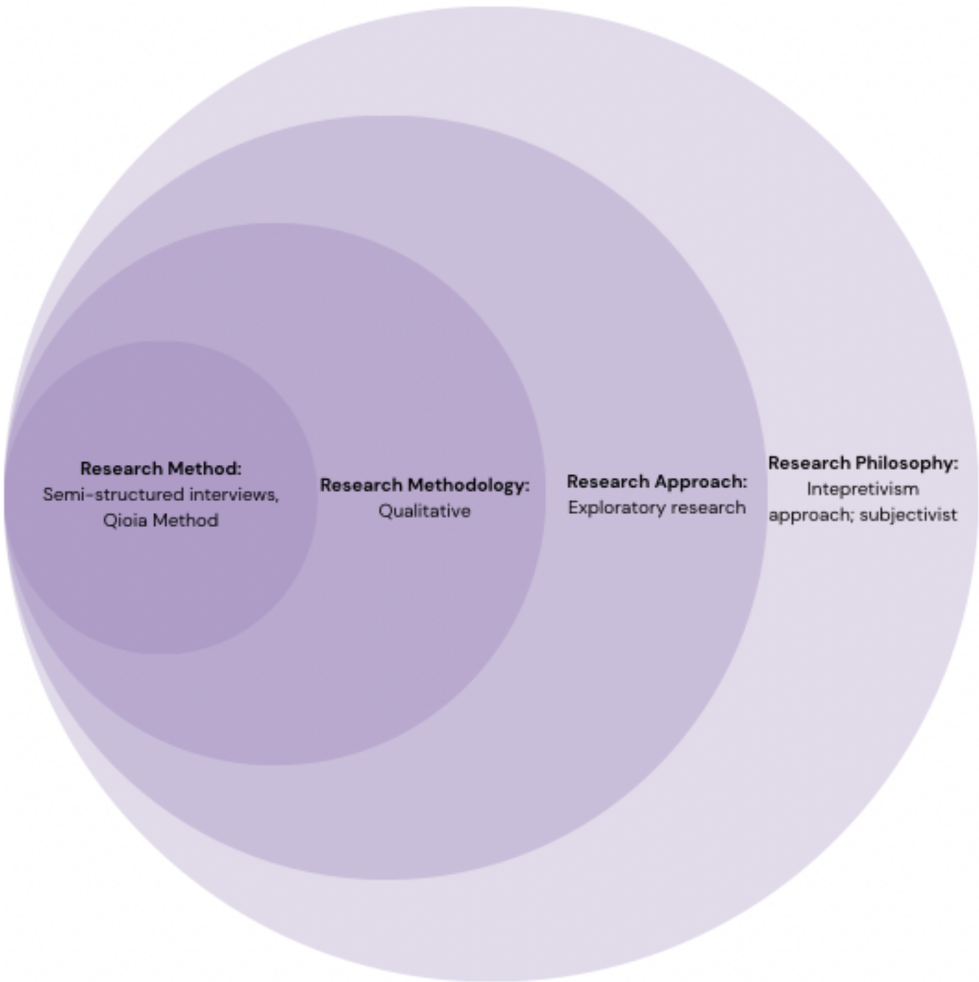

Figure 7 Research design

3.1 Research design and methodology

The research methodology includes the plan on how to proceed with the research when combining the methods and theory. It is about what the researcher will do based on the different elements of the research. Even if two studies used the same research method, for example, a case study, their methodologies can vary. A researcher can adjust their research methodology in an existing project to facilitate new insights. (Leavy, 2014, p.4) The sources and ways of data collection as well as analysing the data are all important factors for designing the research. Firstly the researcher must decide on the methodological choice, either qualitative, quantitative or mixed methods. The research design will demonstrate the achievements aimed to capture from the research. (Saunders et al., 2016, p.162-163)

A qualitative research method is applied in this study. The quantitative approach is concerned with explanation or statistical analysis or hypothesis testing and the qualitative approach focuses on the interpretation and comprehension of a topic (Eriksson & Kovalainen, 2008, p. 6). However, many business research can combine elements from both quantitative and qualitative research (Saunders et al., 2016, p.165). Qualitative research is about learning about social reality. It includes several different research practices and products. (Leavy, 2014, p.2-3). It studies on how and why different things happen in that context as opposed to quantitative research, which studies what happened and how often (Cooper & Schindler, 2011, p.160). With these approaches, qualitative research is more applicable when studying the organisational strategic approach of AI. Qualitative research method is additionally applicable regarding the main research question:

How are organisations strategically implementing AI?

This study follows exploratory research which helps to define and understand a problem that lacked previous understanding of definition. Exploratory study aims to discover what is occurring by using open questions that begin with “How” and “What”. One way to conduct exploratory research is by conducting in-depth or semi-structured interviews that rely on the quality of each respondent’s contribution. This type of interview can bring an opportunity to ask for further clarifications or explanations or even completely new points to the topic. (Saunders et al., 2016, p.174, 394; Simons, 2009, p.43)

3.2 Research Philosophy

The discussion of research philosophy will be discussed to assist in the specification of the research design and strategy as well as becoming familiar with philosophical concepts of the reseach. Research philosophy the refers to the assumptions of knowledge development. The reflection of the research focuses on the reconsideration of how knowledge is produced, defined and justified. (Eriksson & Kovalainen, 2008, p.124,13) Assumptions about knowledge are related to epistemology. (Saunders et al., 2016, p.127)

With qualitative research, the worldviews can be different, for example, critical orientation or interpretivism, which indicates a diverse field of research (Leavy, 2014, p.3). The research philosophy of this study follows the interpretivism approach, where the purpose is to create a new and more in-depth understanding of the phenomenon. This study adopts a subjective perspective from ontology as interpretivism is definitely subjectivist. The ontological assumption indicates the belief in the nature of reality. With subjectivism, reality is constructed socially through people. With interpretivism, reality is complex, and it can have multiple meanings and realities. (Saunders et al., 2016, p.127-129, 140-141) The research paradigm falls under the interpretive paradigm to understand how organisations are handling the adoption of AI. The interpretive paradigm focuses on the way people are attempting to make sense of the surrounding world. (Saunders et al., 2016, p.134)

3.3 Data collection

This study uses the case study method for the data collection. The case study approach incorporates multiple cases to identify similarities within each case. (Saunders et al., 2016, p.187) It can assess multiple perspectives and is a useful way for exploring and understanding processes and reasons (Simons, 2009, p.23) Case study method is relevant to the research since the research question requires an in-depth and extensive description of the topic (Yin, 2009, p.4). The case study investigates the economic or social context in relation to the case. A case can be defined as one economic actor for example an employee or a manager. (Eriksson & Kovalainen, 2008, p.116) A multiple-case study approach was chosen for this study to investigate AI strategy from multiple perspectives that can be compared as each case belongs to the same business field.

The case study research can generate both qualitative and quantitative data (Eisenhardt, 1989) To gain the empirical data for this study, four semi-structured interviews were conducted (*Table 3*). Research sampling was first purposeful sampling where the participant is selected for their experiences and understanding of the topic. Additionally, the research used snowball sampling, where the first participant referred the researcher to other professionals with knowledge and experience on the topic. (Cooper & Schindler, 2011, p.167) The data collection was conducted in March 2025. Two of the interviews were conducted in Finnish and the other three were conducted in English. From the two interviews held in Finnish, the central findings were translated to English. Interviews were conducted to receive high-quality information regarding the research topic. The chosen respondents are highly skilled professionals who are currently dealing with a variety of questions related to the adoption of AI in a strategic manner. Thus, they were able to provide in-depth and quality insights into the topic. The interviews were conducted anonymously to avoid any restrictions from the respondents' side on the answers (Simons, 2009, p. 107).

The respondents are all from the finance sector. Thus, the regulatory environment is highly visible. To gain an international perspective on the topic, the chosen respondents are from different countries in Europe specifically Finland, The Netherlands, and Austria. One organization has international presence in the field. The respondents are all part of large organisations with employee amounts ranging approximately between 4,000- 22,000. Two respondents were from Finland and worked in the same organisation. They both gave different perspectives on the topic since they are not from the same organizational functions and thus were selected for the study. As the business industry is the same among the participants, it gives a good perspective to compare the different strategic choices and their links to the theory.

Table 3 Background information of respondents

Interviewees:	Respondent 1	Respondent 2	Respondent 3	Respondent 4
Interview date:	6.3.2025	6.3.2025	13.3.2025	31.3.2025
Duration:	34 min	34 min	46 min	28 min
Title:	Program Manager	Director	Chief Specialist	Head of data and AI
Role in relation to AI:	Executing program to ensure explainable use	Managing group of AI experts, developing and building AI	Acknowledging the utilization of AI and recognition of	Driving the AI initiatives and coordinating needs and

	of AI regarding regulatory bodies and stimulating the use of AI in all branches.	models and ensuring organizational AI requirements are met.	possible challenges, inspiring people for AI tools, and spark the needs and will towards development of the organization.	objectives through the organisation

The pre-planned open-ended questions (*Table 4*) were the same for each respondent, however, in each interview, there was an opportunity to ask clarifying questions depending on the responses. The interviews didn't require a preparation from the respondents since they were introduced to the research topic when sending an interview request where the topic was proposed. Thus, the interview questions were not sent to the respondent prior to the interviews.

Table 4 Interview questions

Theme	**Question**
Background and role of the respondent	
- Background information of the respondent - Their role regarding AI in the organisation	1. What is your role in the organization? How does it relate to AI initiatives?
AI adoption in the organisation	
- The organisations maturity level regarding AI	2. How would you assess your organization's AI maturity level? (e.g., just starting, experimenting, scaling, fully integrated)?
- Trajectories of AI	3. How has the rapid evolution of AI technologies impacted your company's ability to implement AI solutions? And how do you see that in the future?
- AI implementation process	4. Can you describe your company's AI implementation process? What has worked well, and what challenges have come up?
AI elements in organisation	
- Objectives of AI implementation - Strategic alignment of AI in organizational strategy	5. What is your vision for AI in your company? How does this align with your organization's overall strategy? 6. How often is the company's AI strategy revied?

- Leadership - Culture	7. Can you assess the leadership initiatives and cultural changes that support AI adoption?
- Employee AI literacy - Employees AI perception - Actions towards improvement	8. How do employees perceive AI adoption—are they engaged, resistant, or neutral? What actions have been taken to address concerns? 9. Does the company rely on in-house resources with AI developments or has there been a need for outsourcing (external consultant, AI vendors)? If outsourcing is used, in which areas? 10. What kind of AI training is needed? Is there any existing programs implemented?
- Data maturity - Existing technological capabilities	11. What stage are the company's data availability and existing technological capabilities?
- Measuring the AI initiatives	12. What key metrics do you use to measure AI's impact on business (e.g. performance, efficiency, and risk)?
- Risk management	13. How do you manage risks associated with AI implementation (e.g., privacy, security, compliance)?
- Open comments	14. Any open comments?

All of the interviews were held on Microsoft Teams and video recorded and transcribed. The interviews lasted between 30 minutes and 60 minutes. All together the interviews produced 57 pages of literacy. Each of the interviews began by stating the ethical and confidential considerations of the interview. Additionally, the option to not answer to questions was given and if the respondent felt that something should be removed from the transcripts, they were given the option to do so. The interview questions were formed through the theory by formulating themes of the topic. Then from the topics, the researcher created individual questions that gave the respondent the opportunity to give an in-depth answer to the questions. The interview questions first discussed about the respondent's background and their role and how that is connected to AI. The following theme concentrated on the AI adoption in organisations and then finally the different characteristics and factors of AI in organisations were discussed. The respondents were given the opportunity to add any open comments to the topic if they felt that something should be added.

3.4 Data analysis

After the interviews were conducted, video recordings were transformed into written transcriptions to MS Word documents and then the transcriptions were manually checked, and any mistakes in the output were corrected based on the video recording. Additionally, any information about the respondents and their organisations was removed to ensure anonymity. From the transcriptions, the irrelevant filler words were removed to ensure the flow. The data was first familiarized through to gain overall understanding of it. Then the analysis of the data was carried out in MS Excel.

As the purpose of this study was to find new insights into the topic instead of testing the use of existing frameworks, the analysis method was chosen accordingly. For systematic data analysis, the study utilized the Gioia method, which is a popular qualitative study method. Gioia's method aims to bring "qualitative rigor" to the field, as qualitative research is often critiqued as lacking consistency while keeping the possibility to identify new concepts from the research. It focuses on applying analytical and systematic analysis that will ultimately lead to credible explanations of the data. This approach is beneficial when trying to advance knowledge since it focusing on what is already known can delimit the future developments of knowledge. (Gioia et al., 2013)

In the Gioia method, the data coding process begins with familiarising with the data and taking meaningful phrases from the interviews. These phrases were put into MS Excel and then transformed into 1st order concepts by summarising the key meaning from the phrases. Based on the interview data, 202 concepts were identified. From the two interviews held in Finnish, the 1st order concepts were created in English to ensure flow in the data analysis. After formulating the 1st order concepts, the aim was to identify similarities and differences within the categories and then they were organised by themes to form 2nd order themes. All together 22 second-order themes were constructed, some first-order codes could have been applied to few second-order themes, however the researcher used their own interpretation to choose the singular themes. When the data was coded into 2nd order themes, the final aggregate dimensions were developed. there were six final aggregate dimensions discovered. The aggregate dimensions are broad concepts. The data structure is then beginning to be built, which provides a visual aid of the data analysis process. (Gioia et al., 2013)

3.5 Research reliability and validity

This chapter discussed the validation of the findings through two different analysis strategies. In qualitative research, the accuracy of the findings are validated by employing a set of procedures that are discussed in the following sections. (Creswell, 2023, p. 213) Reliability is classically used as an evaluation criterion in qualitative research and it declares the extent to which the results can be gained from repeated trials. In other words, it is related to establishing a certain degree of consistency meaning that it is replicable. (Eriksson & Kovalainen, 2008, p.293) Reliability can be threatened by participant error where any factor can alter the participants performance. Another threat is the participant bias, where a specific factor can induce not accurate responses. The following threats are related to the researchers reliability. Researcher error and researcher bias are factors that can either alter the interpretation of the researcher or factors inducing bias when recording the responses. (Saunders et al., 2016, p. 203)

Participant error was avoided by giving the participants the opportunity to select the wanted interview date and time. To avoid participant bias, the interviews were conducted anonymously, and this was stated clearly to the respondents first by sending the interview invitation and then before begging the interview. Even though anonymity was ensured, there might have been resistance to answer to specific questions or go into too detail, as the topic can be sensitive if the current practices in the organisation need to be questioned. The researcher error was avoided by preparing for the interviews and asking for clarifications during the interviews if seen necessary. The final threat is the researcher bias, which was avoided by recoding the interviews with MS Teams and then before analysing the findings, the material was familiarized multiple times to make sure all relevant data is taken into consideration.

Validity is likewise an evaluation criterion used in qualitative research and that refers to an accurate description of what happened based on the conclusions of the research and to what extent. Regarding validity, the aim is to generate research where the accuracy is guaranteed. To ensure the accuracy of the research, the researcher can conduct an analytic induction where the analysis of the data is integrated to the theory. (Eriksson & Kovalainen, 2008, p.293) In this study, the validity was ensured with connecting the data and the literature while reflecting on the key parts. Additionally the research can be conducted with a different context. Transferability is connected to external validity, and it refers to providing description of the research such as the questions and context (Saunders et al., 2016, p. 206). In this research, the transferability was ensured by providing the research questions and the context which was the finance industry. Throughout the research, all decisions regarding for example the design, analysis were presented as well as findings and the interpretations. Gioia-method for analysing the data was used to make sure systematic analysis is provided, and all first-order concepts, second order themes and aggregate dimensions are presented in the findings. Although the research aims to ensure validity of the results, there is researcher bias in qualitative research. The interpretation of findings are constructed by the researchers background for example, the culture and history as well as socioeconomic origin (Creswell, 2023, p. 214)

Generalizability was not stated as the aim of the research, thus the number of respondent was not as important for the study than the quality of the data. However the aim is that the insights from this research can be transferred to other cases or contexts. This study ensured appropriate sample since the group of respondents possessed very good knowledge and expertise on the topic that was studied. Additionally, the respondents were from different countries which ensured diverse background that looks at the topic from wider perspective than using only respondents from one country.

4 Findings

In this chapter, the data from the interviews are presented with the help of the actual quotes as well as the data structures with each dimension. As the data analysis followed the Gioia method, the findings are presented according to the final aggregate dimensions to follow a wanted structure. In each aggregate dimension, multiple themes occurred. All together six aggregate dimensions were found from the 2nd order themes and this chapter presents each dimension in their sub-chapters.

Each respondent specified their AI maturity level either as scaling or beginning, but in every organisation, the use of AI is present. However, as the interviewer didn't provide a scale for identifying the maturity level, meaning the respondents made the self-assessment on which stage the organisation belongs to, which can affect the responses. Respondents specified the AI level more in depth during the interview.

4.1 Trajectories

The first sub-chapter concentrates on the trajectories with AI. The *Figure 8* shows the data structure according to Gioia method.

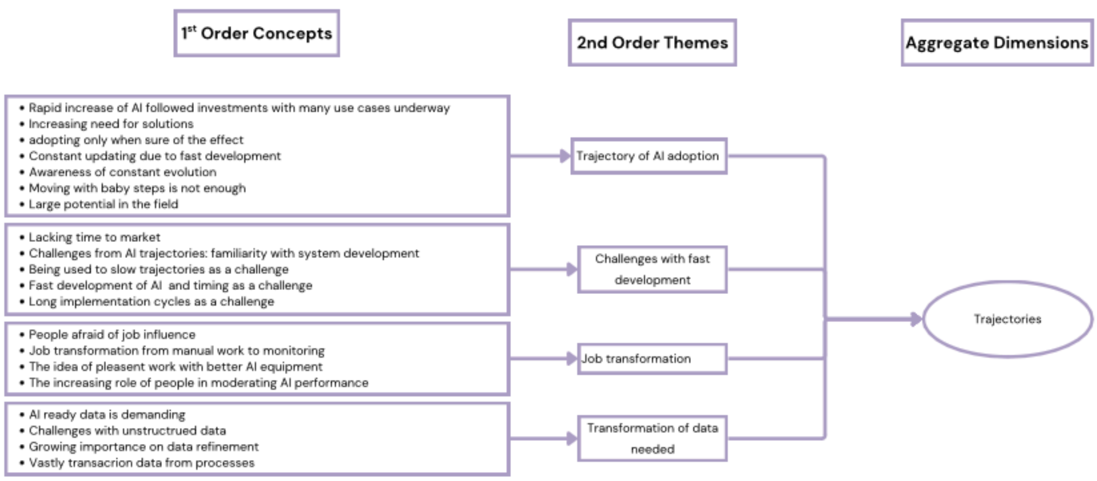

Figure 8 Data structure trajectories

All respondents said that they have many ongoing use cases in the organisation, and there is an increasing need for developing more solutions. Regarding the trajectory of AI adoption, some respondents saw that the adoption of AI is fast in the organisation, and the adaption to developments is rapid. At the same time, other respondent felt that they were taking the process more slowly and only adopting new solutions when they were sure of the effects. However, a respondent felt that the slow adoption was not enough in this scenario. The large potential of AI in the field was mentioned, as well as the need for constant updating to keep up with the fast development. The fast trajectory was mentioned:

> *"What we see is that, with the generative AI technology there is an increased call for solutions and that we have to deliver a quicker way as well."* (R1)

Within the fast development, respondents saw challenges, for example lacking with time to market. Another challenge was that they were accustomed with slow trajectories regarding system development which was highly different from the speed of development within AI. Long implementation cycles were also seen as a challenge for the fast development of AI:

> *"Implementation cycles that we're having in the company, which are longer because many stakeholdres involved personally to convince the people, the first you need to test the technology and proof that it's working, then you need to convince the people that it makes sense to use it then you need to get security approval"* (R4)

The following trajectory focused on transformation of jobs and the data needed. According to the data, there were people afraid of the job influence with AI but it was stated that it might happen that some jobs disappear and others will be developed in the meantime. The job transformation from manual work to more monitoring role of the employees was highlighted and seen as a positive factor. Two respondents mentioned about the transformation of needed data as AI ready data is highly demanding. Currently the data is transaction data from processes and this bring challenges as the data is commonly unstructured. One respondent mentioned the growing importance on data refinement in the future.

4.2 Strategic view

In this sub-chapter, the strategic approach are presented. The *Figure 9* shows the data structure.

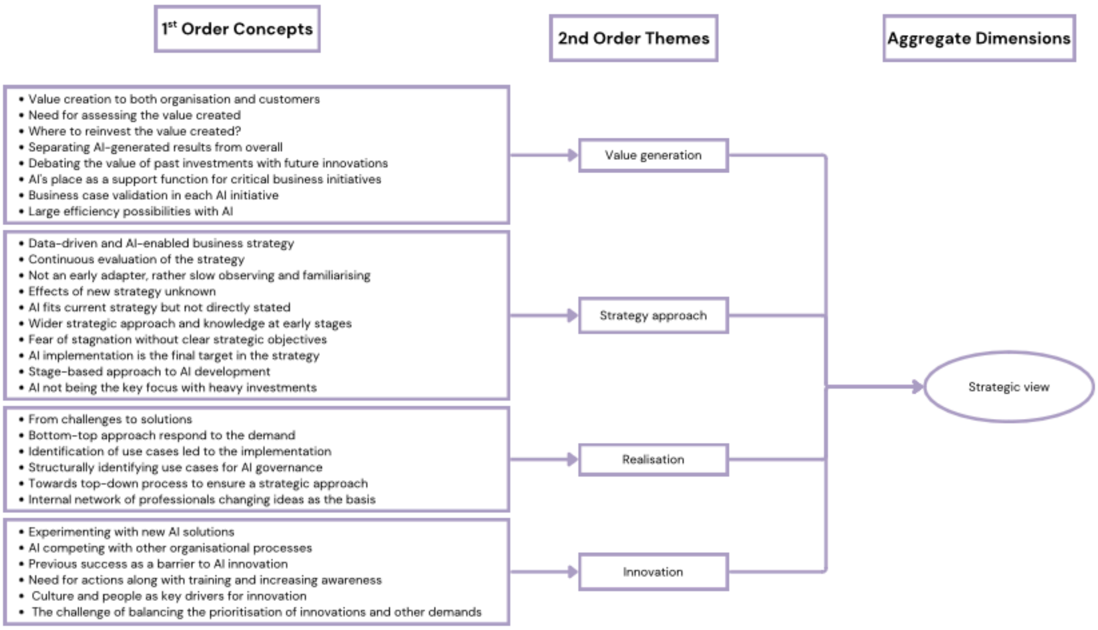

Figure 9 Data structure strategic view

The strategic approach to AI divided experiences. Some respondents mentioned that AI was one basis of their current business strategy and AI vision was integrated into the overall strategy. Even though AI is integrated into the strategy, it's not only about AI implementation, however implementing AI is the final target. The connection of data and AI strategy was mentioned as well as the need for continuous evaluation of the current strategy. According to a respondent, AI is not the key focus that is invested heavily on.

> *"AI is in focus in the company and that we would like to use it, but it's not now like a strategic project by means of like we invest now X millions in AI."* (R4)

> *"we typified the strategy as being a data-driven and AI enabled….Data-driven as well because you have to have good data as a basis for AI...AI enabled because we still need to make conscious choices for using AI in our solutions and sometimes others technical solutions are better fit than AI"* (R1)

> *"The multi-year strategy that has been in place for the last decade has been the digitalisation of our solutions, and this is just another step in that direction."* (R1)

Where as other respondents mentioned that they don't have any separate AI strategies neither AI is directly mentioned in the business strategy. The wider strategic approach, knowledge an culture are still at early stages according to a respondent. Another respondent saw that their strategic approach is not and will not be to become the early adopter of AI but to observe how everything works and see the challenges and risks that could appear. Another respondent viewed their strategic process as a fast but controlled adoption while keeping customer satisfaction as the key factor. The strategic approach to AI is new, and thus, the effects are unknown. A fear of stagnation was also brought up.

> *"The fear is that nothing will change if the matters are not clearly agreed upon or no strategic target stages have been set." (R3)*

> *"We can't take the newest (AI solution) into implementation straight away… we have to monitor and see what is working and what challenges and possible risks there are."* (R2)

The following theme in this strategic approach is innovation. Two respondents saw the challenge of prioritisation of innovations and other demands within the organisation and saw AI as a competing factor with other processes. This might be a limiting factor with AI adoption. One respondent mentioned a key factor for their lack of innovativeness being the previous success of the organisation, where the need for developing processes is seen as less important. Additionally, they proposed that the key drivers for innovation are the culture and people, emphasising the want to change for it to happen.

The way of realisation of the need is then discussed. All respondents saw that their realisation process began with a bottom-top approach. In some cases, the challenges that occurred acted as a base for creating the solutions. One respondent mentioned that an internal network of professionals was created to change ideas in the beginning. However, some respondents felt that to ensure a strategic approach to AI is to move towards a top-down approach, which is then more structured. The top-down approach was seen as more scalable, with the potential for higher earnings. Additionally, the structural identification of use cases is more optimal for AI governance.

> *"Basically still have both (bottom-top and top-bottom approach), but also from a strategic perspective, definitely to come a bit more top down, which means like or orchestrated more structured and more strategy based."* (R4)

The value generation of AI in organisations is then presented from the interviews. Firstly, it was seen as important to identify the key topics for value creation for both the company and its customers. One respondent saw large efficiency possibilities with AI. Many respondents highlighted assessing the value created and validating the business cases in every AI initiative. It was mentioned that identifying the actual value AI brings to any business case can be challenging, the AI-generated results need to be separated from the overall results. One interesting factor that was raised by one respondent was about where to reinvest the value added.

> *"let's say we have a 6% productivity, are we then going to use it as a saving or are we going to add it if it's a customer contact center to the extra time that we can get give to the customer for calls or go put it into innovation."* (R1)

Another interesting factor that was mentioned was about debating on the value of past investments with future innovations.

> *"Then we come to the omit challenge, that if we have invested 100 million into something… is that the reason to stick with the old process because we have been investing 10 on it or should we just be bold and see if you would make the decision today, how would you built things."* (R3)

4.3 Practices

The following sub-chapter presents the data regarding practices and the *Figure 10* shows the data structure.

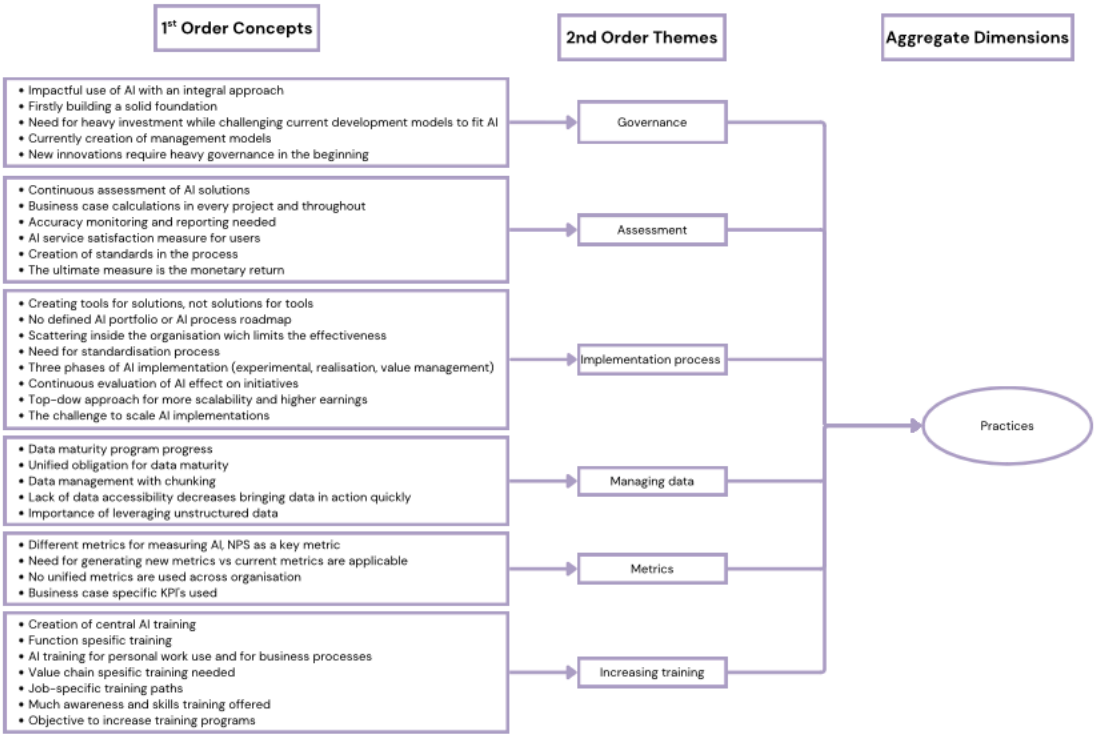

Figure 10 Data structure practices

Then, following on to the theme covering governance from the data. There were mixed percpetions about the current governance in the organisations. Where one respondent saw that they have an integral approach to AI and another saw that there was a lack of governance models currently. According to one respondent, it's important to first build a solid foundation to govern the use of AI. It was noted that new innovations require heavy governance in the beginning. Another respondent saw the need for heavy investment and challenging the current development models to assess whether they appropriately fit into AI.

> *"(according to an outside consulting company, they are) one of the leading organizations, certainly in the top 10% as far as implementing AI in the company, also doing impactful manner, so not with a couple of different projects, but an integral approach company-wide."* (R1)

> *"when it's you're using technology the first time in the company then this takes some time here to convince to get security approvals. Basically all the governance stuff need to do in order to enable this technology. This is then sometimes a bit more burdensome if you do things the first time."* (R4)

The implementation process was another theme found in the data. There were some differences in the organisation's implementation processes. One respondent found that they didn't have a defined AI implementation process, but there is a need for standardisation. Currently, they look for tools for solutions, not solutions for tools, meaning that there can be other technologies more suitable to solve a specific issue than AI. The lack of AI process road maps was highlighted as a challenge. This leads to AI projects scattering inside the organisation which then limits the effectiveness of AI. Another challenge was scaling the AI implementations. Whereas other respondent found that they are currently in the stage of standardisation of the implementation process or have already defined AI implementation phases and follow a set of strategy in the process.

> *"We have a business problem or goal for creating a specific benefit and then we see what is the tool that can execute it and then that is taken into the development tube… it can be AI or it can be blockchain."* (R2)
>
> *"We've got the experimental phase, realization phase, value management"* (R1)
>
> *"It's too early to speak about processes at our organization."* (R3)
>
> *"We are, I would say standardizing the implementation process."* (R4)

Regarding training in the organisations, all respondents found it crucial. Many respondents mentioned that AI act will affect on the training required, however there would have been training without it. A certain level of awareness of AI and the use of AI is the minimum level in the AI act. Every respondent saw there needs to be increased amount of training in the organisations. Few respondents mentioned that they are in the process of creating central AI training or training in general. In one organization there is already implemented much awareness and skills training which is then offered to the employees. In that case the goal was to increase the training programs to match the job function or value chain specific.

> *"we are creating a central AI training...we are going to explain to our colleagues what is AI, what can it do. What can't it do? What are the risks and what are the opportunities?"* (R1)
>
> *"AI will make your personal work more efficient and there the knowledge on the equipment and training for it is important… AI will be part of the business*

> *processes…There the role of the human both legally and ethically needs to be understood."* (R2)

> *"we do a lot of awareness training and skill training of how you could potentially use it… we already have certain programs and the idea is to enlarge this more and more for more learning path and more skill profiles."* (R4)

The next theme that emerged from the data was assessment. Continuous assessment of the AI solutions was highlighted by a few respondents. This assessment goes throughout the business case and sharpens during the development process. There needs to be monitoring and reporting of the accuracy.

> *"From the service satisfaction perspective, we can evaluate AI as it's a service to some matter, so what is the NPS for that service… we can ask the people who was the AI helping how well AI was able to help."* (R3)

> *"whenever we go into the project and especially before we bring a project into production, then of course we evaluate the business case on the way"* (R4)

It was commented that there aren't any standards currently for assessing AI in the organization, however those standards will be developed on the way. From one perspective, the monetary return is the ultimate measure to be followed.

> *"I think in the end euros are money in the ends that counts"* (R4)

Metrics was identified as another theme emerging from the data. Some respondents thought that current business metrics can be applied to AI where as others saw that there is a need to develop new metrics to fit AI use.

> *"it's quite various KPI's that we are focusing on and also quite specific to the use case and as I said, there are no global targets right at the moment being stated by the management like this is what we would like to reach by using AI"* (R4)

Finally, the discussion of managing data is presented. As previously mentioned, AI-ready data is demanding to achieve. One respondent mentioned that they have developed a data maturity program which has increased the data maturity in the organization. This is an organization-wide obligation. Leveraging unstructured data was seen as important.

> *"before you can use AI solutions, your data has to be in a proven maturity level before we allow AI to work with it"* (R1)

4.4 Readiness factors

This sub-chapter presents the readiness factors with a *Figure 11* and the following findings.

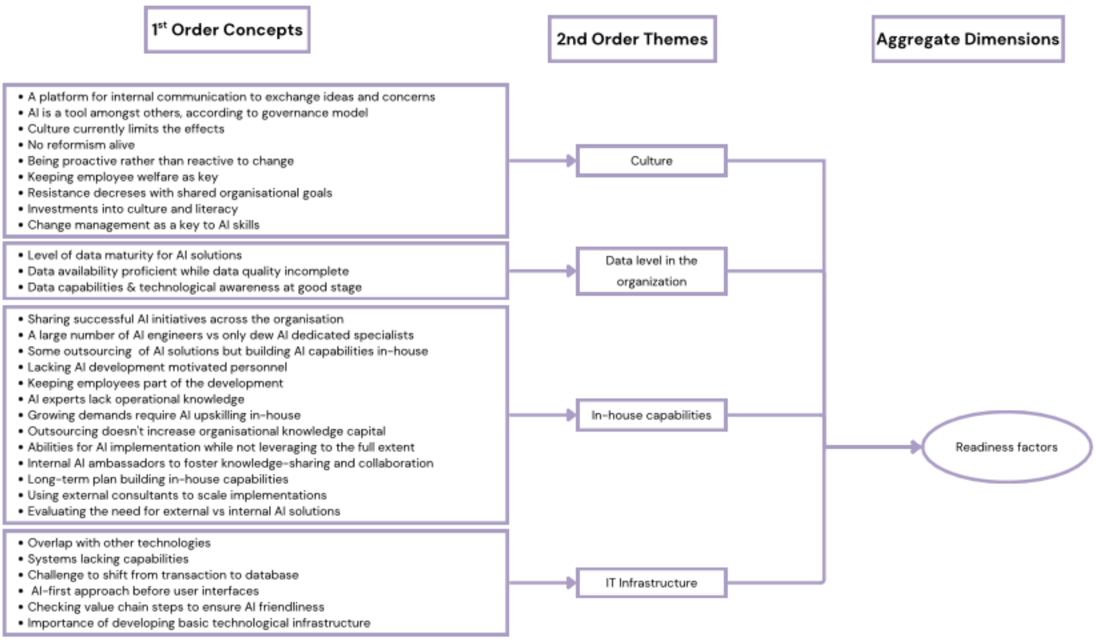

Figure 11 Data structure readiness factors

The next dimension that is to be presented is the readiness factors where four different themes occurred. First theme to be presented is the culture. Some respondents felt that there should be more investments into the culture. One factor that can affect on the organisational culture towards AI is how it is presented, it was mentioned that general governance has specified that AI is just a tool amongst others. General culture, according to one respondent, was currently limiting the possible effects of AI. Another respondent saw that being proactive rather than reactive to change would have been a better approach as well as highlighting the importance of keeping employee welfare as the key.

> *"When it will be discussed together at every organisational level with an objective towards it, then I believe the general resistance will start to decrease."* (R3)

A respondent mentioned that they have created a platform for internal communication for changing ideas and concerns regarding AI. Another respondent saw that there was is currently no reformism alive in the culture of the organisation.

> *"we have created an AI portal for the whole of the company where we communicate about AI...people can join on a voluntary basis ... people in the community which are actively communicating with each other, exchanging ideas for concerns and then that's being tackled by the people that work within AI as far as giving the proper answers"* (R1)

The following theme emerging from the data concentrated on the in-house capabilities. Here the respondent provided different organizational capabilities, some had many engineers solely focused on AI and others didn't quite have those AI-dedicated specialists. However, most of the respondents felt that increasing the in-house knowledge is important. There are some specific implementations where outsourcing is used. As one respondent mentioned, there ius a growing demand for AI and the only strategic choice would be to upskill the current workforce since outsourcing doesn't increase organisations' knowledge capital.

> *"we have a large number of engineers... fifty of those focused on AI"* (R1)

> *"(AI) is something that we must take over ourselves, we can't buy this from consultants or we don't even want to buy from the consultants and we have used external help in singular technical details."* (R2)

> *"We have know-how inside the organization, however there isn't enough of it and we should grow it inside the organization."* (R3)

One key aspect that was mentioned was about sharing the knowledge and successful AI initiatives across the organisation to gain the full benefit. Another fact was having the abilities and capabilities for implementing AI but not leveraging it to the full extent. It was also seen as important to keep the employees part of development since commonly the AI specialists are not the ones that have the knowledge about day-to-day operations.

> *"if one approaches proven itself on one market, then of course is okay, why not to share this also and use this in another market or other domain."* (R1)

As few respondents saw the need for at least some outsourcing, there is an evaluation for the need of external vs internal solutions. But still keeping the long-term plan for increasing in-house capabilities. External consultants are used for scaling out implementations. A way for increasing the know-how across the organization through AI ambassadors was introduced.

> *"in most of the areas, I think we are already quite well set up or doing something about it and especially making this data more accessible. I think in others we need to see whether this is something that any way we see is our expertise to build up like internal models or rerouter trust externals."* (R4)

> *"we're trying to do is like to find some kind of AI ambassadors into various business domains that then connect us like a person that people know in the area that people trust and that can then also help to spread the know-how and the shared skills also with the others"* (R4)

Moving to the current IT infrastructure, some respondents saw a challenge in connecting the technologies to AI. There are some overlapping with other technologies and in some cases the existing system lack the capabilities for AI. The systems have different qualities which are not compatible with the use of AI since every data has been transaction-based, one respondent mentioned.

> *"A big challenge for utilising AI is the shift from transaction-based systems to thinking through databases"* (R2)

> *"Definitely they need to be developed, so especially we trust a lot and focus a lot on the cloud to develop AI and here we are missing definitely basic infrastructure skills etc, to support and ramp up use cases in large scale this is definitely something we're working on."* (R4)

Another interesting factor that was mentioned related to how everything is developed and the move towards thinking AI first. As well as checking every step of the value chain to ensure AI friendliness.

"If our terms are now made in a certain way for humans to use, then should we first make those terms understandable for the machines, accessible with AI and then make the human versions from it, cause it would be easier to do it in that order." (R3)

The final theme in the readiness factor dimension is the data level in the organisation. Again there were differences in the data levels within respondents. Few respondents saw that the data availability is proficient and data quality needs to be imporved and others saa a lack of data accessibility. Lacking data accessibility has decreased the ability to bring data in action quickly.

"The availability of data is good, however the data format and data quality are another questions." (R3)

"What we're probably missing a bit is to bring this data in action quicker, because we are missing this kind of data accessibility." (R4)

4.5 Human factors

In this sub-chapter the human factors findings are presented with *Figure 12* showing the data structure.

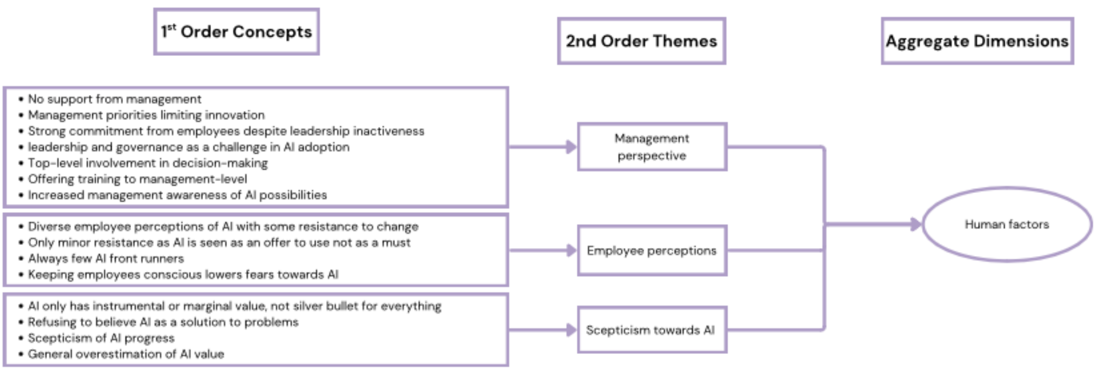

Figure 12 Data structure human factors

The human factors dimension includes three different themes that are presented. Management perspective is the first theme occurring from the data that is presented. There were diverse views on the organisations management level and their perspective. Few respondents saw that the current management offers little support regarding AI implementation. There was only a strong commitment from the employee network to progress things despite the management being inactive. The challenges with AI adoption come mostly from governance models, processes, management and setting the objective level for AI. Other respondent saw that the top management is supporting the process.

> *"Reflects from the management, what emphasis has been selected for them, if innovation isn't part of the top factors then it rarely happens."* (R3)
>
> *"the top of the organization is involved in making decisions as far as the implementation of AI"* (R1)

According to one respondent, there is an increasing awareness from the management towards AI possibilities and the overall awareness level has been increased. There are as well trainings for the management level about AI's effects.

Employee perceptions are then presented from the data. All respondents have identified a variety of employee perceptions from resistance to excitement.

> *"there are people that are really enthusiastic about it and want to be at the forefront…there are people that are really enthusiastic about it and want to be at the forefront."* (R1)
>
> *"It varies a lot between different functions, units and employees."* (R2)
>
> *"So I think under the surface, of course we would have all three categories, but let's say resistance is not so much directly observable, I would say. Yeah, but of course also we have a few front runners that are quite highly interested and is also in respect of our strategies."* (R3)

Respondents said that regardless of what is the new technology there are always employees that are enthusiastic and excited but only a small amount of employees. Hence keeping the employees conscious about AI lowers fears. Another respondent highlighted that only minor resistance could be due to AI being an offer to the employees not a must to use.

> *"So I think under the surface, of course we would have all three categories, but let's say resistance is not so much directly observable, I would say. Yeah, but of course also we have a few front runners that are quite highly interested and is also in respect of our strategies."* (R4)

"That's why this should be managed and keep the people close by systematically when this is discussed and trained, because I belive that most of the fears are related to not understanding it or not trying it or then trying and having a poor experiences." (R3)

The data showed that there is a some level of scepticism towards AI, which is not presented. One respondent mentioned that AI only brings a instrumental value and that there is general overestimation of AI's value. Additionally another respondent has seen sceptism of the AI progress within the organization. Refusing to believe AI as a solution to problems occurred according to one respondent.

"some people think it's a bit scary and that's why we want to explain what it does. But what we also notice is that some people think that that technology will not go as fast as it's being communicated and that some of the people are holding it off a bit." (R1)

"The promises of AI generated increase of profitability and effieciency of processes is generally exaggerated." (R2)

4.6 Compliance

The final sub-chapter presents the compliance findings. The data structure is presented in the *Figure 13*.

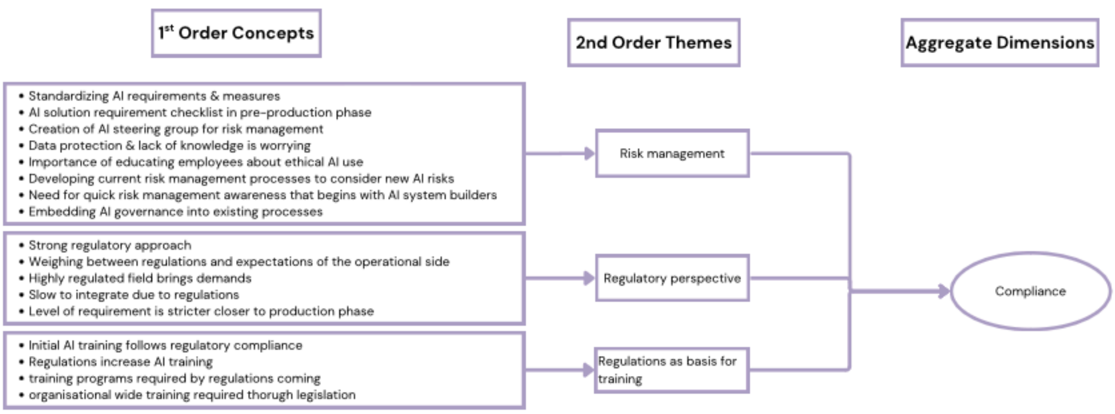

Figure 13 Data structure compliance

The final dimension that is presented is the compliance which covers three different themes. Starting with the regulatory perspective of AI. According to a respondent, the organisation has a strong regulatory approach. Highly regulated field brings demands to the organisations and certain processes need to be adhered. A challenge that was mentioned was about weighing the regulations and expectations of the operational side. Another respondent saw that regulations make the integrations slower. As well as the level of requirement gets stricter the closer an initiative comes to the production phase.

> ”that's a bit of a two way street. One way is that it has to adhere to the regulations, which is not always conducive to the speediness of the delivery, on the other hand, the questions of the business lines are not always realistic as well” (R1)

The risk management was discussed and all respondents have implemented risk management processes. one respondent saw that risk management begins from the building of AI solutions. Developing current good risk management processes to take into consideration risks from AI is needed. Quickly retrieving information about possible risks was mentioned. One respondent covered their risk management practices which was standardised within the organisation. They have a specific ai solution requirement checklist to make sure new solutions are up to the regulations. as well as having a AI steering group for risk management. One respondent worried about the data protection and lack of knowledge of the systems. They mentioned the importance of educating employees for the ethical use of AI.

> *“We developed a pre production checklist so every AI solution has to adhere to this checklist and that has those 83 measures in it. And if you adhere to these measures then you are compliant with all the regulatory requirements.”* (R1)

> *“we have this AI steering group… there we aim to look at the goodness of the solutions being implemented from many different aspects to make sure no forbidden profiling is happening.”* (R2)

> *“IC matters are very familiar to us and we are a forerunner from regulatory perspective but as well we have a strong desire to be the forerunner.”* (R3*)*

The final theme to be presented is the regulations as a basis for training. Almost all respondent highlighted AI acts as the base for developing training programs to ensure that all training is up to the regulations.

> *"we will make sure that people have at least the minimum set of skills required to use AI...legal responsibility from the AI Act."* (R1)

5 Discussion

This chapter brings answers to the research questions by connecting the empirical data that was gathered and the existing literature. The purpose is to find whether the empirical data supports the literature or highlights any contradictions between them. The research questions are broad and to answer them, this chapter is divided into separate themes to make sure every aspect is taken into account. The main research question was:

How are organisations strategically approaching AI?

To gain additional and deeper knowledge about the strategic approach to AI in organisations, the following sub-questions were developed.

Sub-question 1: What challenges have emerged when implementing AI?

Sub-question 2: What organisations should consider when adopting AI?

The answer to the main research question is the following. Organisations within the same field have quite diverse approaches to AI. While all have quite sensible approach that does not take AI into action without analysing the pros and cons, the lack of fully integrated AI strategies was visible. The first sub-question is then answered. Organisations have faced variety of challenges when implementing AI or trying to implement it. The challenges faced related to lack of strategic objectives towards AI, lack of roadmap and implementation processes, and the strong regulatory side. The second sub question answer is then presented. According to the findings, organisations should consider building the internal capabilities of the organisation, with upskilling and training the current employees additionally developing roadmap to avoid lack of structure with AI adoption. The answers to the research questions are elaborated more within the following sub-chapters.

5.1 Trajectory of AI in organisations

The pace of development in AI is tremendous, and it affects though out society (Dwivedi et al., 2021) As discovered from the findings, the fast advances of AI have increased the speed of AI development in organisations. This has brought some challenges to the organisations, for example, bringing AI solutions to the market at a fast pace. According to the literature, quick and effective response regarding the implementation of new technologies will affect on the outcome (Fitzgerald et al. 2014). Findings showed that organisations can face challenges since they are not used to such fast development. As the need for solutions in the market is high and the development speed is fast, the organisations are facing challenges with long implementation cycles. However, this might be related to the specific industry, which is highly regulated as well as the size of the organisations. It needs to be remembered that organisations must be adaptable to changes in the market and use their existing capabilities to make strategic responses (Teece & Pisano, 1998). Bharadwar et al. (2013) indicated that the general decision-making process in companies has fastened with technology.

The literature pointed out that organisations and management shouldn't focus too heavily on past assumptions, but instead assess the possible effects of AI and plan scenarios (Berthon et al., 2024). Even though the findings presented good awareness of AI development within the organisations, they were mostly focused on past trajectories regarding system development processes, which made it more difficult to adapt faster pace. As Iansiti & Lakhani (2020) studied, understanding the AI's impact to organisations is important regardless of their position in the market. Additionally, they saw that conventional strategic approach is too foused on the specific industry and in the future, that approach will become less effective. The findings didn't show any move towards thinking strategically above the industry traditions, this can be related to the inflexibility of the industry. AI is very likely going to affect jobs in organisations (Iansiti & Lakhani, 2020), but it additionally signifies the transition of jobs (Russel & Norvig, 2022). As was highlighted in the findings, organisations are aware of the shift from manual work towards more monitoring positions. AI was seen as a tool for developing the job descriptions and not as replacement for human work entirely. The TOE framework discusses the differences between technologies that enhance innovation and technologies that destroy it. From these perspectives, AI could be seen as an innovation that enhances the competencies of employees by transforming their work to monitoring role and not a technology that makes the current experts irrelevant or not the source of competitive advantage of the organisation. (Baker, 2012)

5.2 Strategic approach

To begin with, discussing the AI strategic approach in organisations, the findings suggested that all of the organisations were implementing AI into their operations. Literature supports this and it can be seen that almost all companies are implementing AI but still lacking a strategic approach. (Schuler and Schlegel, 2021). The specific approaches are discussed in this chapter. Additionally, the emerging challenges and needed considerations are discussed.

The finding suggested that there is a diverse approach to AI from strategic perspective, as in some cases AI is directly part of the organisational strategy where as others didn't have specified AI in their core strategy. Additionally, AI fits into the current strategy however it was not directly mentioned and the strategic approach to AI is still at early stages. As seen from the literature, digital transformation showed the differences within organisation, where some held back on implementing new technologies and their approach was rather sceptical and slow and other organisation took even a aggressive approach to the new technologies. Meaning that there will always be organisations that want to be the digital leaders. (Fitzgerald et al., 2014) This study findings validated that since some organisations took slower approach where the objective was not the be the early adapter and other showed a fast and controlled approach to AI. At this early stage of AI development, it's impossible to know for sure which approach is the best for strategic use of AI, but for example with digital transformation the digital leaders were able to gain more profitability with quick and effective response to emerging technologies (Fitzgerald et al., 2014). However as Johnson et al. (2007,p. 326) described the dilemma of focusing on technology push or market pull, either strategy can lead to undesired outcome, thus a balance should be seeked.

The findings already showed a fear of leaving behind without developing clearly defined strategic objectives. Literature supports this view, as it is important to have clear goals in any IT strategy development (Herremans, 2021). Knowing what is wanted from applying AI in the operations is required with AI implementation (Chishti et al., 2020). This is related to the identification of the possible value generation of AI. As the findings suggested, there is a approach of seeing AI only to generate marginal value and on the other hand an approach where AI was not part of the strategic focus with the lack of heavy investments towards it.

Polisetty et al. (2024) studied that to drive organizational strategic development towards AI, it's important to be aware of the potential benefits of AI. Less experience the organisation has with AI, the perceived benefits might be limited to tool for cutting costs (Bughin & Hazan, 2017). An issue with the seen value of AI in the findings can be related to not identifying the value directly as its commonly interconnected to other factors as well. Even though the large possibilities with AI was seen the identification of generated return was lacking. An interesting finding that didn't present in the literature was about reinvesting the value created. The organisation should determine where to put the extra value that was gained with AI, this needs to be considered in the organisational strategic process.

Another issue emerged from the findings related to value. In this scenario, the problem was debating whether the past investments for example, to a specific technology, should be replaced by AI and whether it can create more value. Making those strategic choices of leaving an existing and usually working process or solution to something innovative where the generated value can't be guaranteed can be difficult. In that scenario, another factor is the emotional attachment to the past investment, and in that case, the management should be able to see what is more beneficial for the organisation in the long run and which fits into the future strategic objectives. Although this specific scenario wasn't presented in the literature, Vial (2019) acknowledged the existing components that are highly connected to organizational practices, which can then create barriers to introducing new technologies. Another highly related factor is the organisation's dynamic capabilities, where adaptability to a changing market is the key (Teece & Pisano, 1998). Here the organisations needs to evaluate the relative benefit of both solutions.

As the findings suggested, some organisations' realisation process for AI solutions currently operates mostly from the bottom-top where employees who have an interest towards developing the initiatives bring that forward to the management or the identification of needed use cases come from operations. This was seen as less effective and lacking structure, thus the objective is to move towards top-down approach. The implementation process is connected to the realisation of the need. In the findings, some organisations had acquired an implementation process whereas others lacked the AI process roadmap. The organisation with AI implementation strategy followed three phases with experimenting, realisation, and value management. Herremans (2021) suggested building an AI team in the organisation and organising the AI development in the company, which would create a structure for the realisation process and increase the speed of development. The AI team is either hired or current employees upskilled to the positions. (Herremans, 2021) This would make the implementation process increasingly standardised and more scalable, as those issues were identified in the findings. Additionally the lack of structure with the implementation process resulted in the AI initiatives scattering inside the organisation which limits the effectiveness. Even though the findings suggested that some organisations struggle with formulating the implementation process roadmap or have problems with scaling the implementations, it was identified that all have quite sensible ways of creating new AI initiatives. This means that organisations didn't just start using AI just because it exists but always there has been a need for new solutions or improved processes. To highlight a finding that shows such an approach: creating tools for solutions, not solutions for tools.

Innovation was another theme emerged from the findings. The innovation drivers according to the findings are not the processes or quality data, it's the culture and people in the organisation. This was supported by the literature, as effective implementation of AI needs the supportive and encouraging culture where innovation is promoted (Heo et al., 2022; Radhakrishnan et al., 2022; Khanfar et al., 2025). The findings suggested that there are barriers for innovating with new solutions. These barriers are the prioritization and competing against AI. Organisations must decide which projects are worth the prioritization and AI can be the competing factor against other operational processes. Another barrier that was highlighted from the findings related to organisation's previous success as a hindering factor behind the lack of innovativeness. This is again connected to the priorization, if the organisation management sees that they are doing well in the market, the lack of urgency with emerging innovations is present. According to Fitzgerald et al. (2014), organisations in the digital transformation were experiencing a lack of urgency when the competition didn't show visible signs of activeness in the area. Additionally, Radhakrishan et al. (2022) found that pressure from the industry drivers the AI adoption process forward. It can be analyzed from the findings that there is no visible leaders in the field with AI adoption and thus the change is taken more conservatively.

5.3 AI readiness

According to the existing literature, organisational culture is a significant factor for AI adoption. As previously mentioned, culture is a key indicator for innovativeness. Culture should enable change and pursue experimentation in the organisation. (Ali et al., 2024) The findings suggested that some organisations struggle with the current culture or there is a need for investments towards it. The struggles with current culture related to the limiting effect of the current culture. Another factor emerging from the findings was the need for creating culture that is proactive to change rather than reactive. However it was found that internal communication for AI as part of the culture is being improved with communication platform for sharing ideas and concerns. Additionally opting for change management for bringing the cultural awareness. These approaches are supported by literature, as Jöhnk et al. (2021) showed that creating a favorable culture in the organisation, is supported by doing collaborative work and that change management helps with understanding the organizational change happening from AI.

Continuing to discuss the management's role in the organisational culture and its effect on AI readiness and innovativeness. Again, the findings showed different views on the current support from the top management. Both management involvement and lacking support were found. The literature emphasises the importance of management support for AI implementation. Behind innovative and encouraging organisational culture, there is support coming from the top management. (Radhakrishnan et al., 2022; Khanfar et al., 2025) The findings suggested that the awareness level for AI on the management side is increasing in some cases, but it was also seen as part of the challenge of adopting AI. Chishti et al. (2020) highlighted that organisations need visionary leaders who understand new technologies and are showing interest towards them as part of the strategy. The findings showed that there are programs for educating the management of AI. This was supported by Barro & Davenport (2019), as they acknowledged the importance of educating the leaders about the changes happening through AI. New leadership skills might be valuable to develop to be able to manage AI technologies (Bughin & Hazan, 2017). However, the findings came from large organisations, the influence of the top management might be limited compared to smaller organisations where the top management is closer to the overall employees and the development of processes.

As above mentioned, the importance of creating a suitable culture in the organisation as well as having support from the management for innovativeness is crucial in AI adoption. The findings suggested that employees show a strong commitment to implementing AI even though the leadership doesn’t show activeness towards it. According to Fitzgerald et al. (2014), the embedded attitudes in the organisational culture or resistance from the organisation can increase the fear of pursuing the adoption of new technology and it creates additional risks for employees to try to pursue the transformation.

Employees are significantly affected by the development of AI either the employees are replaced by AI or using AI will become the key factor (Iansiti & Lakhani, 2020; Fountaine et al., 2019). Taking the employees as part of the decision making processes, can change their perceptions towards AI. Lack of knowledge can increase the intimidation, thus keeping their awareness level high will pursue excitement towards AI. (IBM, 2024) Additionally the fear of elimination of jobs can create reluctance for using AI (Borges et al., 2021), which then limits the effectiveness. The findings were consistent with the existing literature. It suggested that each organisation is experiencing many different perceptions towards AI from the employees. There are some resistance to change, which is the case for implementation of any new technology, thus that is not a new phenomenon just regarding AI. Increasing the conscious level of employees with AI as a way to decrease the resistance was confirmed from the findings. Additionally the findings suggested that the low level of resistance has emerged due to the organisation only promoting the use of AI as an option for the employees rather than something that must be used. This approach might be beneficial in the beginning of AI implementation process, however it would be beneficial to decrease the resistance by providing knowledge about the topic. As it was mentioned above lack of knowledge is one factor for creating resistance towards AI. In addition to that, the lack of trust towards the AI system should be considered. According to Russel & Norvig (2022, p.1047), the key factor for using AI systems is building trust. Faruqe et al. (2023) highlighted trust and intention to use the AI system as employee’s perception towards AI.

The general perception towards AI can vary. According to the literature, AI can create a revolutionary impact on general operations or strategic perspective, thus understanding the possible value is important for organisations (Iansiti & Lakhani, 2020). The findings suggested that some people refuse to see AI as the solution to problems or are somehow sceptical about the development speed of AI and think that there is a general overestimation of the possible value AI generate. As Berthon et al. (2024) highlighted, the trajectory of AI is likely to change from the believed pattern, as happened with the development of the Internet. Thus organisations as well as leaders should start expecting the unexpected and try to plan for possible scenarios instead of taking all of the past assumptions. (Berthon et al., 2024) The literature shows that while the possible effect of AI is huge, it can't be implemented in every possible process without thinking about the strategic side of it (Kruhse-Lehtonen & Hofmann, 2020). Part of the findings supported this statement by indicating that AI can't be looked at as a quick fix to every problem.

5.4 In-house capabilities

Literature shows the importance of organisation's in-house capabilities, concentrating on the employees and people within the company. (Herremans, 2021; Schuler & Schlegel, 2021; Polyviou & Zamani, 2023; Ashri, 2020; Alsheibani et al., 2020; Kruhse-Lehtonen & Hofmann, 2020) There will possibly be an increasing need for highly skilled employees (Brühl, 2024) and organisation must recruit and train their employees to meet the new demands (Barro & Davenport 2019). The findings showed variable amount of AI specialists within the organisations and some organisations lack the needed employees motivated for AI developments. For an organisation to develop an internal AI development team, it requires a technical skill set and domain knowledge (Herremans, 2021). The findings suggested that commonly the AI experts lack operational knowledge, thus hiring and training the current employees would be needed. Barro & Davenport (2019) suggested hiring new employees or upskilling the current ones aiming to built the knowledge of the AI systems instead of utilizing consulting firms as the source of knowledge. According to the findings, organisations aim to increase the in-house capital as outsourcing doesn't increase the knowledge capital of the organisation. The growing demands require in-house upskilling. However, the organisations are currently utilizing some outsourcing for the AI development. External consultants are used for scaling the implementations and currently they are evaluating the need between external and internal AI development. The findings showed that some organisations are aiming to get internal AI ambassadors to foster the sharing of knowledge and collaboration, this could possibly have a positive affect on the cultural aspect regarding the general perceptions of AI.

The literature highlighted the importance of having compatible existing technology and software to be able to integrate AI efficiently. Any incompatibilities can delay the effectiveness of AI adoption. (Heo et al., 2022; Radhakrishnan et al. 2022; Polisetty et al., 2024; Jöhnk et al., 2021) The findings suggested that organisations are aware of the issues with current technologies and that there is a need to develop the basic technological infrastructure to meet the demands of AI. The current systems sometimes lack the capabilities. Another challenge organisations are facing is the shift from transactional processes to database thinking. According to Fitzgerald et al. (2014), the complexity of updating the existing systems to fit new technologies can create challenges for the organisation. One interesting point from the findings suggested changing the way of thinking towards an AI-first approach, where for example the terms are initially made for the AI so that the ability of AI to work with the system is higher. After they are made for AI, the user interfaces can be developed. This would require going through the value chain step to ensure that the output of the value is in the right format.

The importance of data in AI strategy development is highlighted in the literature (Herremans, 2021; Schuler & Schlegel, 2021; Polyviou & Zamani, 2023; Ashri, 2020; Chishti et al., 2020; Polisetty et al., 2024). According to the findings, the transformation of the data needed has created challenges. The AI ready data is highly demanding creating challenges for the organisations. Another issue emerged which was the challenge of dealing with unstructured data which is then not ideal for AI utilisations. In this industry, the data aquired is heavily transactional data from processes. Organisations starting without having existing data is referred to as cold-start problem (Vomberg et al., 2023), the findings didn’t present this as a problem for the organisations, this is due to the maturity level of the organisation. With new organisations, the cold-start problem can be futher present. The findings suggested the variety of data levels within the organisations, some saw the data availability as a problem whereas other highlighted the quality and form as incomplete. The lack of data accessibility decreased the possibility to bring the data in action more quickly. Radhakrishnan et al. (2022) found that many organisations are struggling with lacking the adequate data or additionally dealing with available data that is then biased. In such highly regulated industry, the deidentification process is evident and that is costly for the organisations and the process can damage the key features of the data (Chishti et al., 2020, p.44). The deidentification of data was not directly mentioned in the findings. One additional factor mentioned in the findings was the growing importance on refinement of the underlying data to use in AI solutions. The practices of developing the data in the organisations was highlighted in the findings, which was not thoroughly discussed in the literature in this study. Some organisations are developing data maturity programs to make sure each department has the adequate data for AI initiatives. There is a unified obligation determined within the organisation for data maturity.

As discussed previously, organisations are aiming to build their internal recourses instead of utilising only outsourcing as a way to adopt AI solutions. To develop the organisation's resources, they can possibly gain a sustained competitive advantage from the human capital instead of outsourcing the development process. Additionally developing the IT infrastructure and data capabilities can aid in the process. (Barney, 1991) For the organisations, building resources regarding AI, they can opt for first mover advantages in the field, as it was discussed that no early adapter has been identified in the field. As the development process has rapidly increased, organisations need to determine their strategic approach to be able to gain competitive advantages.

5.5 Implementing AI

Looking at the strategic management process, after the strategy formulation where the long-term plan to effectively manage the organisational environment is developed the implementation phase is structured. Implementation process is about taking in action of the strategies and possibly making structural changes. (Hunger & Wheelen, 2011, p.21-25) The findings suggested that some organisations are already founded an integral approach to use AI with an impact. Another perspective was currently in the process of creating the management models. According to the literature, choosing the wanted direction for the organisation is challenging as many perspectives need to be considered (Fitzgerald et al., 2014). It was highlighted in the findings that building a solid foundation for AI implementation is valued rather than starting too soon in relation to the organizational readiness for such a large change. Findings indicated that some are waiting for heavy investments towards challenging the current development models to suit AI properly. As AI is a relatively new technology in the organisations, it requires more heavy governance in the beginning.

From employee perspective, the trust towards the AI as a system is the key factor for them to start using it. Trust towards AI relates to the perceived transparency about the fairness, privacy and explainability. (Faruqe et al., 2023) Even though the system would technically act accurately and fairly convincing of others about it is a challenge. (Russel & Norvig, 2022, p.1047) The findings highlighted the importance of keeping the employees aware of the AI development and the objectives within the organisation. Additionally, the increasing need for developing training for AI was confirmed. As Jöhnk et al. (2021) brought up, upskilling employees with AI related skills is valuable if they don't posess adequate knowledge and as mentioned there will be an increasing demand for highly skilled employees (Brühl, 2024). Findings confirmed that there will be training spesificed to AI skills. Some organisations have already implemented training programs although saw that there is still a need to develop the existing ones. Barro & Davenport (2019) mentioned training the employees for specific roles or redesigning the existing roles. The findings supported the need for function specific training. Additionally the need for creating job-specific training paths was mentioned. Suitable distribution of skills as there isn't a need for the entire organisation to develop similar technical skills to develop AI for example. The more important factor is building the AI literacy capabilities to fit into the specific roles. (Cetindamar et al., 2024) There are limited amount of AI talents and keeping as well as attracting experts that have technical skills and domain-knowledge is important (Herremans, 2021). The findings didn't indicate a need for hiring new people as much as training the existing ones. It was mentioned that there isn't enough skilled people for developing AI, thus the only solution would be to hire or resolve into outsourcing.

Tracking the performance of AI systems is necessary and to be able to evaluate the performance, success measures need to be developed. The success measures can be used to justificate the investments to AI projects. As Hunger & Wheelen (2011) studied, the final step in the strategy process is the evaluation and control. evaluating the performance can then lead to discovering of new strategic needs to continuously develop the processes. The findings showed that there is continuous assessment of the AI solutions as the business cases are calculated in every project. However, some organisations highlighted the need for developing accuracy monitoring and reporting as well as a sort of standardisation in the entire organisation. In addition to only measuring the effectiveness outcomes, there could be measurements of the AI service to the users to evaluate their experiences and value of the solution. Organisations can opt for value delivery by using AI for decision support, automation of processes, or creation of new products (Borges et al., 2021). The ultimate measure for assessing the AI solution delivered value for some organisations is the monetary return from it, but according to Borges et al. (2021) the variety of value sources can vary between organisations. The literature suggests that the revenue growth from AI adoption is minimal if the adoption level is low, thus more signifant revenue growth emerged with heavier AI adoption as well as investments into complementary technologies and R&D (Lee et al., 2022). Organisations should consider the value of the AI solution in relation to the investments required to deliver the solution to the period of value creation. As some AI solutions can create quick results, the solutions requiring heavy investments can ultimately bring more impactful value. (Kruhse-Lehtonen & Hofmann, 2020)

Setting key performance indicators for measuring the effects is the key for receiving reassurance about what are the expected benefits from the process (Fitzgerald et al., 2014). The findings suggested differences within the metrics used to measure the performance of AI. Some organisations use the same measurements to analyse the effectiveness of AI as they measure specific processes, such as NPS. The need for developing new metrics was also introduces. The findings showed that some organisations don't have unified metrics across the organisation. The debate of generating new metrics versus seeing the current metrics as applicable for AI solutions was highlighted in the findings. Literature in this study didn't indicate whether existing metrics are applicable for AI or new should be developed. This would have required more thorough analysis of the specific AI solutions, however, the scope of the research limited this.

Implementing AI can create legal and ethical challenges for organisations (Dwivedi et al., 2021). AI system delivering good results isn't the only thing required, it needs to meet the regulatory requirements and privacy concerns. The regulatory pressure will keep increasing. (Akerkar, 2019. p13) According to the findings, all organisations have a high level of awareness on the regulatory perspective and managing risks. These factors have been familiar with them as the regulatory pressures in the financial industry are high, thus AI implementation is not an entirely new consideration. However, AI brings new factors that need to be filled, and this requires developing the current risk management processes to consider risks emerging from AI. The findings suggested that some organisations have already developed an AI solution requirement checklist. Some saw data protection and the lack of knowledge as a worrying factor with the risk management.

According to the literature, the BFSI sector faces increased challenges with the changing regulatory environment. Adapting to technological changes is needed. (Saxena et al., 2024, 57-81) The findings suggest that the highly requlated field creates demands and the regulations were seen as slowing the integration of AI. As already mentioned, the need for developing AI literacy within the employee roles is important. The findings suggested that ethical AI use come from educating the employees for using it in a safe way. European Commission (2025) introduced the first legal framework for AI with addressing its risks called AI Act. Findings indicated that all organisations are well aware of the changes that will be brought with AI Act such as increasing training.

6 Conclusions

This final chapter of the study presents the key results to highlight the important findings. Then it discusses the managerial implications for how to strategically approach AI within different organisations. Finally, the limitations and future research recommendations are presented.

6.1 Key results

This study aimed to understand organisations strategic approach to adopting AI and the practical perspective of the organisations AI implementation process. It explored different factors organisations might need to be able to apply AI strategically in their operations to gain better value of the investment. Additionally, the different challenges organisations might face when trying to implement AI was studied. There is a lack of research in AI strategies in organisations and the strategic implementation practices, thus this study addressed a gap in the literature. The focus on AI in organisations has been rapidly increasing and new literature is constantly emerging.

Organisations are utilising AI, but in some cases, deal with the absence of strategic guidelines to make the most out of it. Making AI operations more scalable with strategic processes is the objective. Diverse approaches to applying AI were identified while the need for applying AI to remain competitive was seen throughout the study. Developing the internal capabilities of the organisations with upskilling the employees and developing current systems and data maturity, was highlighted. Additionally, the top management awareness level was emphasised as well as developing the organisation’s culture. It was found that employee resistance towards AI decreases when their knowledge of it increases, however some level of resistance is normal in new technologies and AI is not an exception.

The study found that organisations face different types of challenges with implementing or trying to scale AI adoption. The fast trajectory of AI has brought difficulties with developing the solutions and bringing them to the market at the needed speed, which could be related to organisations being unaccustomed with such speed of development. The technology development processes need to support the fast trajectories. Another challenge was not being able to identify the value generated with AI or comparing AI value to past investments.

6.2 Managerial implications

The existing literature and the findings from this study suggests that organisations should develop objectives for the use of AI and its implementation, as without clear objectives, the organisation can face issues with lack of support from the top management and the lack of needed investments towards it. Even though there would not be heavy investments towards AI directly from the beginning, it should be clearly discussed in the organisation where do they see AI in the future within the organisation compared to competitors. Clear objectives shows the employees what is wanted from them and what is aimed at organisational level. As mentioned previously, this decreases resistance from the employee's side. Strategic objectives towards the AI adoption can help with prioritization, as currently in some cases AI is competing with other initiatives. With objectives set out, the implementation process of AI can be developed and a roadmap from the ideation phase to implementation of the technology are defined. Creating the roadmap to support the fast development is important.

Strategy development and setting out objectives for implementing AI increases the awareness level of the organisation which then makes the organisation more adaptable to changes in the environment. When the organisation is aware of surrounding trends and their own objectives, they can develop their existing capabilities to remain competitive additionally adjust to expectations of the customers. This includes evaluating the current strategy and transforming the strategy to fit the constantly changing environment due to AI. Even though the context of the study focused on finance industry, the organisations could benefit from thinking outside the boundaries of the current sector with creating new ways of value generation or even just analysing the possible effects of AI and then making scenarios to be prepared (Berthon et al., 2024). Culture was found to be central element to AI adoption. The organisational culture should be developed to further aid with the transition and bring innovativeness to the employees and the management.

When the roadmap for implementation has been created the organisations needs to look at their current capabilities and whether those need to be developed. The capabilities include skills of employees, technology systems, mature data. With AI changing the roles of employees, organisations need to focus on upskilling their employees to fit into the new roles which can include monitoring the AI systems. Upskilling can include developing training paths to employees where the intended training focuses on specific functions. If the organisation leaves the development of AI solutions to outsourcing partner, they don't increase the own knowledge capital, which can be needed in the future. With developing the AI solutions, the organisations should consider creating AI team where the solutions can be developed and then the process does not scatter over the organisation but stay within the chosen team. This can improve the scalability of AI solutions.

The existing technology and systems need to work seamlessly with AI and organisations need to evaluate whether the current ones cater the needs of AI. If an organisation aims to develop AI solutions, they need to ensure data maturity across the organisations and value chains. Before the AI solutions are implemented, organisations should consider generating suitable measures to make sure the effect of AI is taken into account and then the value of it can be proven.

6.3 Limitations and future research

This study provided an understanding of organisations strategic approaches to AI. From this study, some limitations were discovered and with that possible future research topics was identified. This is related to the recent emergence of AI solutions and the lack of current research. The empirical data gathered from the interviews was extensive. Implementation of AI in organisations is still at early stages, thus it was challenging to find respondents that have the specific strategic knowledge about AI and not only technical knowledge. Even though the respondents gathered were from three different countries, the representation was relatively small. Future research should take a wider approach from more countries. Additionally, the study was limited to financial sector organisations and in the future the research should gather data from other industries. The empirical data was collected from people from large organisations, thus their approaches and challenges can be different from smaller companies. The future research should study different sizes of organisations with more limited resources and more flexible organisational structures.

As this research focused on the general strategic approach to AI instead of thoroughly analysing each different factor and aspect, the future research could take in more detail of certain aspects such as the influence of corporate structures or in-house resources. This study didn't consider the changing views of the customers, thus the future research could analyse the development of consumer perspectives on AI in organisations.

The research focus was relatively short-term. The development of AI is still at early stages and there is a constant updating of the solutions and systems. It would be beneficial to gain longitudinal approach that analyses the long-term effects of such strategies. This would provide information about what kind of approach is the most profitable and which factor is the most important when formulating the AI strategies.

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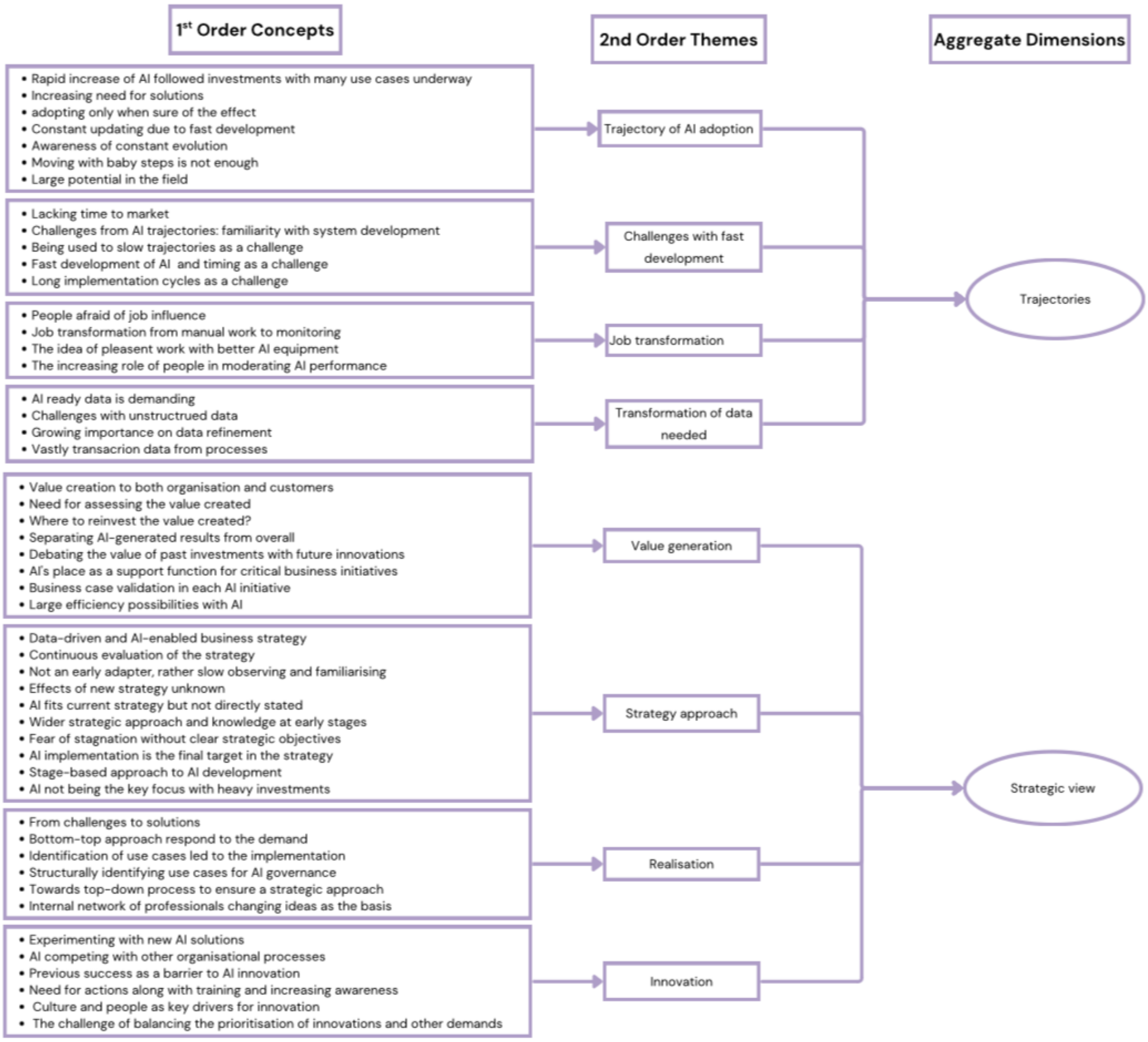
Appendices

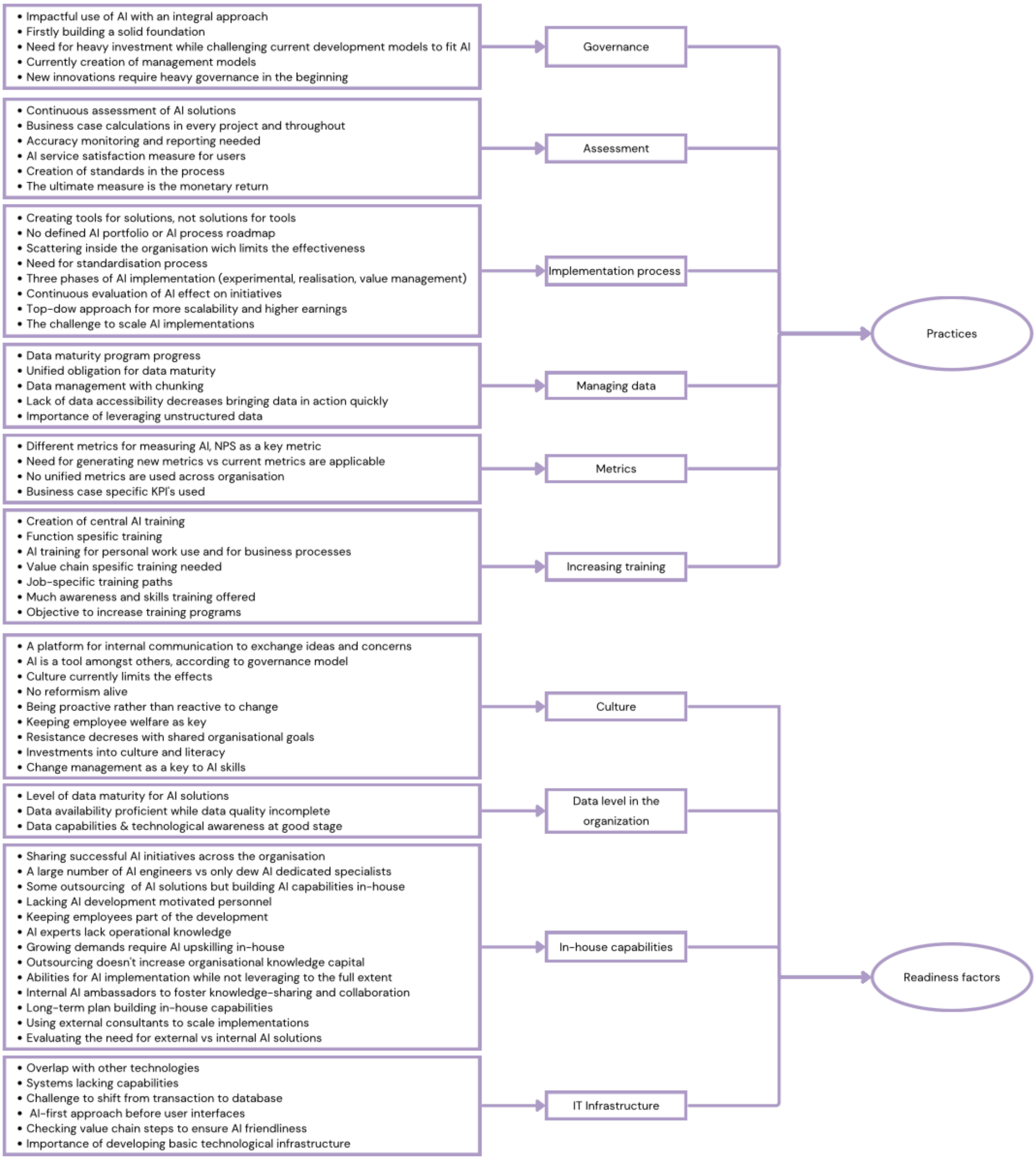
Appendix 1. Interview questions

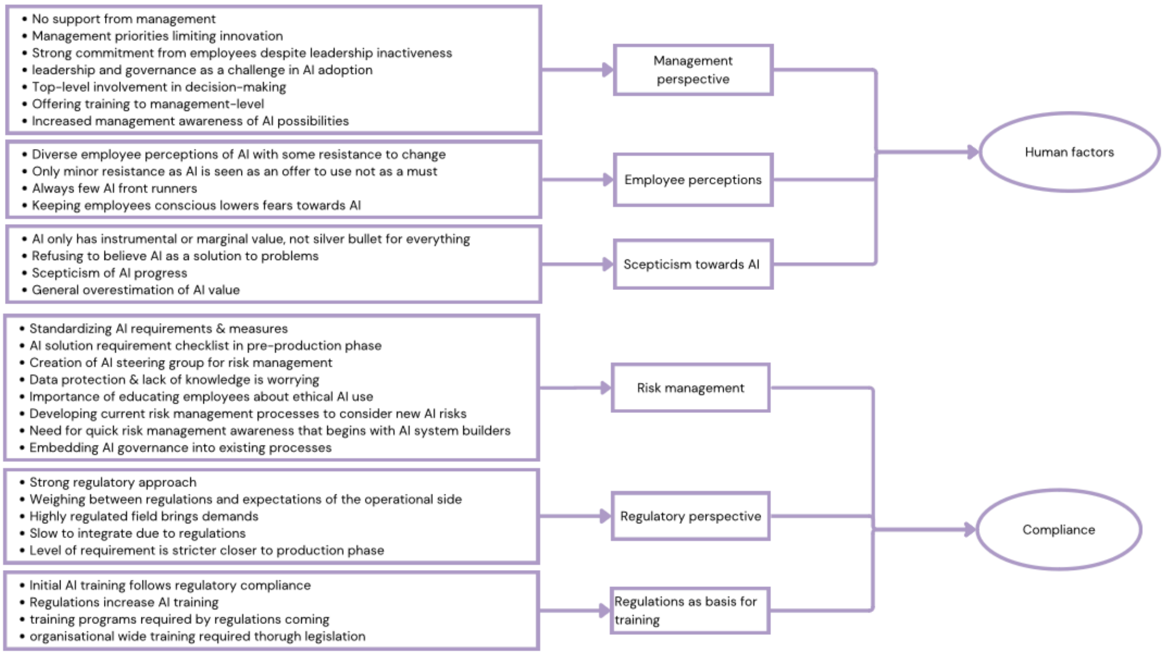
Theme	Question
Background and role of the respondent	
- Background information of the respondent - Their role regarding AI in the organisation	15. What is your role in the organization? How does it relate to AI initiatives?
AI adoption in the organisation	
- The organisations maturity level regarding AI	16. How would you assess your organization's AI maturity level? (e.g., just starting, experimenting, scaling, fully integrated)?
- Trajectories of AI	17. How has the rapid evolution of AI technologies impacted your company's ability to implement AI solutions? And how do you see that in the future?
- AI implementation process	18. Can you describe your company's AI implementation process? What has worked well, and what challenges have come up?
AI elements in organisation	
- Objectives of AI implementation - Strategic alignment of AI in organizational strategy	19. What is your vision for AI in your company? How does this align with your organization's overall strategy? 20. How often is the company's AI strategy revied?
- Leadership - Culture	21. Can you assess the leadership initiatives and cultural changes that support AI adoption?
- Employee AI literacy - Employees AI perception - Actions towards improvement	22. How do employees perceive AI adoption—are they engaged, resistant, or neutral? What actions have been taken to address concerns? 23. Does the company rely on in-house resources with AI developments or has there been a need for outsourcing (external consultant, AI vendors)? If outsoursing is used, in which areas? 24. What kind of AI training is needed? Is there any existing programs implemented?
- Data maturity - Existing technological capabilities	25. What stage are the company's data availability and existing technological capabilities?
- Measuring the AI initiatives	26. What key metrics do you use to measure AI's impact on business (e.g. performance, efficiency, and risk)?

- Risk management	27. How do you manage risks associated with AI implementation (e.g., privacy, security, compliance)?
- Open comments	28. Any open comments?

Appendix 2. Data structure




• Impactful use of AI with an integral approach
• Firstly building a solid foundation
• Need for heavy investment while challenging current development models to fit AI
• Currently creation of management models
• New innovations require heavy governance in the beginning
Governance
• Continuous assessment of AI solutions
• Business case calculations in every project and throughout
• Accuracy monitoring and reporting needed
• AI service satisfaction measure for users
• Creation of standards in the process
• The ultimate measure is the monetary return
Assessment
• Creating tools for solutions, not solutions for tools
• No defined AI portfolio or AI process roadmap
• Scattering inside the organisation wich limits the effectiveness
• Need for standardisation process
• Three phases of AI implementation (experimental, realisation, value management)
• Continuous evaluation of AI effect on initiatives
• Top-dow approach for more scalability and higher earnings
• The challenge to scale AI implementations
Implementation process
• Data maturity program progress
• Unified obligation for data maturity
• Data management with chunking
• Lack of data accessibility decreases bringing data in action quickly
• Importance of leveraging unstructured data
Managing data
• Different metrics for measuring AI, NPS as a key metric
• Need for generating new metrics vs current metrics are applicable
• No unified metrics are used across organisation
• Business case specific KPI's used
Metrics
• Creation of central AI training
• Function spesific training
• AI training for personal work use and for business processes
• Value chain spesific training needed
• Job-specific training paths
• Much awareness and skills training offered
• Objective to increase training programs
Increasing training
Practices
• A platform for internal communication to exchange ideas and concerns
• AI is a tool amongst others, according to governance model
• Culture currently limits the effects
• No reformism alive
• Being proactive rather than reactive to change
• Keeping employee welfare as key
• Resistance decreases with shared organisational goals
• Investments into culture and literacy
• Change management as a key to AI skills
Culture
• Level of data maturity for AI solutions
• Data availability proficient while data quality incomplete
• Data capabilities & technological awareness at good stage
Data level in the organization
• Sharing successful AI initiatives across the organisation
• A large number of AI engineers vs only dew AI dedicated specialists
• Some outsourcing of AI solutions but building AI capabilities in-house
• Lacking AI development motivated personnel
• Keeping employees part of the development
• AI experts lack operational knowledge
• Growing demands require AI upskilling in-house
• Outsourcing doesn't increase organisational knowledge capital
• Abilities for AI implementation while not leveraging to the full extent
• Internal AI ambassadors to foster knowledge-sharing and collaboration
• Long-term plan building in-house capabilities
• Using external consultants to scale implementations
• Evaluating the need for external vs internal AI solutions
In-house capabilities
• Overlap with other technologies
• Systems lacking capabilities
• Challenge to shift from transaction to database
• AI-first approach before user interfaces
• Checking value chain steps to ensure AI friendliness
• Importance of developing basic technological infrastructure
IT Infrastructure
Readiness factors


• No support from management
• Management priorities limiting innovation
• Strong commitment from employees despite leadership inactiveness
• leadership and governance as a challenge in AI adoption
• Top-level involvement in decision-making
• Offering training to management-level
• Increased management awareness of AI possibilities
Management perspective
• Diverse employee perceptions of AI with some resistance to change
• Only minor resistance as AI is seen as an offer to use not as a must
• Always few AI front runners
• Keeping employees conscious lowers fears towards AI
Employee perceptions
• AI only has instrumental or marginal value, not silver bullet for everything
• Refusing to believe AI as a solution to problems
• Scepticism of AI progress
• General overestimation of AI value
Scepticism towards AI
Human factors
• Standardizing AI requirements & measures
• AI solution requirement checklist in pre-production phase
• Creation of AI steering group for risk management
• Data protection & lack of knowledge is worrying
• Importance of educating employees about ethical AI use
• Developing current risk management processes to consider new AI risks
• Need for quick risk management awareness that begins with AI system builders
• Embedding AI governance into existing processes
Risk management
• Strong regulatory approach
• Weighing between regulations and expectations of the operational side
• Highly regulated field brings demands
• Slow to integrate due to regulations
• Level of requirement is stricter closer to production phase
Regulatory perspective
• Initial AI training follows regulatory compliance
• Regulations increase AI training
• training programs required by regulations coming
• organisational wide training required thorugh legislation
Regulations as basis for training
Compliance