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# Succeeding in strategic AI adoption: Role of analyzing organizational and technological readiness

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**ABSTRACT:**

Artificial intelligence is a complex set of technologies which are developing fast and have created enormous possibilities for businesses. This is why organizations have become interested in how AI could help them. Because AI is new for many organizations, and due to its fast development, many organizations adopting AI are not achieving their set goals for adoption. The current literature on AI is however more focused on how AI is affecting organizations, its performance, business, and processes, but also on studying the success factors, barriers, and performance advantages of AI. Some studies on the area have found out that the results of AI adoption are connected to the organizational and technological readiness to adopt AI. Yet, there are only a little research on the actual process and the assessment of organizational readiness for adopting AI. Current research on this specific area shows that many organizations failing in AI adoption are lacking strategy. Based on the existing literature a framework was developed to analyze organizations AI readiness. The purpose of this thesis is to study organizations' readiness factors for the strategic adoption of artificial intelligence. By recognizing these readiness factors organizations can evaluate their current level of readiness in terms of the technology that is being adopted, and develop it in order to reach the set strategic goals with AI. This empirical study was carried out with qualitative methods. Data was collected by conducting six semi structured interviews with people from different organizational levels within two case organizations. The analysis was conducted by first analyzing each case company separately in relation to the themes used in the interview structure. Then a cross-case analysis was conducted to see which readiness factors have risen in the cases individually, which readiness factors are common between the cases and which factors differ. The findings show that the developed model was suitable for analyzing organizational AI readiness. Findings also support strategy's relevance and support for other readiness factors. AI is argued to be a complex technology that requires decision makers to understand the technology in order to align their readiness to the AI model being adopted. The established theory in this research area got support from the findings of this thesis. Furthermore, this study also broadened the current theory by arguing the strategy's relevance for AI readiness, and by developing the AI readiness framework. Decision makers need to understand their organization's AI readiness factors in relation to their plans and goals for AI adoption. Their strategy needs to support the purpose of AI adoption, and by analyzing and developing their current AI readiness, organizations are able to have better chance in achieving their goals for AI adoption.

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**KEYWORDS:** Artificial intelligence, strategic adoption, organizational readiness, technological readiness

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## Abbreviations

AI

LLM  
GenAI

## 1 Introduction

Artificial intelligence (AI) as technology has received greater public spotlight ever since the release of OpenAI's ChatGPT (Afjal, 2023). Although AI can be said to have existed for public since 1950 when Alan Turing presented the test related to the thinking of machines (Afjal, 2023; Göcke & Pütten, 2020). Today, AI is developing fast and has created enormous possibilities for businesses (Chui et al., 2023; Grand View Research, 2024). This fast development is due to the development of supporting technologies such as machine learning, computing power, data processing and data storing capabilities which has enabled the training of large language models (LLMs) (Uren & Edwards, 2023; Afjal, 2023).

Due to the surge of AI, organizations have become interested in how AI could help them. Many organizations are testing, planning, conducting studies, piloting or already adopting AI as part of their day-to-day business operations in different industries (Kim & Seo, 2023; Leavy, 2023; Uren & Edwards, 2023). Although, it has been pointed out that AI is much more complex technology to implement, as it is not just a technology but rather a set of technologies (Janiesch et al., 2021; Ojanperä, 2023). Hence, when comparing the adoption of AI to previous technologies, it is requiring a lot of change and adaptation withing an organization (Agrawal et al., 2024). Hence, it is crucial for the management of these organizations to understand how complex AI is, how it works, how it could help them and how it should be adopted to gain the expected value. That is because decision makers has been shown to be the central part of the AI adoption process (Cortellazzo et al., 2019, 2019; Enholm et al., 2022).

Researchers have become more and more interested in how AI will affect the decision making progress (Booyse & Scheepers, 2023; Duan et al., 2019; Kim & Seo, 2023). There has been studies on how AI is affecting organizations, its performance, business, and processes (Enholm et al., 2022; Leavy, 2023; Shaik et al., 2024; Sturm, 2023) and what are the success factors, barriers, performance advantages when adopting one (Booyse

& Scheepers, 2023; Duan et al., 2019; Perifanis & Kitsios, 2023). All this increasing research regarding AI and interest towards its potential in businesses has shown the overall importance of this developing technology.

However, even though AI has gained a lot of attention, the research regarding AI adoption and the organizational readiness for it is only developing (Jöhnk et al., 2021). There are only a little research on the actual process and the assessment of organizational readiness for adopting AI, thus showing a clear research gap (Holmström, 2022; Jöhnk et al., 2021; Tehrani et al., 2024; Uren & Edwards, 2023). Furthermore, the development pace of AI has created high expectations for decision makers regarding the results of AI adoption to which some researchers are referring as hype (Holmström & Hällgren, 2022; Vinsel, 2023). This has created a distortion between the outcome of the AI adoption projects and the set goals (Mabad et al., 2021). In addition, it is clear that organizations are lacking clear AI adoption strategies. In fact, it is argued that only 7% of organizations that are adopting AI would have one (Atsmon, 2023). This shows that there is a need to create an understanding for the decision makers on what is required by an organization to increase the chances of successfully completing a strategic AI adoption.

Jeyaraj et. al (2006) have argued that each innovation has its own characteristics and that they should be examined separately in terms of adoption. Some researchers have already found evidence, that the results are connected on the organizational and technological readiness to adopt the technology (Haan & Watts, 2024; Jöhnk et al., 2021). For example, Jöhnk et al. (2021) state that "...companies need to assess whether their assets, capabilities, and commitment are ready for the individual AI adoption purpose" (p. 5). Furthermore, Mendes et. al (2024) concluded in their article of risk management perspective, that companies need to align their technology adoption decisions with their organizational needs and capabilities to manage the risk of adoption better. Additionally, Uren & Edwards (2023) found out that people, processes, technology and data readiness are required to achieve success with AI adoption. Yet, there is only a little analysis on what is the relevance of strategy in AI adoption, how strategy affects AI readiness factors,

does AI differ from previous technologies in terms of adoption, how can organizations explore and understand their current readiness for AI adoption, and what organizations really need to consider when adopting AI.

Hence, the purpose of this thesis is to study organizations' readiness factors for the strategic adoption of artificial intelligence. As organizations are lacking clear strategies to support the adoption of AI, and as AI is a complex set of technologies, the role of organizations readiness factors in supporting AI adoption requires examination. By recognizing these readiness factors organizations can evaluate their current level of readiness in terms of the technology that is being adopted, and develop it in order to reach the set strategic goals with AI. Regardless of the complexity of the research area and the limited previous research in the area, this thesis boldly broadens and builds on top of the existing research on strategic AI adoption and AI readiness. Therefore, the research question is:

*How can organizations analyze and start developing their readiness for strategic adoption of AI in order to achieve the strategic goals set?*

The main research question is supported by the following questions in order to examine each area separately:

*What is the role of strategy in AI adoption and what kind of readiness factors do organizations need to succeed in AI adoption?*

*How should organizations view AI from an adoption perspective?*

This thesis consists of five different sections. First, the introduction chapter explains the purpose of the research and the research questions. It introduces the reader to the researched problem and the background of the research. The second chapter explores and reviews current literature and studies the existing academic background by following the

research questions. It starts with a reviewing the relevance of strategies in terms of technology adoption. It compares the views of digital strategy literature to existing AI strategy literature. The second part explores AI as technology. It briefly reviews the history of AI development and shows the importance of why decision makers should understand technology. Finally, it moves to discuss the adoption models for AI specific technologies and technologies overall. By analyzing these models, the readiness factors are introduced. Then by building on top of existing AI adoption models, a theoretical framework is established that includes strategy as a readiness factor. This framework is the key theoretical contribution of this thesis, and is later used to analyze case companies AI readiness.

After the thorough literature review, the methodology of this study is described in the third chapter. This chapter introduces the research approach, case organizations, data collection methods, data analysis, and reviews critically the validity and reliability of the study. Then the fourth chapter then discusses the findings of the empirical research by first analyzing the cases individually and then through cross-case analysis. The final chapter concludes the theoretical and empirical contributions of this thesis. It also shows the limitations and suggests avenues for future research.

## 2 Theoretical background

### 2.1 Relationship of strategy and technology adoption

Adopting a new technology has become the source for competitive advantage in many industries (Chiu & Yang, 2019). Today new technologies, especially digital technologies, are not anymore just means for increasing operational efficiency (Morton et al., 2022). Due to the accelerating phase of digital transformation, organizations have integrated digital technologies in their strategy formulation and decision-making process (Mendes et al., 2024). Furthermore, these new technologies have become facilitators for the new strategic shifts (Rêgo et al., 2022). However, not all technologies, especially legacy technologies, hold that high strategic value. Vice versa, it could also be argued that technologies, such as laptops, printers, and the internet, has become more or less essential for all organizations (Ali et al., 2022). On the other hand, these technological innovations that once were top management acquisition decisions have now become more commodity technologies to support the execution of everyday business operations (Mendes et al., 2024). More specifically, these commodity technologies do not act as a source for competitive advantage anymore (Mendes et al., 2024). Nevertheless, legacy technologies act as a basis for newer technology, for example internet and laptop is needed to run a business software (Sting et al., 2024).

Strategic technology is an innovation that is adopted into an organization with the aim of achieving strategic goals, such as adapting into the changes in the business environment, or gaining competitive advantage (Mendes et al., 2024). More specifically, strategic technologies can enable the transformation in business models or support existing ones, and they can be used in strategizing processes (Zhou et al., 2024). Reflecting this, as technologies are playing an increasingly important role in organizations strategy, it should be important for companies to understand the adoption process. Hameed et. al (2012) argue that the technology adoption process is a crucial part regarding the

successfulness of the adoption. They state that in order for the innovation adoption be successful, the technology should be accepted by the individuals and by the organization, it should be part of the business operations, and that it should be actively used and updated by the individuals over time (Hameed et al., 2012).

Strategic technology adoption as a concept refers to a process where an organization decides to acquire a new piece of technology and integrate this innovation into their main business operations (Mendes et al., 2024). Simply, it means that the organizations look for suitable technologies that align with their strategy and strategic objectives, evaluate their suitability, and adopt them in to their main business processes (Sun et al., 2024). Such technologies could be, for example, machine learning algorithms that use customers' data to predict their next needs and offer them the correct items or services automatically (Janiesch et al., 2021). This would then generate a competitive advantage for an organization if they, for example, were able to create a complete offering for the customer before they were even able to consider competitors' products and services.

It is also important to consider the meaning of the term adoption. The term adoption should not be mixed with the term implementation that is often used as a synonym in the context of getting new technology into an organization (Kyratsis et al., 2012). Implementation refers more to the process of installation and configuration of the technology, mostly done by the IT department, whereas adoption refers to a more comprehensive process (Damanpour & Schneider, 2006). Adoption is often referred as a process that is initiating the actual adoption process, making the decision to acquire new technology, analyzing the potential benefits, setting goals, analyzing prerequisites, acquiring relevant know-how and resources for the implementation, and only then implementing the technology (Damanpour & Schneider, 2006; Hameed et al., 2012; Kyratsis et al., 2012; Sun et al., 2024). Adoption considers the whole life cycle of technology and also takes the results in consideration. In a way, implementation could be seen as a later stage of whole adoption process and thus should not be used interchangeably (Hameed et al., 2012; Kyratsis et al., 2012). Thus, in this thesis the term adoption is more useful for the purpose

of this thesis, wanting to discuss the process from a broader view, from the decision making to the implementation, whereas implementation would delve deeper into the details of the actual process steps.

Based on reviewed literature, strategic technology adoption can be viewed as a process from decision making to the implementation of the chosen technology. This adoption is done to the organization's core business process and it aligns with their strategy and set strategic objectives aiming (Kyratsis et al., 2012; Mendes et al., 2024). Furthermore, it considers the set objectives, requirements, and results for the adoption process (Sun et al., 2024). This concept is applied to formulate a framework to showcase how strategic adoption should be managed in the context of organizational and technological readiness.

### **2.1.1 Digital Strategy and AI adoption strategies**

Strategy is referring to comprehensive goals, objectives and plans that helps to guide an organization's decision making and business operations within the work system (Alter, 2013). The same idea applies for overall technology adoption, as organizations need to have clear view and destination with their technology projects and right means to achieve it (Jöhnk et al., 2021; Sun et al., 2024). In the case of adopting AI, the role of strategy can be viewed in two ways. First, digital strategy literature supports the adoption process and supports organization's readiness and capabilities of adopting new technologies, such as AI (Rêgo et al., 2022; Zhou et al., 2024). Second, organizations that are already moving into adoption can have AI adoption strategies which explore how the organizations are approaching different AI technologies and their adoption (Kim & Seo, 2023; Tehrani et al., 2024). Even though these two concepts are not completely separated from each other it is nevertheless good to address them separately. Digital strategy literature supports the view of having a strategy that guides how technology is helping organizations in achieving their goals, as it focuses on the interconnectedness between digital technologies and strategy (Zhou et al., 2024). Digital strategy is used in

organizations to recognize the core digital technologies and harnessing them in a way to achieve strategic goals (Rêgo et al., 2022). Digital strategy should be connected with the organizations' core strategy, as separating it would increase the risk of causing the creation of silos within the organization and thus decrease probabilities of success within their technology ventures (Morton et al., 2022). However, it has been found out that many organizations struggle when they are trying to align their organizational strategy with their digital strategy (Morton et al., 2022; Rêgo et al., 2022; Zhou et al., 2024).

In a more recent study field regarding AI readiness, adoption, satisfaction, and implementation literature, Tehrani et. al (2024) aimed to recognize different AI adoption strategies. However, there is no clear body of research for AI adoption strategies specifically yet, at least in the readiness, adoption, satisfaction, or implementation contexts (Tehrani et al., 2024). In addition, this can also be seen that companies are lacking clear AI adoption strategies as it is argued that only 7% of organizations that are adopting AI would have one (Atsmon, 2023). However, there are studies that do somewhat consider the topic of AI adoption strategies in light of the AI adoption and readiness factors. Yet, they are not focusing on these themes solely but do produce support for them (Borges et al., 2021; Kim & Seo, 2023). It could be seen from these studies that as they have been published before the so called AI hype which started in the November 2022 and accelerated towards the end of 2023 (Holmström & Hällgren, 2022). Before the hype, AI adoption has not been that timely for everyone as the AI solutions on the market have not yet filled any viable use cases for most organizations (Vinsel, 2023). This shows that AI has been available for broader markets for a limited period which is one reason that studies on AI adoption strategy area are still scarce. Nevertheless, similar issues seems to appear within digital strategy research and when compared to strategic AI adoption studies. This is, as AI adoption can be included within the theme of digital strategy, as it is a digital technology (Zhou et al., 2024).

The views between digital strategy and AI adoption strategies needs to be compared to understand their interconnectedness. Through several interviews with managers that

have been involved in AI adoption projects, Tehrani et. al (2024) recognized that the AI strategies that managers have used in recent years, have been following the distinction of the two strategic dimensions – cost reduction and differentiation – made known by Michael E. Porter (Tehrani et al., 2024). The cost reduction strategy ultimately aims to achieve cost leadership within the markets. This means that an organization produces its services and/or goods with the lowest unit price on the market without losing too much in quality. In another words, they make the most of their current situation in their relative market. This strategy is usually used to attract the more price sensitive customers (Porter, 1997). The differentiation strategy, on the other hand, is used to stand out for your customers by offering somewhat different products and/or services than the competitors. The difference can be based on the different characteristics of the offering, such as quality, means of distribution or features. Organizations aim to gain relative advantage to their competitors with differentiation. The ultimate aim is to increase the amount of perceived value from the point of the view of the customer so that they are willing to pay extra for the company's offering (Porter, 1997).

Recent study in the field of digital strategy offers support for the findings for these strategies with a slightly different view. Sting et. al (2024) studied in their research the difference between disruptive and adaptive technology strategies. Disruptive technology strategy aims to leverage the new technology in a way that creates the organizations relative competitive advantage (Baiyere et al., 2023). This strategy is similar to Porter's differentiation strategy. In means of technology, the disruptive strategy requires advanced digital resources and technological readiness, strong and visionary leadership that does not shy away from risk, resource allocation, and flexibility and innovativeness from the people (Sting et al., 2024). On the other hand, the adaptation strategy aims to leverage the technology in order to make the most of their current business environment under uncertainty and ambiguity (Pich et al., 2002). The adaptation strategy is lower in terms of risk and it aims to improve the absolute performance of an organization, for example in order to remain competitive on a market (Sting et al., 2024). The adaptation strategy requires an organization to have processes in place that can be easily enhanced

with digital solutions, such as automation. Furthermore, it is used to incrementally increase the digital innovation, the leadership wants to gain more stability with lower risk implementations and thus aim to make their current market positioning stronger (Sting et al., 2024)

However, the managerial aim is not the only factor affecting the chosen strategy. It is also influenced by the risk factors (Mendes et al., 2024; Sting et al., 2024). The risk factor with AI adoption is related to success of the adoption meaning that the more complex AI adoption have higher risks as there are more factors involved such as the organization technological readiness (Tehrani et al., 2024). The managerial goals and the risk factors recognized by Tehrani et al. (2024) are presented in the figure 1 in which they form an AI adoption strategy matrix together with the different strategies recognized by Tehrani et al. (2024).

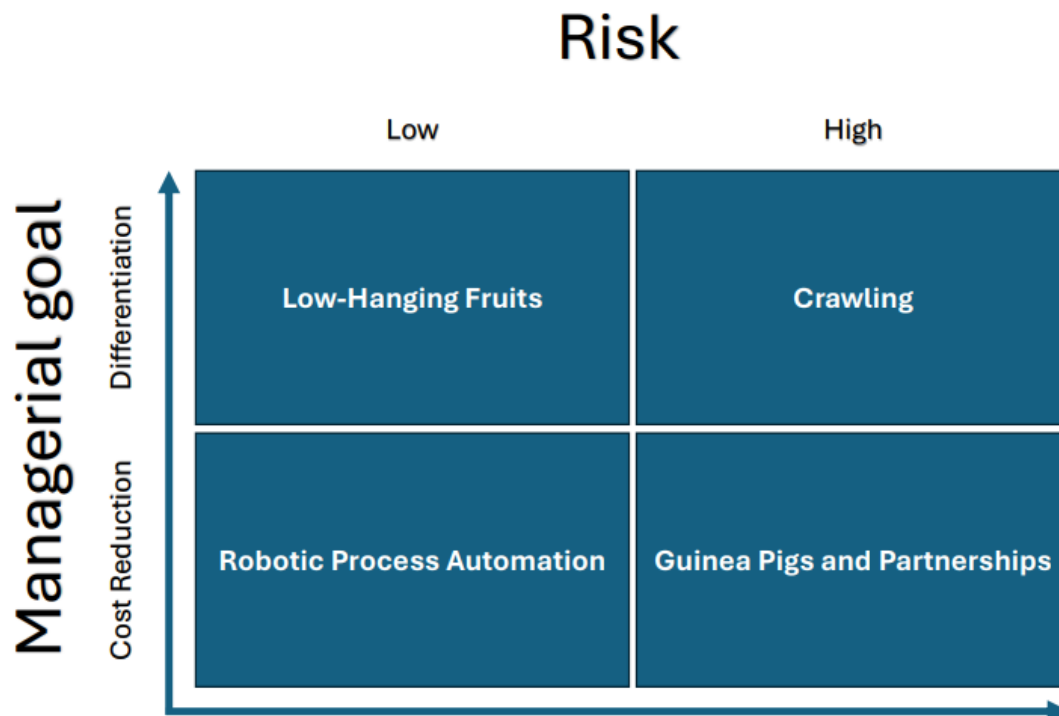


Figure 1 AI adoption strategies matrix (Adapted from Tehrani et. al, 2024)

The crawling strategy was recognized to be used by those organizations that had higher risks for AI adoption and were aiming for differentiation. This higher risk was caused by mostly their current technological capabilities and lack of them. For these organizations it was convenient to go with technologies that were easier and faster to adopt, and which required less technological capabilities. Once they had implemented these smaller use cases which did not affect their processes too much, they could move on to adopt more complex AI technologies. Thus the name is referring to the fact that these organizations needed first learn to “crawl” before they could “walk” (Tehrani et al., 2024). A similar approach but with a different perspective is suggested by Kim and Seo (2023) as they proposed that SMEs could first start building their AI capabilities and thus gradually increase their AI adoption as they go. They emphasized that this gradual adoption should also be aligned with their strategy to ensure that they do not get sidetracked with the adoptions, similarly that Tehrani et. al (2024) suggested in their article.

The low hanging fruits strategy recognized by Tehrani et. al (2024) is also a differentiation strategy but now with lower adoption risk. In this strategy, organizations can pick those areas of their business that already has the potential to start using AI technologies. Thus they have so-called “easy picks” in their organization offering fast adoption and faster results which is where the name of the strategy refers to. After doing the adoption in some parts of their organization they could move on to other more complex use cases (Tehrani et al., 2024). A similar strategy recognized by Kim & Seo (2023) was a management-enhancing strategy. In this strategy, organizations do have AI capabilities, but they do not yet have intents to use it on the market. Rather they are using AI to improve internal processes and decision making to come out with new production or service delivery processes (Kim & Seo, 2023).

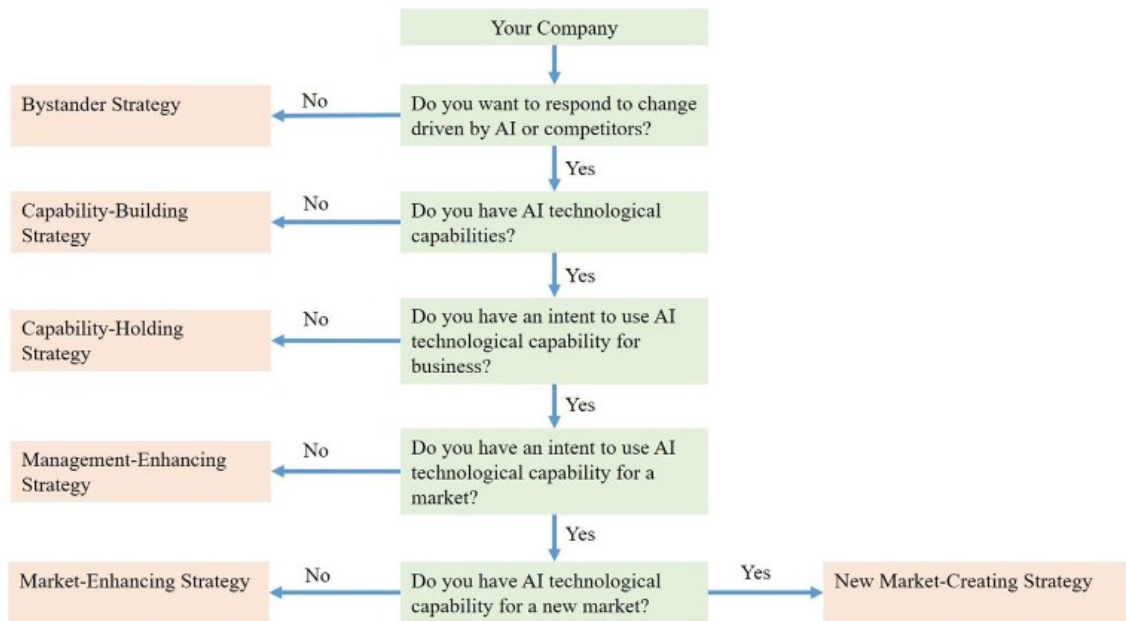
The robotic process atomization strategy refers to low risk adoption environment where an organization has the required capabilities and are adopting an AI related technologies to automate their internal workflows with it. However, to achieve such an low risk environment for AI related technology adoption, the organizations needs to already have the

necessary level of AI readiness required to adopt the chosen technologies (Tehrani et al., 2024). This is classified as a cost reduction strategy because the AI is used to automate such tasks that would otherwise require human working hours and thus fills the criteria for cost reduction (Porter, 1997). It could be presumed also that at least at the beginning of adoption these task would be quite simple tasks which would free up time from the humans to do more creative tasks the current AI is not yet capable of doing. Kim and Seo (2023) has similar observations with the “capability building” and “management enhancing” strategies. The management enhancing strategies uses AI to improve organization internally. However, as suggested in the process automation strategy the company can only adopt those parts of the technology they are already capable of. Thus they need to enter again to the capability building phase if they were to adopt other AI technologies later (Kim & Seo, 2023; Tehrani et al., 2024).

Lastly, the guinea pig and partnership strategies are separate strategies that both refer to a more comprehensive AI deployment. In guinea pig strategy larger organizations lets other smaller operators in markets test and develop AI solutions and then depending on their success the larger organization will try to acquire them, their technology and knowledge. Whereas in partnership strategy a larger organization can partner up with solution developers and start developing new AI capabilities. The end game would be a more sophisticated and more developed AI solution (Tehrani et al., 2024). Again, here we can see similarities to the strategies proposed by Kim and Seo (2023).

All in all, when comparing these articles and their approach to AI strategy we can see similarities. In the article of Kim & Seo (2023) there is support for the strategies recognized by Tehrani et. al (2024) and Sting et al. (2024) but the approach is more dynamic. Kim and Seo propose a decision tree where organization can choose a strategy by answering a question as shown in figure 2. They could choose from following strategies; a bystander strategy where they do not engage in AI adoption; capability-building strategy where they increase their readiness before adopting; capability holding strategy where they are waiting for a right moment for adoption; management enhancing strategy

where they improve their internal operations but do not engage the markets directly; market enhancing strategy where they use AI to harness the potential of current market; market creating strategy where they use AI to enter or create totally new market (Kim & Seo, 2023).



**Figure 2 Strategy Decision Tree (Kim & Seo, 2023)**

Comparing the decision tree to the strategy matrix proposed by Tehrani et. al (2024) we can see that the matrix pictures a more static “as-is” situation where an organization has chosen their development track based on their current level of readiness. Whereas the decision tree model by Kim & Seo (2023) pictures may be a more dynamic model and shows the readiness development over time. When compared to the digital strategies by Sting et al (2024) we can see interconnectedness to both Kim & Seo’s decision tree, and the matrix by Tehrani et al (2024). By combining these models, we can see a more fluid process model where an organization could choose their “as is” situation, build on it and maybe change their development track over time. For example, an organization could begin by “crawling” strategy and combine it with “low hanging fruits” and move on towards the “robotic process-automation” and finally for the “guinea pig and partnership” strategy as their capabilities progress and they are able to pursue more

comprehensive solutions. Whereas in the decision tree the organization could repeat these steps over and over again with different AI solutions. For example, an organization could choose a bystander strategy with more comprehensive AI models, but would continue with the “guinea pig” strategy and wait until there is a suitable player on market to be acquired after which they could jump all the way to the “market-creating” strategy. Meanwhile, they could pursue the “low hanging fruits” with “management-enhancing strategy” by adopting easier and simpler AI solutions. Although, it is important to note that Tehrani et. al (2024) did propose similar development track with the “crawling” strategy but without going further with the idea. All in all, it is argued that these models would need to recognize the changing environment with AI technologies. Not only are the technologies developing fast, but also there are many different AI solutions to consider that require very different readiness factors (Holmström, 2022; Martínez-Plumed et al., 2021; Uren & Edwards, 2023).

Overall, it is important to note that the chosen AI adoption strategy, whether it is one presented in this thesis or something else, is related to organizational and technological readiness. Without a proper readiness factors, the chosen strategy cannot be executed (Lokuge et al., 2019). Most importantly, these strategies show that in order to adopt more complex AI solutions, organizations should have experience with more simpler AI solutions in order to lower the risks of failing with the adoption (Mendes et al., 2024). An organization that is engaging into AI adoption needs to have a strategy in place so that the adoption supports their current strategy and strategic goals. This is, because each adoption strategy includes different types of AI technologies, some of which are easy to adopt and has lower readiness requirements and those that require higher readiness and resources from an organization (Jöhnk et al., 2021; Sting et al., 2024; Sun et al., 2024; Tehrani et al., 2024; Uren & Edwards, 2023).

## **2.2 The Role of AI Knowledge in Successful Strategic Adoption**

Artificial intelligence has been found out to be a complex technology (Agrawal et al., 2024; Berente et al., 2021). This complexity has caused misperceptions amongst the decision makers leading into misalignment and unrealistic expectations of AI's performance (Jöhnk et al., 2021). Thus it is crucial for decision makers to understand how AI works to minimize the risk of unsuccessful adoptions caused by these misperceptions (Holmström & Hällgren, 2022; Jöhnk et al., 2021; Mendes et al., 2024). In most cases the problems that appear when adopting an AI is due to the lack of understanding the technology and thus misaligning the needs with the chosen solution (Alet, 2023). This underlines the importance for decision makers to understand the difference between these technologies, because instead of adopting complex and expensive AI system built around generative AI, organizational needs could be filled with more simpler AI solution like machine learning algorithms (Holmström & Hällgren, 2022; Janiesch et al., 2021). This is linked to what digital strategy research and AI adoption strategy researches has also found out (e.g. Tehrani et al., 2024; Zhou et al., 2024). However, the level of required knowledge is dependable on the decision makers roles and the technology which is being adopted. In practice, for organizations that are and will be heavily dependent on the AI, need a deeper understanding of it, but in most cases conceptual knowledge of AI and its sub-technologies is sufficient for coherent decision-making (Duan et al., 2019; Jöhnk et al., 2021; Mabad et al., 2021).

One of the main reasons why understanding AI is so important for decision makers is that even though the Artificial intelligence as a concept has existed for a long time, yet there is no clear or unified definition for AI (Feuerriegel et al., 2024; Hoffmann, 2022; Uren & Edwards, 2023). As technological development is advancing all the time – new technologies are being introduced, existing technologies are being updated, and they are getting new features constantly – clearly defining new technologies have become harder. Meanwhile, as the word “Intelligence” in AI is in most cases compared against human intelligence, the AI as a technology is being refined all the time while the human intelligence is staying relatively stable (Berente et al., 2021). However, in a nutshell AI as a technology is a system that has been developed to solve advanced problems. As the

development continues, new use cases appear, and the way of development might change (Janiesch et al., 2021). Overall, AI today is based on different analytical models and technologies that produces human like outputs from the input data and prompts. This output is a mixture of answers, reasoning, predictions, recommendations, analyses, calculations or similar that aims to mimic human behavior (Hoffmann, 2022; Janiesch et al., 2021). Furthermore, the terms AI and Generative AI should not be mixed or used in parallel. The term AI is often referred to as the umbrella term of AI technologies capable of operating around existing data, whereas generative AI is a more sophisticated subsystem and can create seemingly new data such as images (Feuerriegel et al., 2024).

### **2.2.1 Development of AI technologies**

In order for decision makers to understand what AI really means, and which technologies are connected to it the development of AI should be examined. The first time the term AI was introduced to the public was in the beginning of 1950s by Alan Turing (Hoffmann, 2022). This first AI was named Turing's test which was used to recognize whether it was possible to differentiate a computer's answer from a human's answer (Hoffmann, 2022). In the summer of 1956 a group of leading researchers, Marvin Minsky, John McCarthy, Claude Shannon, and Nathaniel Rochester organized the world's first AI seminar. It is argued that McCarthy came up with the word Artificial Intelligence and persuaded others to use it (Ojanperä, 2023). However, even though the technology during that period was groundbreaking, as it was the first computer program capable of making automated decisions, the development of AI slowed down after that period (Ojanperä, 2023). During the following decades AI started becoming popular as researchers and scientists were excited about developing the first true machine intelligence. However, the overall technology development was not progressing fast enough, and they faced multiple challenges that the technology of the time could not overcome (Hoffmann, 2022). The scientists realized that as the AI of the time was answering in preprogrammed way, it could not solve complex problems which guided the researched towards discovering machine learning (Ojanperä, 2023).

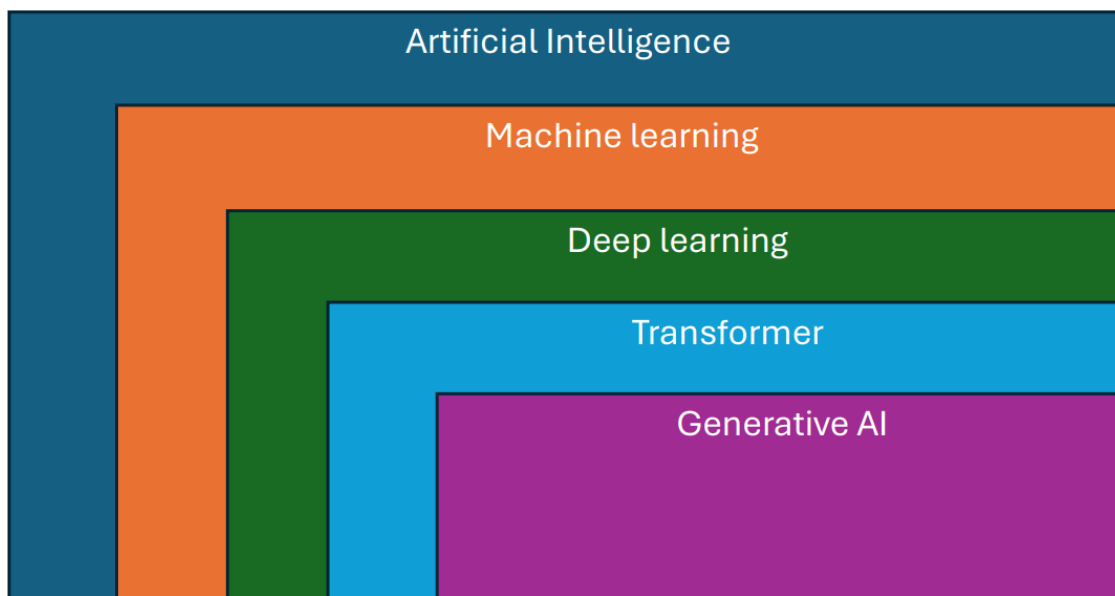
The idea of machine learning is simple and the technology essential for modern AI (Janiesch et al., 2021). Machine learning is a computer program that processes a substantial amount of data, recognizes patterns from the data and thus learns from the data. It is often referred as a subsystem of AI (Janiesch et al., 2021; Ojanperä, 2023). Machine learning systems were designed to use algorithms that recognizes different patterns and links between different sets of data. These algorithms could then be used to perform more complex tasks such as translations or detecting faults in data or objects (Bishop, 2016). Learning is done in three different way, supervised learning, unsupervised learning, and reinforcement learning (Janiesch et al., 2021). In supervised learning the models will be given the input data with the correct output data. Whereas in unsupervised learning the models should learn without giving it any correct outputs. Lastly, in reinforcement learning the model is learning from its own actions in a pre-described environment with set rules. (Janiesch et al., 2021; Ojanperä, 2023).

As machine learning developed, researchers started developing even more sophisticated machine learning algorithms called neural networks. These neural networks were inspired by the way that human brains work (Janiesch et al., 2021). In neural network there are a set of nodes (or neurons) that are connected to each other, and the machine learning algorithm is being altered by the network by changing the weightings between different nodes. They process the input data between the nodes and produce an output based on the algorithm while learning from the processed data (Goodfellow et al., 2016; Ojanperä, 2023). As traditional machine learning is capable of only a more simpler tasks, such as predicting detached house prices in certain area based on the number on rooms and living space from source data, neural networks are able to solve more complex problems (Goodfellow et al., 2016). These so-called artificial neural networks (ANNs) are used for example to recognize handwriting from images. Compared to traditional machine learning models which could only recognize the general fonts used in computers (Goodfellow et al., 2016).

Furthermore, the development of neural networks led to the development of deep learning that is a multi-level neural network that has multiple hidden layers of neurons. The deep learning networks are even more efficient of processing and learning from even larger and more complex data sets (Goodfellow et al., 2016). Deep neural networks are used for example to not only recognize speech but also produce human like speech (Janiesch et al., 2021). These technologies are relevant to AI because they enable the AI systems to learn from new and changing information thus separating it from traditional programs that operate in pre-programmed way (Janiesch et al., 2021; Ojanperä, 2023; Sturm, 2023). This groundwork for machine learning, neural networks, and deep learning happened between 1980's to 2000's. During these decades the first industrial applications were developed and taken into use (Ojanperä, 2023; Uren & Edwards, 2023).

In parallel, the development of these new technologies required the development of hardware as the algorithms and software required an increasing amount of processing power and computing power (Ojanperä, 2023). This technological advance happened during 2010s and thus made it possible to broaden the use of AI technologies for various different purposes (Ojanperä, 2023). In parallel, the role of data in our society has increased and which the technology has been able to process (Holmström & Hällgren, 2022). This development led maybe to the most significant AI technology innovation yet which is the development of transformer technology by the researchers of Google (Ojanperä, 2023). Transformer technology can be described as a subset of deep learning. Transformer technology has been developed to deal with sequential data, such as spoken natural language (Feuerriegel et al., 2024; Siebers et al., 2022). The developers have created a so-called attention mechanism within this technology, which weighs in the importance of different parts of the given input. The transformer technology is designed to process the whole input at once and based on the weighting of the input, it will recognize the dependency between, for example, the words and thus understand the contextual dependencies. Furthermore, it also learns from the contextual data (Ojanperä, 2023; Siebers et al., 2022). This transformer technology is the technology on top of which most of the modern AI solutions are based on (Ojanperä, 2023). It is important for decision makers

to understand the difference between these technologies, because instead of adopting complex and expensive AI system built around generative AI, organizational needs could be filled with more simpler AI solution like machine learning algorithms (Holmström & Hällgren, 2022; Janiesch et al., 2021). The relationship between these different technologies is visualized in figure 3.



**Figure 3 Artificial Intelligence technologies (Adapted from Janiesch et. al 2021)**

Today, generative Artificial Intelligence (GenAI) can be said to be dominating the AI scene, at least publicly (Vinsel, 2023). GenAI is a machine learning model, that is often a transformer based technology, which's idea is to produce seemingly new content based on a input prompt and training data (Feuerriegel et al., 2024). It is operated by giving it inputs which can be text, pictures, files, code, web addresses, numbers or basically any kind of triggering data which initiates a response process in which the GenAI learns from the input data, figures out the context, looks for matching cases from its teaching data and returns an answer as an output (OpenAI et al., 2024). The response can also be in any data form, as the prompt can be. Basically, it uses the different AI technologies together to execute these tasks (Feuerriegel et al., 2024). Maybe the most important technological aspect of the most common GenAI's today is that they are based on large language

models (LLM) (Teubner et al., 2023). These LLMs are a combination of large sequential deep learning neural networks. These networks are pre-trained with a large amount of text data in the wanted languages (Ojanperä, 2023). This training is so called self-supervision training where the model learns from the training data overall without giving it questions and correct answers rather than training it to do any specific tasks. In the context of LLMs, this training includes predicting the next word (Teubner et al., 2023). Basically, the models learns to predict the words coming next based on the given context. Later the model can be trained by more specific data to predict words for more specific use cases (Feuerriegel et al., 2024; Martínez-Plumed et al., 2021; Ojanperä, 2023). Through this, the model can generate outputs that seem natural for people operating the systems, as the name implies, in natural language.

## **2.2.2 Unrealistic Expectations and Their Impact on AI Adoption**

The fast development phase of AI has created new use cases but in parallel unrealistic expectations towards the technology (Vinsel, 2023). Most use cases were developed specifically by the developers of the AI technologies such as doing calculations, translating text, acting as a chatbot, writing code, generating images, and generating audio (Vinsel, 2023). Something that has been surprising even for the developers of these models is that the models have been able to execute tasks that the models have not explicitly been trained to do. One example is creating a calendar entry in the .ical file format when asked to do so (Feuerriegel et al., 2024). All in all, these possibilities have caused some probable exaggerations in public regarding the capabilities of AI. It is said that people are tend to overestimate the true effects of a change in short run and under estimate them in the long run (Vinsel, 2023). One main reason for this is that the Open AI's ChatGPT has been the fastest growing application to gain new users. It achieved 100 million users in only two months after its release (F. Duarte, 2024; Hu & Hu, 2023). The public have been very impressed with the application's capabilities, and it has in many ways been a technology to amaze even the most experienced industry experts. One example was, when the owner of Microsoft, Bill Gates, wrote in his blog about meeting with OpenAI's staff

(Gates, 2023). He had set a challenge for OpenAI's ChatGPT to complete a complex biology test, which was something that it was not specifically trained for. ChatGPT scored a 5 on the test, which is the highest possible, and the exam was rated by the industry experts (Gates, 2023). Gates wrote that "In my lifetime, I've seen two demonstrations of technology that struck me as revolutionary...The whole experience was stunning. I knew I had just seen the most important advance in technology since the graphical user interface" (Gates, 2023, p.1). This kind of encounter has sparked both utopistic and some more dystopic discussions of what AI could do in future, ranging from huge increases in productivity to tremendous increases in unemployment. This has resulted in so-called hype around the AI. (Vinsel, 2023).

The modern development around AI is fast and the publicity of the new language models after the release of ChatGPT has resulted in AI hype (Vinsel, 2023). This hype has brought AI into everyone's lips and computer screens and has made AI more of a day to day tool more than it has ever been (Vinsel, 2023). However, this hype has had its downsides for organizations. First of all, the hype has distorted the concept and meaning of AI. Even though researchers have not reached a conclusion of the definition of AI, the public has started to talk about generative AI as a concept of AI. However, this can be argued to be misleading explanation as AI is a highly complex ensemble (Afjal, 2023; Jöhnk et al., 2021; Leavy, 2023). Second, the public discussion has loaded distorted expectations to the capabilities of the current development stage of AI (Vinsel, 2023). Whereas what many do not seem to understand, when talking about generative AI in public, is that the generative AI is still just a software which just predicts appropriately styled and sounding words around the entered prompt (Feuerriegel et al., 2024). It could be even argued that the term "intelligence" in AI could be misleading as the program itself does not own human like an intelligence. Rather it is based on development happening during the pretraining and probability based predictions (Hoffmann, 2022). However, on the other hand there have been promising showcases where AI has been able to execute tasks that it has not been explicitly been programmed to do (Feuerriegel et al., 2024; Gates, 2023). However, this whole misunderstanding has left the management of companies with a mixed

understanding of what the current stage of AI is and what it is really capable of. Thus, it is argued that it is important for organizations to have a way to align their goals for AI adoption with correct measures of readiness to reach realistic understanding and chances of success. The external pressure for the adoption has grown strong and has an puts a pressure for organization's management to adopt AI (Vinsel, 2023).

Hence, an overall argument is made, that AI is a complex technology, as there is no unified explanation for the concept, the used concept depends on the context, and there are many other technologies that are used parallel to AI (Agrawal et al., 2024; Berente et al., 2021; Feuerriegel et al., 2024; Janiesch et al., 2021; Ojanperä, 2023). Therefore, AI needs to be examined in a different way than other new technologies. Uren and Edwards (2023) argue that previous management information systems could be approached in similar manner. However, AI brings adopters new challenges and completely new levels of considerations that it cannot be adopted with the old lessons learned from pervious information management systems (Uren & Edwards, 2023). Although, this could be said to be a slightly sharpened argument as AI has still a lot in common with legacy technologies (Ali et al., 2022; Jöhnk et al., 2021). For example, there are socio-technological factors, such as the need of improved technical skills, top management support, and the need of developers and technical support, that has been known to aid the adoption of new technologies (Alsheiabni et al., 2019; Gill, 1995). Nevertheless, due to the complexity surrounding AI, in this thesis DeCanio's (2016) proposed technology-neutral definition of AI used. The author states that AI can be understood as a variety of different coworking technologies that surpasses humans capabilities especially in those functions that require cognition (DeCanio, 2016).

### **2.3 Adopting new technologies**

Once the decision makers understand the technology behind AI and they have set their strategic goals, the next step is to adopt the technology into their organization where they need to understand what aspects they need to take into consideration (Jöhnk et al.,

2021; Uren & Edwards, 2023). Technological development has been said to be the creative power of humanity, and the phase of innovation has accelerated through human history (Ede, 2019). Technological development and the adoption of new technologies has been studied a lot. In their article, Jeyaraj et. al (2006) review different technology adoption theories and their characteristics. These theories offer: different perspectives to examine innovation adoption in different kind of organizations; different steps of the adoption process; and different characteristics affecting the adoption (Jeyaraj et al., 2006). The first perspective is the organizational levels, which are functional units or organizations as a whole. Later adaptations of these adoption models have introduced more variables, such as projects and project teams (Uren & Edwards, 2023). This thesis concentrates in organizations as a whole as there is a lack of comprehensive approaches on organizational level adoptions and readiness.

The different steps of the new technology adoption process, that Jeyaraj et al. (2006) recognized, were the decisions to adopt, intentions to adopt, implementation, and diffusion. The decision point refers to a particular point in time where the organization makes the final decision to begin the usage of certain innovation technology (Grover, 1993). The intention to adopt refers to the plans, goals and willingness of the organization to continue the adoption process and begin the implementation in future (Plouffe et al., 2001). The implementation then refers to the actual process of implementing the technology as a part of the organization (Grover & Goslar, 1993). The diffusion means the spread of technology to the rest of the organization (Teng et al., 2002). These process steps can also include substages in closer examination (Jeyaraj et al., 2006). These stages of innovation have remained relatively unchanged and the basic idea still applies to modern technology adoption, however organizations need to consider for unique factors in technologies, and the changing dynamics of new technology adoption (Ali et al., 2022; Hameed et al., 2012; Sun et al., 2024). Hence, the adoption is examined in this thesis to capture the overview of the organization process and readiness. The adoption process is looked at from a general perspective to support the adoption decision making to begin the adoption process. Although, specifically focusing on different process steps could

generate different findings and through them it would be possible to find which readiness factors to underline in different stages of the process.

The different characteristics affecting the adoption, that were found by Jeyaraj et al. (2006), were the different characteristics affecting adoption, that can be divided into three groups: innovation characteristics, organizational characteristics, and environmental characteristics. Innovation characteristics are focusing on the innovation being adopted. It examines the relative advantage, complexity, compatibility, observability, and trialability of the innovation (Rogers, 1983). The Innovation characteristics have grown to be increasingly important to consider especially when looking into newer and more complex technologies such as AI (Agrawal et al., 2024; Teng et al., 2002). As technological development proceeds further, the new technologies are often based on older technologies and the complexity tends to increase (Sting et al., 2024). The organizational characteristic on the other hand examines the organization's top management support, championship, organizational structures, centralization, formalization, internal influence, external influence, organization's size and organizational slack (Jeyaraj et al., 2006). Lastly, the environmental characteristics are external pressure and competition. The organizational characteristics was found to be the most influential factor affecting the technology adoption (Jeyaraj et al., 2006). This finding is supported by more recent studies, that have recognized the relevance of organizational factors, such as technological and organizational readiness, when adopting new technologies into an organization (Jöhnk et al., 2021; Uren & Edwards, 2023).

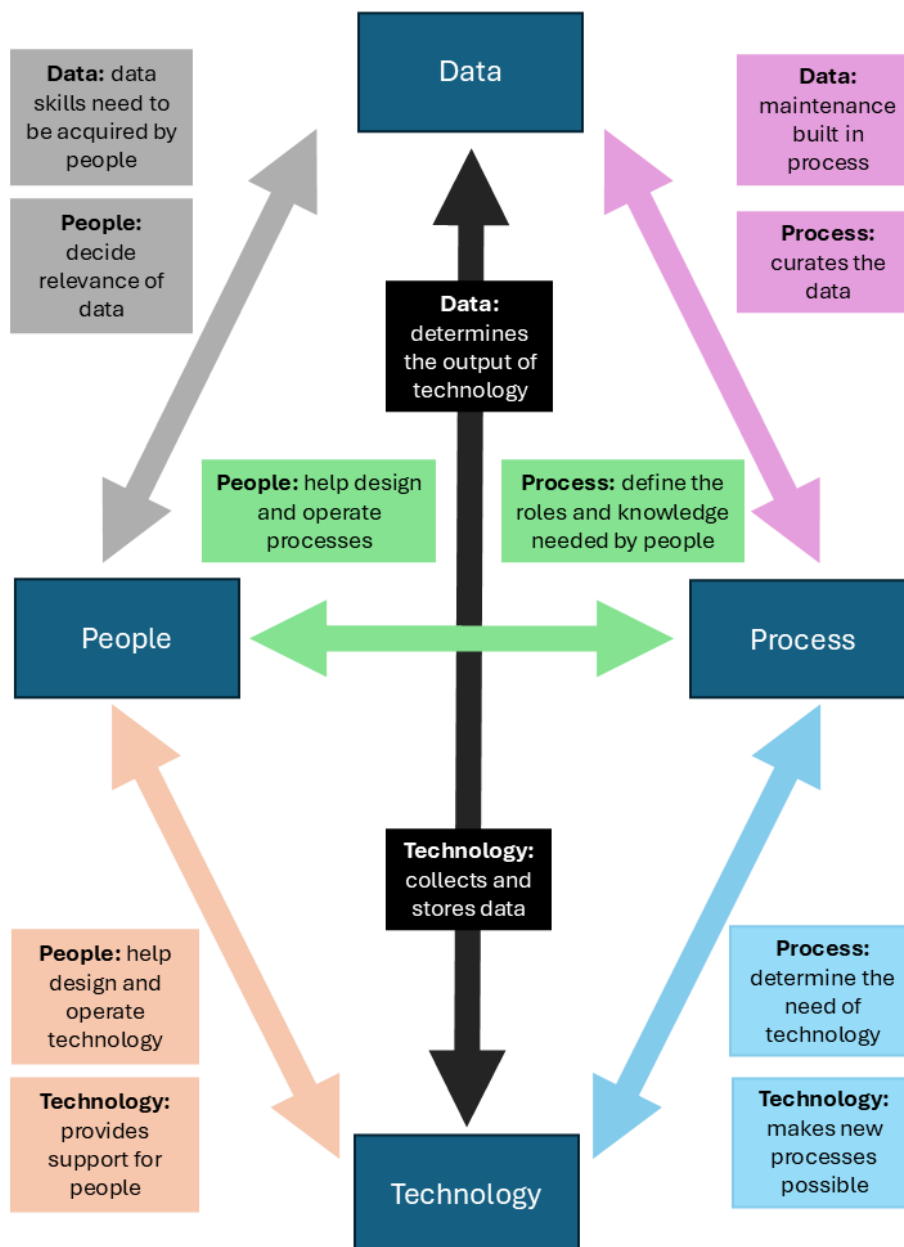
As a conclusion, Jeyaraj et. al (2006) state that the best predictors for technology adoption on individual level are the top management support, computer experience, perceived usefulness, behavioral intention and user support. Whereas they show that on an organizational level the best predictors are top management support, external pressure, professionalism of the IT unit and external information sources (Jeyaraj et al., 2006). However, the research under review in the article by Jeyaraj et al. (2006) mostly focuses on individuals or organizations while leaving out a lot of room to examine the interplay

between the different parties. Furthermore, they do not consider yet the interplay or special characteristics of the specific technology being adopted.

In 1964 a so called “diamond” model was developed by Leavitt’s to emphasize the importance of different elements in an organization regarding technology adoption and how to manage them (Leavitt, 1965). The original model consisted of four elements: technology, people, tasks, and structure. Leavitt underlined in this model the gravity of these four elements and how managers should pay attention to the interactions between them (Leavitt, 1965). However, they did not focus on analyzing the specific nature of the interactions, that was lacking also in the review by Jeyaraj et al. (2006), which has later been discovered to be a crucial factor in the model (Uren & Edwards, 2023).

This model was later adapted by Edwards (2005) when he added the relationships between the elements into the model. This visual description of the socio-technical systems within an organizations captures well the complexity of technology adoption (Edwards, 2005). In this model, people does not only mean the employees executing the processes but also the managers making decisions and governing the organization. People need to have the right skillsets, experience, motivation, support and knowledge to adopt the technology and to design and operate processes (Makarius et al., 2020). Process, on the other hand, means the workflows designed by people by which tasks are done and operational efficiency is secured (Saari et al., 2019). Lastly, technology refers to IT systems and tools that are used to enable the creation of processes and to support the employees (Edwards, 2005). Furthermore, Edwards (2005) made also a significant contribution of initially exploring the role of data due to technological advancement. Data is produced on a continuous basis in modern society by machines, people, sensors and society overall and has become very valuable for organizations. Overall, there has been a paradigm shift from data as a byproduct of technology to the fuel of modern industrial ecosystem and decision making, which has been due to the increased ability of technology to store, produce, and process data (Kalinaki et al., 2024). The importance of data is discussed in depth in chapter 2.5. In fact, data was later added to the model

by Uren & Edwards in 2023 while the rest of the model was kept the same, as presented in figure 4. In their updated people, process, technology and data (PPTD) model they underline the effect that data has on the other elements of the triangle especially regarding AI adoption. That is, to determine the output of technology, build data maintenance into processes, and to make sure that people have required data handling skills while technology is used to collect and use the data (Uren & Edwards, 2023).



**Figure 4 People, process, technology and data (Adapted from Uren & Edwards, 2023).**

Overall, this model helps to understand the interconnectedness of the organizational elements in technology adoption that the previously reviewed models have referred to. Jeyaraj et al. (2006) found similar factors from the models they reviewed, where on individual level, the top management support and computer excellence was pointed as success factors, which are also presented in the PPTD model. Meanwhile on the organization level Jayaraj et al. (2006) underlined that professionalism of the IT unit and

external information sources can be linked to the people and technology part of the model which can also be found from the PPTD model. However, at the same time the PPTD model did not consider the external factors that were presented in the models reviewed by Jayaraj et al. (2006) and in the TOE model by Eveland and Tornatzky (1990).

Nevertheless, these models do not yet specifically address the strategy of an organization and picture the status quo of an organization. Maturity models are used when examining the development of technology within an organization throughout the time. They are helpful when wanting to see the symbiosis of the technology itself, the organization and supporting technologies (Sadiq et al., 2021). The original capability maturity model (CMM) was released in 1991 by Software Engineering Institute to examine the software's maturity within organizations. It consisted of five levels; the "initial" phase was described as chaotic and ad hoc, the "repeatable" phase meant that the process was now somehow documented and it was somewhat possible to repeat the steps, the "defined" phase meant that the process was now a standard process, the "capable" phase meant that the process was achieving some of the KPIs set for it, and the "efficient" phase meant that the process is going through consistent improvement and iteration (Paulk, 2002).

Since, the original model has been used in many companies across the world for software process improvements and have since been used as a reference for later maturity models (Sadiq et al., 2021). In their review of these AI maturity models, Sadiq et. al (2021) finds out the critical success factors after reviewing 13 different artificial intelligence focused maturity models. They conclude that these maturity models are especially useful for organizations in reviewing their readiness of adopting and developing software within an organization. Furthermore, they state that it is important to do this to increase their success in achieving set goals and gaining a competitive advantage from the software. To explore and understand these factors, the identified success factors are data, analytics, technology, tools, automation, governance, personnel, and the organization itself (Sadiq et al., 2021). On the other hand, in their similar review of AI maturity models,

Fornasiero et al (2024) create their own version of technology maturity model as shown in figure 5. In their model, the most significant difference is the addition of strategy. They argue that the strategy dimension allows companies to explore and understand whether their view of the AI application is aligned with their strategy and thus with the top management's commitment. Furthermore, the consideration of strategy will reveal whether the company has realistic targets of gaining competitive advantage from the AI (Fornasiero et al., 2024). Otherwise, the models reviewed in research of Fornasiero et al (2024) includes similar findings and dimensions as presented in the review of Sadiq et al (2021) as they review same and similar models. Comparing these findings to previously reviewed models, we can see that similar findings appear. Although, as the aim of this thesis is not to specially examine the development of maturity throughout time , it will however consider the maturity frameworks on the parts relevant to the objectives. This is, because depending on the time of making the decision to adopt an AI, organizations do have different levels of readiness (Kim & Seo, 2023; Lokuge et al., 2019). Thus, some organizations might have achieved certain maturity levels already or at least parts of them should be considered when examining the readiness.

|  | Maturity Dimension | Sub-Dimesion   |
|--|--------------------|--|
| Organization-related maturity dimensions | Strategy           | Importance of AI for strategy                                    |
|  |                    | Interest in the organizations culture                            |
|  |                    | Value adding potential of AI                                     |
|  |                    | Consideration of ethical, legal and social implications          |
|  |                    | Monitoring strategies for ethical, legal and social implications |
|  | Organization       | Transparency of the governance                                   |
|  |                    | Organizational responsibilities                                  |
|  |                    | Budget allocation to AI  |
|  |                    | Data privacy   |
|  | People             | Division of responsibilities                                     |
|  |                    | Employee engagement  |
|  |                    | Skill development  |
| Solution-related maturity dimensions     | Technology         | Alignment to technological changes                               |
|  |                    | Integration of processes and applications                        |
|  | Data               | Balance between technology and human intervention                |
|  |                    | Data access  |
|  |                    | Transparency of data   |
|  |                    | Updating of internal and external data                           |
|  |                    | Quality of data  |
| Processing data                          |                    |  |

**Figure 5 Maturity model dimensions and sub-dimensions (Adapted from Fornasiero et al., 2024)**

These reviewed models give a good overall understanding of the dimensions and characteristics that affect technology adoption within organizations. As they consider the adoption of new technologies from different perspectives and timeframes, they help to understand also why the readiness factors are important to consider when planning on acquiring new technologies into an organizations. These reviewed models, their authors, and core ideas are summarized in the table 1.

| <b>Authors</b>   | <b>Theoretical model</b>                             | <b>Core idea</b>  |
|--|--|---|
| <b>J.D. Eveland and L. G. Tornazky, 1990</b>                             | Technology- Organization- Environment (TOE)          | To Recognize which internal and external factors affected the organization during the adoption  |
| <b>V. Uren and J. S. Edwards, 2023</b>                                   | People, Process, Technology, and Data (PPTD)         | Shows the interconnectedness between the technology, process, people, and data dimensions.  |
| <b>Software Engineering Institute, 1991</b>                              | Capability Maturity Model (CMM)                      | Examines the technology's maturity within and organization throughout time.   |
| <b>R. Fornasiero, L. Kiebler, M. F. Sardesha, and S. Sardesha, 2024.</b> | Artificial Intelligence and Big Data maturity model. | Shows the maturity of the technology within an organization through organization-related and solution-related dimensions and sub-dimension. |

**Table 1 Models and theories used in technology adoption**

## **2.4 Organizational and technological readiness for AI adoption**

Artificial intelligence is a complex technology that has a manifold of adoption opportunities in organizations (Jöhnk et al., 2021). These various possibilities are indeed enabled by the complex nature of this technology, especially if compared to legacy technologies that are usually easier to use and easier to adopt (Lokuge et al., 2019). Due to these possibilities and complexity, organizations often face drawbacks when trying to

implement AI (Jöhnk et al., 2021). The most common setbacks that organizations tend to face in technology adoptions, are the costs of the implementation, lack of relevant data, internal strategic misalignments, lack of user adoption and lack of technological capabilities, which all are relevant to insufficient readiness factors (Jeyaraj et al., 2006; Sadiq et al., 2021; Venkatesh et al., 2003). These pitfalls have been studied in the context of other technology adoptions and a connection has been made to lack of readiness factors (Jöhnk et al., 2021; Lokuge et al., 2019; Tehrani et al., 2024). This body of research has found out significant results to support the idea that when organizations consider their readiness factors carefully before adopting new technology, their chances to achieve the set performance goals are much higher (Lokuge et al., 2019; Mabad et al., 2021; Uren & Edwards, 2023). In other words, by considering their readiness for adoption, organizations are able to mitigate their risks in the adoption. Mendes et. al (2024) recognized that the three main risks organizations can mitigate are mismatched requirements, supplier dependance, and unmanaged life cycles. The dependance was found to be significant because when an organization have clear requirements, they have supplier selection strategy in place, and they manage the adoption life cycle effectively, it has a straight correlation to the risks possibility to materialize (Mendes et al., 2024). In fact, Mabad et al (2021) found that 80 to 90 percent of organizations that are adopting new technologies are not meeting their performance goals due to realization of these risk through not ensuring proficient readiness.

Although, it is important to note that the readiness factors go hand in hand and are sometime troublesome to be considered separately (Uren & Edwards, 2023). It is important to understand that the more complex use cases, more sophisticated AI systems, and larger organizations would require different levels of readiness (Holmström, 2022; Tehrani et al., 2024). To examine the readiness factors, the PPTD model by Uren's & Edward's (2023) is used as a basis to examine the readiness factors in combination with the strategy entity as Fornasiero et. al (2024) found in their review of adoption and readiness models. This is, because there are a myriad of readiness models and factors and to examine them effectively this division has been chosen.

### **2.4.1 Organizational readiness**

In this thesis organizational readiness factors are considered to concern organization's strategies, people and processes. Organizational readiness refers to organizations capabilities to adopt an AI solution across its different functions while making sure that it is ready for the adoption process and what comes with it (Jöhnk et al., 2021).

#### **2.4.1.1 Strategy readiness factors**

Strategy as a readiness factor can be considered as an umbrella term for readiness factors as it is linked to other readiness factors (Borges et al., 2021; Rêgo et al., 2022; Zhou et al., 2024). Even that it is a more abstract readiness factor, it does not lower its significance. As discussed in chapter 2.1 adoption strategies specifically have not yet received much attention regarding AI adoption, but it has been argued to play a significant role (Kim & Seo, 2023; Tehrani et al., 2024). This has been shown especially in digital strategy research as AI adoption strategies fall under the digital strategy. Borges et. al (2021) emphasize the relevance of adopting strategically relevant digital technologies in terms of their strategy. They link the importance of the strategy to the stakeholders considered by the adoption but also other dimensions such as processes, automation, support from decision makers and the interaction between personnel within the organization (Borges et al., 2021). Furthermore, Fornasiero et. al (2024) also link strategy the organization related maturity dimensions and solution related dimensions to strategy which connects the relevance of strategy to organization, people, technology and data dimensions, as presented earlier in figure 5 in chapter 2.4. Even though strategy is connected also to technological readiness factors it falls under the organizational readiness factors because the organizations needs to first integrate their strategy into the organization before they are able to exploit it with technological readiness factors (Fornasiero et al., 2024)

Strategies are needed in organizations to gradually increase their use of the chosen AI technologies over time. Otherwise, if the AI adoption is in isolation from strategy and not united with the comprehensive business plan, the attempts will wither over time and the company lacks strategy as a readiness factor (Fornasiero et al., 2024; Uren & Edwards, 2023). As AI is developing fast with new versions, use cases, and applications coming in all the time, it requires continuous investments from the adopting organization. It was found out by Lamberti (2019) that even those organizations that could be considered as “AI leaders” in their industries needs to constantly improve and invest in AI after adoption. Only by doing this, they ensure that their strategic goals of AI adoption remain aligned and significantly lower their chances of losing the possible gained advantage from AI adoption (Sadiq et al., 2021). Furthermore, they state that neglecting this constant development would eliminate the advantage in the near future (Lamberti et al., 2019). This is, because AI is developing quickly and the way of using it is changing constantly (Feuerriegel et al., 2024). By including AI in strategy and in the strategy work, organizations have much higher chances of remaining and expanding their use of AI technologies over time and thus also increase their AI readiness (Holmström, 2022). It is argued that in order to gain and retain competitive advantage AI should hold a place in the company’s strategy, as gaining competitive advantage is one the main aims of having a strategy in the first place.

#### **2.4.1.2 Process readiness factors**

Processes, or activities as they are referred to by Holmström (2022), form a key dimension for organizations to consider in the AI adoption. This is, because in its current form AI is considered to maybe the most helpful for organizations to develop more efficient processes by automating repetitive manual tasks (Chui et al., 2023; Holmström, 2022; Shaik et al., 2024). It was also stated by Uren & Edwards (2023) that AI projects should be in straight link with the core business value creation through making cost savings, increasing productivity or by creating new revenue streams. Similarly to what Porter’s

(1997) competitive strategy theory suggests. Still, whatever the aim for AI project, and even though AI might be the most useful in aiding organizations to make more efficient processes, the processes need to be suitable to be executed together with AI (Holmström, 2022; Uren & Edwards, 2023). This is also included in the figure 4, the PPTD model by Uren & Edwards (2023) reviewed earlier in this thesis. In their model the processes are connected to technology, data and people. The interconnectedness with technology from process perspective means that processes determine the need of technology (Edwards, 2005). In means of readiness, when organizations plan and design their AI adoption and set goals for it, they need to think is their current level of technology is aligned with their core processes (Holmström, 2022). They should understand what processes need to be changed, and how the processes will change and what technology is needed to support this redesign. Furthermore, they should consider if the process itself is even capable of such change (Frick et al., 2021). Second, as processes are connected to people, organizations need to consider whether the personnel is capable of handling such changes in the chosen process. Do they have needed knowledge, is this change even helping them in the long run, and will the change even be utilized by people after adoption (Tehrani et al., 2024). It should be in the adopting organizations' interest to make sure that the personnel is willing to make use of the new process change. Lastly, as the data plays a key role in AI as technology, the adopter needs to consider if their main processes collect relevant data to be used for the AI. This is maybe the main difference between AI adoption and previous technologies. (Tehrani et al., 2024; Uren & Edwards, 2023). Although, this is very dependent on if the chosen AI needs even internal data to be used which is often the case with market ready solutions (Futterer, 2024; Kim & Seo, 2023; Tehrani et al., 2024). However, this is considered more in the data readiness part and will be discussed further there.

#### **2.4.1.3 People readiness factors**

People is maybe the most important readiness factor there is. This is, because people are the ones operating the company, deciding on the AI adoption, using the AI, and are

the ones who in the end from the organization (Holmström & Hällgren, 2022; Jöhnk et al., 2021). In fact, without the people there would not even be AI to adopt. The role of the people in AI readiness is that the processes the AI is to be adopted by, have been, or will be, designed and operated by the people of the organization (Uren & Edwards, 2023). Hence, people need a certain level of knowledge regarding the AI adoption process itself in order to be engaged and understand the needs and wants. One of the easiest and most efficient ways to ensure the needed knowledge level is through training the personnel (Jöhnk et al., 2021). This means that people on every level of an organization that will be engaged with AI need to be trained. Hence, the success of the project depends how the change is communicated, how personnel are prepared for the change, and if the people understand the goals to have the motivation needed to go through the change (Frick et al., 2021). Second, people must have the correct level of know-how required to do their part of the AI adoption whether it is aiding with the process design, helping with technical parts, working with data, or making decisions. In the minimum, this means the knowledge to operate the adopted AI in the end (Tehrani et al., 2024).

However, not all people related to readiness are individual skills and knowledge. One of these factors is that organizations need to include and make ready multiple stakeholders for the AI adoption (Uren & Edwards, 2023). The most important stakeholders are the technical functions group and business function group. These stakeholders must collaborate together to ensure that both technological business critical factors are considered. This collaboration will ensure smoother adoption (Uren & Edwards, 2023). It was interesting to find out that Uren & Edwards had the only paper related to AI readiness that had really considered stakeholder involvement as a readiness factor even though AI adoption has been shown to require both business and technology acumen. Although, they did not consider other stakeholders, whereas Tehrani et. al (2024) found out that customer readiness is also crucial especially if the chosen AI solution is within the customer touchpoint. They posed an argument that organizations often disregard customers as a third party for such technological adoptions which could lead in to failure of the project.

Overall, all of this creates a lot of change within the organization and with the change there will most likely be resistance to change. It could be argued that the bigger the AI adoption is and the more change it brings, the more there will be change resistance (Tehrani et al., 2024). Thus, the company must also have a change management plan in place. Employees will have natural fears of job loss due to automation and cost savings, or other discomforts with the new technologies such as lack of information or lack of knowledge to operate the new process. The organizations needs to be able to foster a culture that embraces the possibilities of AI and promotes the importance of knowing how to use the AI to make the best of it (Tehrani et al., 2024; Weiner, 2009). To assure a more accepting culture, and to fulfill the information need of people, this will require very decisive and transparent communication throughout the adoption process to ensure that people understand the benefits of the new technology (Jöhnk et al., 2021).

#### **2.4.2 Technological readiness**

In this thesis technological readiness factors will include the technology itself but also data as a separate factor. The separation of data to as its own entity is because its strong relevance for AI (Kalinaki et al., 2024). Overall, technological readiness refers to the organizations capabilities to adopt and efficiently implement the chosen AI technologies meanwhile making sure that supportive technologies and current infrastructure supports the AI solution (Uren & Edwards, 2023).

##### **2.4.2.1 Technology readiness factors**

The required level of technology readiness is highly dependent on the organization's current technology level and the wanted outcome of the AI adoption. Simply put, the lower the existing level of technology is, and the greater goals the organization aims to achieve with AI adoption, the higher the technological readiness level needs to be (Uren &

Edwards, 2023). However, even though AI is a complex set of different technologies, it does not mean that organizations have to necessarily adopt all of these technologies separately to gain the chased advantage. Rather it depends on what are the final aims and goals for AI adoption. The complexity of AI systems can increase as the AI readiness as maturity increases (Sadiq et al., 2021). Some companies could achieve their goals without investing and developing complex language models but rather by using shallower neural networks and machine learning algorithms. As shown earlier, some of these technologies are also subsets with each other and some of them are already built in the more sophisticated AI systems, such as generative AI models like ChatGPT (Janiesch et al., 2021). There are several different ways to adopt AI systems.

Hence, the AI model itself also forms one technological readiness factor that an organization needs to consider. To produce an example, here are four possible steps to do AI adoption presented according to the progress of TRL model by Mankins (1995) and the AI readiness and maturity. These are viewed from the innovative characteristic view that Jeyaraj et al. (2006) found in their review of adoption models. To begin, an organization could start by using external existing pretrained public AI models, such as Google Gemini or ChatGPT with a license as these are easy to use and immediately accessible for most of the organizations (Ojanperä, 2023). Similarly, they can use AI's that are built in other software. Such software could be for example Microsoft Co-pilot, Salesforce's Einstein. Thus, they would access public pre-trained models with inbuilt technologies purposefully designed to help in general issues or to help within a context of certain software. However, as a downside they are not very scalable as there is for example data privacy to consider, they are not customized, and organizations become dependent of the software suppliers which was one of the main risk recognized for AI adoption (Futterer, 2024; Mendes et al., 2024). Here the level of technological readiness required is very low and thus the adoption risk very low, as the technology is provided as a software-as-a-service product over internet. These models offer better productivity, good integration, user familiarity, and differentiation and cost saving possibilities (Tehrani et al., 2024).. This is very similar as the crawling and low hanging fruit adoption strategies discussed in

chapter 2.1 However, in this case the cost of subscription can become expensive over time, the user's adoption could be unsure, there is limited flexibility and there is a limitation of data that can be used due to privacy concerns (Jeyaraj et al., 2006; Martínez-Plumed et al., 2021).

The second option would be that organizations could develop their own customized AI versions on external AI platforms. These platforms offer ready basic general AI models that the organizations can configure to their liking, and which are pre-trained to some extent (Futterer, 2024). With these models, organizations could achieve a higher level of customization, better control over data and higher flexibility. However, not all publicly offered customizable models are very flexible and it depends on the use case and the model provider. Here those models that are harder to use require a lot of expertise to customize, the costs can get very high, the time to develop these can be long and results unsure. Of course, there are also simpler and easier models to use, that do not require high IT expertise to configure, but in most cases, organizations could face similar limitations as on the first example (Futterer, 2024).

Third option for organizations is to create their own model through partnership or an in-house built model from scratch, a so-called proprietary model (Futterer, 2024). This option offers complete customization, higher possible competitive advantage and high data security and control. However, this option requires extremely high expertise, very high costs, and a long development time. The organization has to start building or sourcing their own technologies needed for the basis of their wanted model. This option is very similar to the partnership strategy presented earlier (Tehrani et al., 2024). For example, if an organization wants to build their own generative AI model with natural language processing capabilities, they need to start from the machine learning models, neural networks, deep learning models, transformers and so on until they can even begin to train their model (Ojanperä, 2023). Of course, this could be done based on an earlier developed custom model on an external platform and companies can have the same of these readiness's already. Nevertheless, in here the technology readiness level is the highest.

For those organizations with already high experience with AI solutions and related technologies, and thus maturity, this could be viable option for gaining more stronger competitive advantage (Fornasiero et al., 2024; Sadiq et al., 2021).

In all of the AI use cases, the core of technology readiness is formed by the IT infrastructure within the organization. This infrastructure refers to the hardware that the company owns and its capabilities to handle and support the AI adoption. Such hardware could include high speed connections, servers, computational power and high-speed data storage (Martínez-Plumed et al., 2021). Furthermore, as nowadays cloud systems are highly popular, organizations do not need to own all of these in hardware by themselves. They have also an option to outsource, for example their data storage, external data access, and computing power rather than keeping it as hardware on the premises. In addition, they of course need their enterprise software to manage their day to day operations and data generated by them (Ojanperä, 2023; Uren & Edwards, 2023). Organizations need to make sure that their infrastructure is AI capable and if not, they need to be ready for upgrades. In fact, they need to be ready to scale their IT infrastructure as their AI adoption progresses and their AI maturity develops (Sadiq et al., 2021). As shown in the examples above, it is very common in AI projects to start from smaller test projects and proofs of concepts and then progress towards a more complex solution. In parallel this requires technology's readiness to progress at least at the same pace. Back in time this would have required a huge hardware and IT personnel investment (Tehrani et al., 2024). However, cloud technologies companies offer software-as-a-service solutions, such as Amazon Web Services, that offers the subscriber scalable computing power, data storage, external big data access through data lakes, and analytics tools (Amazon, 2024). These solutions makes for example, AI development much more accessible for even younger organizations with smaller capitals.

Overall, referring to the PPTD model we can see a lot of similarities. According to the model, technology does make new processes possible whereas processes determine the need for technologies. As discussed, this is the requirement of the IT infrastructure to

make possible the new processes that AI is planned to be used in. Then, people are using and designing technologies while these technologies are providing support for people. This is at the core of AI readiness. AI technologies are designed and developed by people to help people in different operations and use cases (Uren & Edwards, 2023). Lastly, we have the relationship between technology and data which is discussed in the next sub chapter.

#### **2.4.2.2 Data readiness factors**

The significance of data in the current business and industry ecosystem has risen. In fact, data can be said to become a crucial resource, or even a “lifeblood” for the new industrial ecosystem (Kalinaki et al., 2024). However, on the downside the dependency on data has raised security concerns in organizations especially in sectors where companies are handling confidential data. Thus organizations must make sure that their data protocols are in place (Kalinaki et al., 2024) Data is continuously generated and collected by people, technology and sensors. It is not just a byproduct anymore but rather something that could become a strategic asset for more informed and real-time decision making, more efficient and optimized processes, and overall enhanced efficiency, if utilized correctly (Kalinaki et al., 2024). When it comes to AI data readiness, the usefulness of data culminates in an organization’s ability to collect, store, and process data. But maybe even more importantly the data needs to be high in quality and there needs to be enough of it for the chosen purpose (Jöhnk et al., 2021). This is, because the usefulness of data is not measured by the quantity or quality alone, but rather by its ability to produce insights for organizations (Kalinaki et al., 2024). Ultimately, this is dependent on having sufficient data infrastructure, processes, and people in place (Uren & Edwards, 2023). In fact it was found out by Uren & Edwards that “successful adoption of AI requires data to be first understood, available and managed ” (Uren & Edwards, 2023, p.6) thus also pointing out data’s importance as an readiness factor for AI adoption. However, the data does not need to be only internal data as there are loads of external data also available. Some data is publicly accessible, such as weather data, and some data requires certain

licenses to be accessed. Overall, the vast amount of data that is available, whether it is produced internally or comes from external source, could be summarized under the term Big Data (Kalinaki et al., 2024).

What is highly important for the context of data readiness are the connected processes. As discussed earlier, organizations need to be sure that their processes are relevant to be used with the chosen AI model. But more relevantly for the technological part of AI relevant data readiness is to make sure their processes are able to capture the needed data (Fornasiero et al., 2024; Uren & Edwards, 2023). This is, because without having sufficient core processes in place, the needed data for AI adoption might not be produced in the first place. This also connects the data and the processes to people, as they need to make sure that management and the experts align whether their current processes are supporting the aims of AI adoption in means of data, or if they need to make adjustments (Uren & Edwards, 2023). Although, it is important to note that the need for data in AI adoption is dependent on the chosen AI model as it determines the need to be efficient and useful. Yet, data could be argued to be crucial for most of the AI projects (Duan et al., 2019; Fornasiero et al., 2024; Kalinaki et al., 2024).

According to the PPTD model by Uren & Edwards (2023) technology is used to collect and store data while data is used to determine the outputs of technology. This relationship, that reminds of a symbiosis, is highly relevant for AI. Especially if it is a model that requires pretraining as it is this data that determines how useful will the model become to the organization (Ojanperä, 2023). However, it is not only the AI that falls under the technology, but it also includes the data management technology framework. This framework consists of technologies that are used to analyze the data, ensures proper data governance protocols, and integrates the systems with each other to ensure the required level of data flow (Fornasiero et al., 2024). The data analytics goes hand in hand with the data processing. The data processing is based on machine learning algorithms that process the data for the organization. The organization uses different visualizations tools to display and research the data and to use it for decision making or other

processes. The based on the insights they get from their own data, they can make real time adjustments to their data processes (Fornasiero et al., 2024). Within this framework the organizations is also able to alter their technological infrastructure as well based on the data insights they get (Martínez-Plumed et al., 2021). Overall, without having sufficient technology set up for data management an organization cannot start optimizing their processes (Uren & Edwards, 2023). This is also a good example that shows the relevance of data in the current business environment.

As mentioned, the relevance of data in the context of AI is not only about the amount of data but also the quality of the data. Without high quality data the AI systems could produce incorrect outputs and unreliable answers (Fornasiero et al., 2024). This could increase the costs of the project and could cause a loss in organizations trust towards the model and thus cause lower user adoption (Jöhnk et al., 2021). Data quality can be ensured with proper data governance that states the protocols of data collection, storage, validation, cleansing, and usage (Patel et al., 2023). During the collection of data an organization can save a lot of resources by ensuring maximum quality data captured through process design upfront (Mendes et al., 2024). After the data is collected the organization should monitor the data throughout the process to detect any irregularities. If there are irregularities or something else that requires some intervention, the company can cleanse the data by removing, anonymizing or correcting some parts or putting the data into the right format. This is also known as data cleansing (Patel et al., 2023). The data governance should also make sure that the collected data is not biased so that the AI model does not discriminate in any way and overall make sure that the data complies with the regulation (Ojanperä, 2023). In relevance, according to the General Data Protection Regulation (GDPR) by EU, if an organization stores and handles data from their customers, they need to make sure that the data is not saved physically outside the EU borders. And in case it does, the organization is responsible for assuring that the data stays protected according to GDPR (General Data Protection Regulation, 2016). This could be relevant, for example if a company decides to adopt an external AI model, they will pre-train for internal use. In this case they need to make sure that the data used for

training and operating the model complies with GDPR. Overall, insufficient data readiness could lead into the failure of the project through increased costs, unreliable or ineffective model, low user adoption or through failing to comply with data ethics requirements and regulation (Mendes et al., 2024; Uren & Edwards, 2023).

## **2.5 Framework for AI adoption**

The literature review focused on discussing first the relation of strategy and AI adoption. It then discussed AI as a technology and then moved on to examine the readiness factors relevant for AI adoption. The figure 6 presents the framework that sums up the concepts that are discussed in the literature review of this thesis. This framework presents the role of strategy in AI adoption in relation to other readiness factors. The framework shows how the different areas of readiness are interconnected with each other. It is visualized how weakness in some readiness factors affects the other areas thus affecting the probability of successful AI adoption. Finally, the framework uses different indicators to show an organization's current level of readiness with the color of the node. Green means good readiness, yellow means intermediate readiness and red means weak readiness. In addition, as each node is connected to other nodes, the arrows are color coded in the same manner as the nodes. The node's color is the sum of the arrows' colors. This framework can be used to analyze organization's AI readiness and see in which areas the readiness needs to be developed. The framework is applied to the case organizations later on.

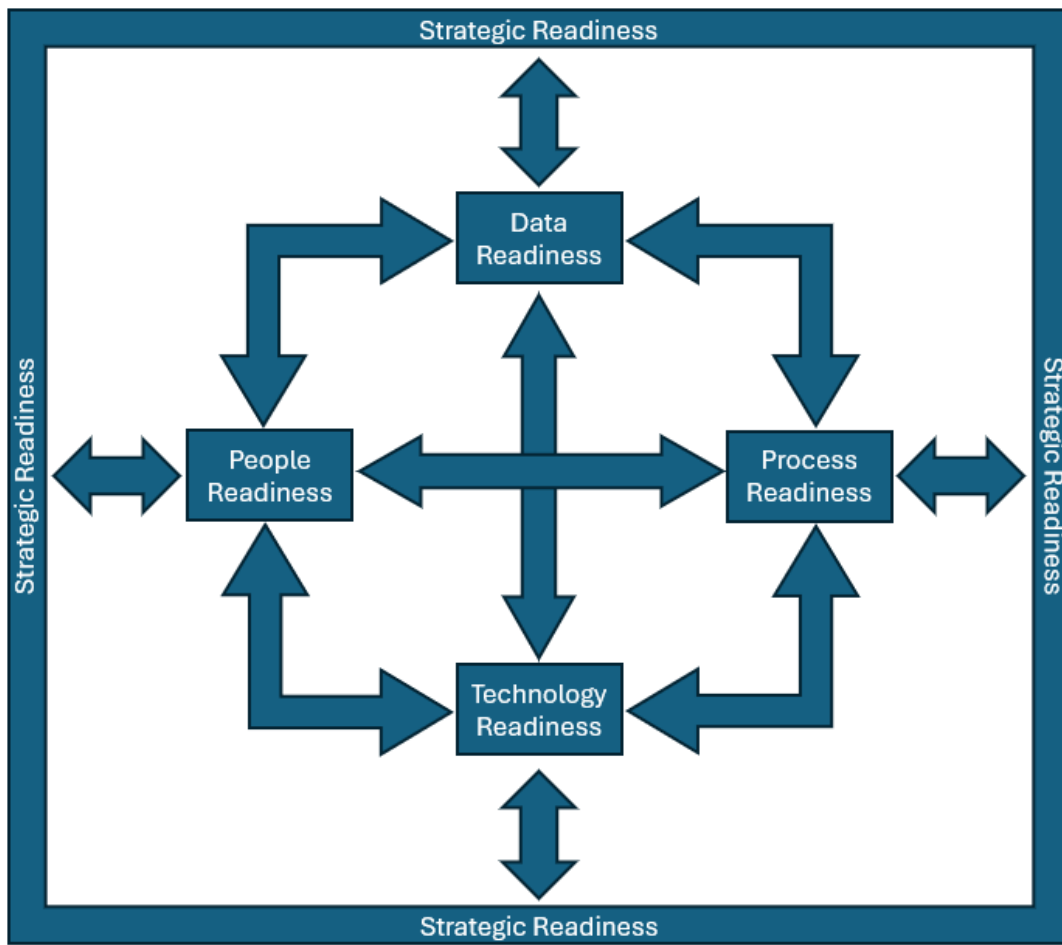


Figure 6 Strategic AI Adoption readiness framework

### **3 Methodology**

This chapter presents the research methodology and research approach used in this thesis. Then the chapter covers the data collection methods and then moves on to discuss the data analysis. Lastly, this chapter covers the quality of the data and its relevance to the reliability of this study.

#### **3.1 Research approach**

This study uses empirical research approaches to examine the research problem. Empirical studies link theory into practice and it has been recognized to be a beneficial approach to examine complex phenomena (Beverland & Lindgreen, 2010; Eisenhardt & Graebner, 2007). This linkage makes it useful especially when doing research on phenomena that have not been researched thoroughly yet (Eisenhardt & Graebner, 2007). Thus, it is an optimal choice for examining the strategic adoption of AI and AI readiness, as the subject is complex and has not yet been studied comprehensively. When conducting this kind of empirical study, the methodological fit is important (Edmondson & Mcmanus, 2007). Methodological fit ensures that the internal parts of the study work together and are lined up. This reduces the risk of using wrong methods to study unknown areas and increases the coherence (Edmondson & Mcmanus, 2007). Thus, this study uses qualitative research methods to answer research questions. Qualitative research examines real life and aims to picture it comprehensively (Lee & Saunders, 2017). Therefore, it is typical for this type of research to collect data from people in their natural and ordinary settings and situations. When compared to quantitative research, qualitative research tends to be more flexible as it accentuates the finding of unexpected outcomes and findings (Patton, 2015). In this thesis, this type of data is collected through semi structured interviews. This interview method was chosen as it suits the purpose and research philosophy of this study the best. To ensure that the interview situation is fluid and natural, the semi structured interview allows a slight adaptation between the interviewees. This

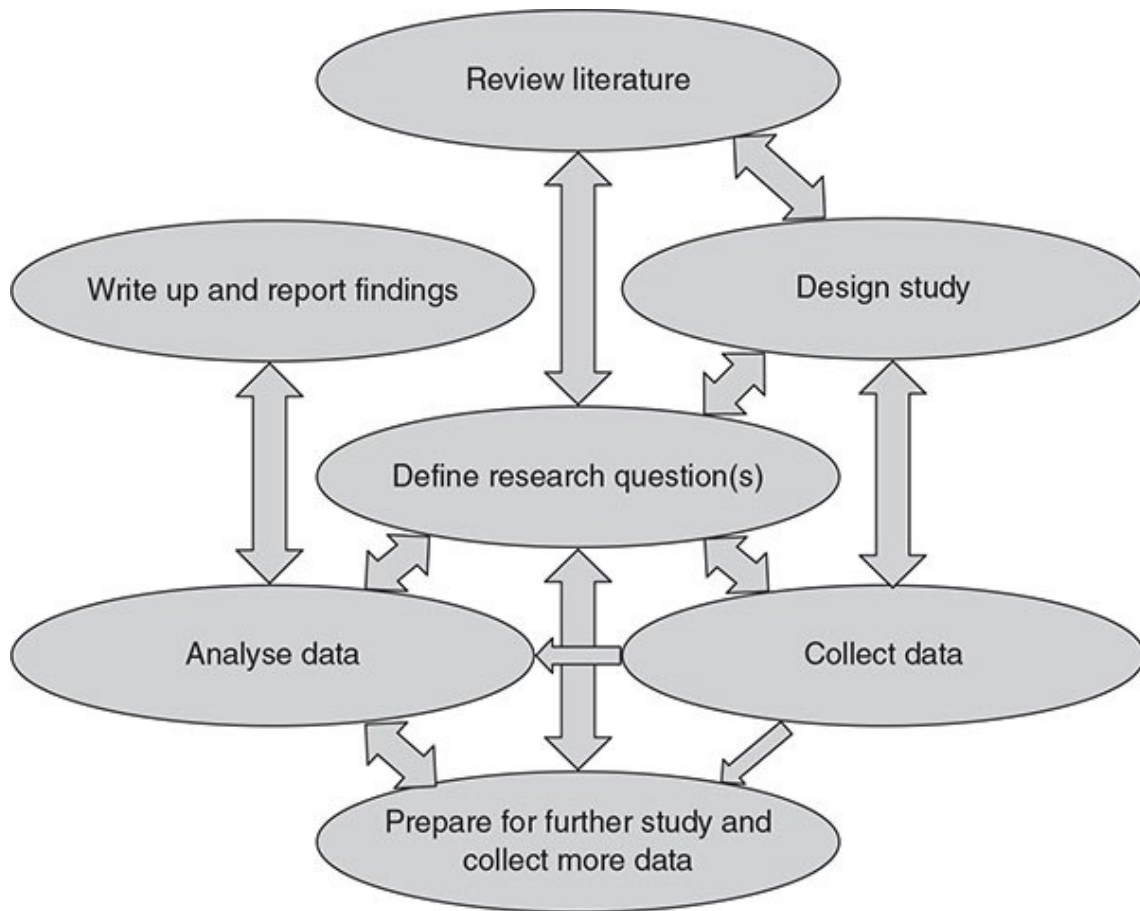
makes the interview situation to feel like more conversational (Eriksson & Kovalainen, 2016).

Every study has a research philosophy (Saunders et al., 2007). Because this research approaches AI from the complexity perspective the research philosophy is considered to be interpretive combined with critical realism, as described by Saunders et. al (2007). This philosophy helps to understand how the managers and experts within organization view the complexity of AI, and how they form their understanding how this complexity affects the adoption (Saunders et al., 2007). This understanding is important, as shown before, the public discussion around AI has caused some misunderstanding regarding the technology, its capabilities and adoption process (Vinsel, 2023). Interpretivism helps here to analyze comprehensively the view of individuals regarding the issue. On the other hand, critical realism helps to combine the perceptions of individuals into the objectivity of technology, because in critical realism experiencing world happens through sensing the thing itself and then by processing the what the thing means to us (Saunders et al., 2007). In more practical terms, it aids in showing that the adoption of the AI is dependable on more invisible factors, the organizational readiness factors (Uren & Edwards, 2023). Additionally, due to the aforementioned reasons, this study utilizes an inductive approach for theory development. Induction in a research is used to build new theory without using predefined hypotheses (Saunders et al., 2007). Induction is useful when there is a need to, comprehensively and based on collected and analyzed data, understand a phenomenon without prior strict hypotheses and theory. Thus, in the context of this thesis it is important to leave room for the experiences and views of the people who have contributed to this research (Eisenhardt & Graebner, 2007).

Every study should have a research strategy (Yin, 2003). The chosen research strategy for this study is a case-study that incorporates multiple cases. Saunders et. al (2007) argue that case research strategy supports exploratory research that is examining recent phenomena within the real life context. Furthermore, they are able to answer "what" and "how" research questions which supports exploratory research (Saunders et al., 2007).

It also aids in understanding the context of the phenomenon at hand (Morris & Wood, 1991). In regards of this study, the context is formed by the characteristics and the quick development of innovative AI technology in relation to strategic AI adoption. However, the findings of single case studies have been rarely found to be generalizable as they are focusing on real life settings of a single case unit (Yin, 2003). Using multiple cases in a study can offer better generalizability as the cases can offer similar results. However, it is also possible that the results are considerably different which on the other hand shows that the phenomenon could be inconsistent between the units (Yin, 2003). Therefore, multiple cases were chosen for this research as it allows to examine the similarities and differences between the cases and thus offer a broader view to the phenomenon at hand.

Lee & Saunders (2017) discuss in their book two different case study strategies, orthodox and emergent approach, from which the emergent approach was selected for this study. The orthodox approach is a linear approach starting from reviewing literature, then designing the study, then preparing the study and collecting data, then analyzing the data, and only then writing reporting the findings. Whereas the emergent approach is moving back and forth between these steps (Lee & Saunders, 2017). This is visualized in the figure 7. The emergent approach was chosen as it gives more freedom in conducting this type of study that is examining research that is only establishing and new studies are release in constantly. The subject of this thesis has not been studied thoroughly, and the emerging findings have required some changes to the initial design and research questions within the study.



**Figure 7 Emergent Approach (Lee & Saunders, 2017)**

### 3.2 Case Organizations

As mentioned, this study incorporates multiple cases. In this thesis, a case refers to an organization which is adopting or planning to adopt an AI solution. There are two different organizations that were chosen for this study. They are both large Finnish organizations operating in different industries. The names of these organizations are not revealed in this study and also certain characteristics that would give the organizations identity away are not stated in this study as per their request. The organizations will be referred to as organization A and organization B hereafter.

The selection of these cases is based on their similarities but also due to their differences. Their similarities offer insight and validity based on the replication logic. Both of the case organizations are large corporations operating in industries that are technology centered. They have both already adopted some AI solutions and are further exploring suitable ways of adopting more AI technology-based solutions. Their difference on the other hand helps to broaden the view of this study because the required readiness factors can vary between different sectors as organization A is on manufacturing industry and organization B on financial sector. Thus, these two cases offer a unique view to examine which readiness factors are shared between different sectors and which factors are more important for other sectors.

### **3.3 Data collection**

Semi structured interviews are often used to cover different themes around research topics. The interview questions are designed to cover these themes during the interviews. This interview method is more freely structured, and the sequence of interview questions is not that important. Thus, the interviewee can answer the questions more freely and the interviewer has a chance to ask clarifying questions depending on the interviewee's answers (Saunders et al., 2007). Therefore, this study used this interview structure on one-on-one interviews for data collection. Each interview was divided in three main themes; strategic readiness, organizational readiness and technological readiness. This division was based on the different areas of AI readiness discovered in the literature review. As the AI readiness as a research subject is relatively new, the view of digital strategy was reflected with the AI readiness studies when designing the interview structure.

There was a total of six interviews, three from each organization, and the interviews were conducted over a one-month period. The interviewees were from different organizational levels and from different departments in order to gain a better understanding of the whole organization. By selecting interviewees from different organizational levels

in multiple case study, the researcher gains better understanding of the overall phenomena and can make better comparison between the organizations (Bouncken et al., 2025). Hence, in the data collection, the different organizational levels were management level and expert level. This division offers the decision makers a more transparent view of what the expert level keeps important in AI adoption. Furthermore, the division to different departments amongst the chosen interviewees is divided into IT function and business units. As the study focuses on organizational and technological readiness factors, the IT function has a more comprehensive understanding of the technological theme whereas the business units offer more insight on the organizational theme, and managers from strategic theme. IT functions are more capable of commenting on the IT strategy, infrastructure, data management, and software. The business unit experts are involved in executing and developing processes. Meanwhile the managers are more involved in the strategy and competence development.

All of the interviews were conducted online with cameras on in order to see the facial expressions and observe the body language as much as possible via the camera. The interviewees were all their own home during the interviews, which gave them a familiar location and gave the interview a more secured feeling as there was no colleagues around for the interviewees. This allowed them to feel more comfortable sharing confidential information and speaking as they felt about the issues without any external pressure. The length of the interviews varied from 47 minutes to 57 minutes with the average interview length of 51 minutes. The interview language was Finnish because this was natural for the interviewees. All of the interviews were recorded and transcribed. The total length for the transcribed text was 134 pages long for the organization A's interviews and 121 pages for organization B. The quotes used in this study were translated into English by the author. It was made sure that the translations would not affect the content in any way by carefully analyzing the context of the quotes in order to find matching translations for each word. Some repeated words were removed from the translations. The interviews are summarized in table 2

| Interviewee | Date      | Organization | Experience (years) | Title                        | Length of the interview |
|-------------|-----------|--------------|--------------------|------------------------------|-------------------------|
| 1           | 12.1.2025 | A            | 9                  | Category Manager             | 57 minutes              |
| 2           | 16.1.2025 | A            | 3                  | Supply Planner               | 54 minutes              |
| 3           | 16.1.2025 | A            | 6                  | Business System Analyst      | 53 minutes              |
| 4           | 11.2.2025 | B            | 7                  | Operations manager           | 49 minutes              |
| 5           | 9.2.2025  | B            | 4                  | Corporate Finance Specialist | 51 minutes              |
| 6           | 14.2.2025 | B            | 17                 | Product Owner                | 47 minutes              |

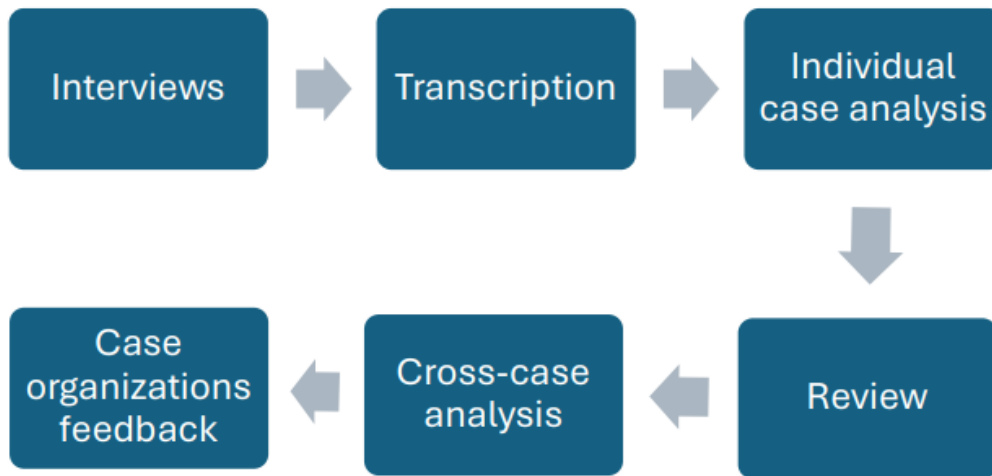
**Table 2 Interview details**

### 3.4 Data analysis

The data analysis in this multiple case study was done with Eisenhardt's (1989) two-phase method. As the name suggests, the two-phase method includes two steps in analyzing the cases in a study; within-case analysis and cross case analysis (Eisenhardt, 1989). First both of these cases were analyzed individually which is purposeful for the objective of this study. As the organizations are different and their AI use cases also differ, both organizations got thorough analysis by only considering their characteristics. The analysis started by first going through the transcriptions after all interviews were done.

The cases were then analyzed separately by using the research framework presented in chapter 2.5. Each readiness factor was first analyzed separately and then continued by analyzing their interconnectedness. The color coding was first established during the analysis and then was later reviewed to confirm that the color coding was still accurate. Furthermore, as Bouncken et. al (2025) suggest, the individual case analysis also included analysis on different organizational levels. This way the analysis includes different organizational and hierarchical levels of the organizations to produce a better inter-firm analysis. Thus, the framework gave a more comprehensive view on the whole case organization.

After this, the cross case analysis was conducted as the researcher was first familiarized with each individual case and could then draw conclusions on their similarities and differences (Eisenhardt, 1989). The individual case analyses were reviewed and their similarities and differences were marked down. These findings were then analyzed individually. This cross-case analysis was also conducted by analyzing and comparing the different levels of organization and different views of different departments, as Bouncken et. al (2025) suggested. Thus, individual organization levels of organization got similar attention in the analysis and ensured that the case organizations received similar treatment. After the analysis the individual case assessments were sent back to the interviewees to ensure that the researchers perception was correct and not biased after analyzing the both cases. The data analysis process is pictured in figure 8.



**Figure 8 Data analysis Process**

### **3.5 Validity and reliability of the research**

Validity and reliability are imperative aspects of academic research. Validity measures whether the study examines what it is supposed to be examining. In other words, it tells whether the findings of the study are relevant in the light of study objectives, and whether they are correct and justified. On the other hand, reliability measures how consistent the research is and how repeatable the findings of the study are. In practice, this means that if the study was to be repeated with the same methodology, would it yield similar results (Lee & Saunders, 2017; Saunders et al., 2007). However, there is a known issue with the reliability of research that use semi-structured interviews, as the responses are bound in time when they were collected (Marshall & Rossman, 2011). This means that if this research was repeated the interviewees' responses could differ from the responses given for this particular research. Yet, reliability can be increased by a careful description of the research methodology, data collection, and data analysis

methods. This way other researchers could validate and validate the analysis done in the research, and if applicable, they could repeat the analysis (Saunders et al., 2007).

The validity of the organizational readiness analysis was ensured by sending the analysis back to the interviewees. This increases the validity of the research, and it is a common approach in qualitative interview research to increase the validity of the research. Furthermore, as presented by Saunders et. al (2007) the threats for research validity were considered during the process. There were no apparent historical, testing, instrumentation, or mortality factors that could have decreased the validity of this research. The only recognized threat to the validity of this research was maturation as the research venue was new it was apparent that new studies would be released during the time of the study. This was addressed by an effective research timetable and by regularly monitoring new studies.

## **4 Findings**

This chapter is divided into two sections. First, each case is introduced and thoroughly analyzed one by one. After this thorough analysis, the findings from each case are combined and analyzed with cross-case analysis. This reveals which readiness factors have risen in the cases individually, which readiness factors are common between the cases and which factors differ. Furthermore, it reveals how the case organizations are building and assessing their AI adoption readiness and how they compare to each other.

### **4.1 Within case introduction and analysis**

The within case analysis starts with a description of the case organization. The introduction is then followed with an analysis of the case. The within case analysis is done with the same approach for each case. It is divided into different sections based on the themes used in the interview. First, the strategic readiness factors and how the organization has approached their AI adoption is analyzed. Second, the analysis focuses on the organizational readiness factors, considering people and processes. Lastly, technological readiness is being analyzed. Each section considers the organization's current readiness and how they are building up their readiness for AI adoption. Finally, the level of readiness is summed up into the framework to see what is the current level of readiness in the organization and on which areas it should be developed.

#### **4.1.1 Organization A**

Organization A is a large Finnish corporation that operates globally. This organization operates in the mechanical engineering industry in which they have two main sub industries they are focusing on. They are very technology intensive organization, as they produce and develop their own technological solutions, but also sources technologies from

their markets. All of the interviewees were from the sourcing unit as the organization operates with an outsourcing and contract manufacture principle and the sourcing play a major role in the organization's overall operations. The corporation has already fully adopted their own GPT based AI model which can be freely used by employees within the organization. In addition, they had already started looking for an AI based sourcing tool from the markets and had developed their own spare part management system. Interviewee 1 is a manager, interviewee 2 is a sourcing planning expert, and interviewee 3 is an IT expert and they all are employed by organization A.

#### **4.1.1.1 Strategic readiness**

In the discussions regarding AI and how it is linked with organization A's strategy, the interviewees were unanimous that organization A has an unclear digital strategy. All of the three interviewees were sure that the organization has a digital strategy in place which includes AI in it, but were unaware or unsure of what this strategy actually holds. Interviewees working in an expert position and in IT function were the most unsure while the manager was saying that their organization would have a digital strategy, but they could not specify whether AI was specifically part of it.

*"Surely we had some sort of a digital strategy where artificial intelligence is incorporated. But if you consider, for example, the basic coders who worked in my team, then they have no idea what the management wants. - - When it comes to us, we of course have some idea what the management has in mind for AI solutions as they had asked us to monitor solutions on the market but there has not been anything concrete." (Interviewee 3)*

*"I would say that we do not have an AI strategy in place. Or at least I have not been told about it. I would say that in our company it is on every business unit leader's responsibility to have their own market intelligence and keep a lookout on new market trends and technologies. So in that sense one could say that AI is linked to the overall strategy as part of everyone's job... We do have a digital strategy but I do not remember what is in it but I can look for the documentation for you and send it over if I can (the documentation was never received)." (Interviewee 1)*

*“Well I think we have some level of (AI) strategy in place at some level because we have had some AI relevant events and internal competition. In the competition the company was looking for AI enthusiasts with ideas and the best one won and I think their idea gets implemented but I have not heard anything about it ever since “*  
*(Interviewee 2)*

This shows that in organization A the experts were less informed or at least less aware of the company’s strategic approach with digital solutions and AI. Yet, they are working with digital solutions, they have had internal events and communication relevant for AI, and they have already an internal GPT in use. The interviewees had similar views and understanding about their organization’s overall readiness and capabilities regarding new AI adoptions and how they would strategically approach them.

When discussing their upcoming plans with AI and their strategy on approaching them, the manager was sure that it would be an internal development project based on external products because of the data sensitivity and technological readiness they possess. The IT unit thought that AI solutions, depending on complexity and purpose, should be bought from markets as it would be impossible for non-IT technology sector companies to develop anything by themselves from scratch. The IT unit emphasized that it would not be wise to try to adopt complex AI solutions organization wide but rather implement them gradually. The expert level had similar thoughts, as they had already thought of the market ready solutions they could buy from the markets and then configure for their use to automate tasks.

*“In our situation, I think we would build it like inside our company, but I do not think we would build it ourselves from scratch, i.e. it would be done on the basis of a solution sourced from the market. - - Our job (in business) is to identify the need, report it forward and then go with the blessing of management to take it forward and these would always be done one need at a time and one project at a time.”*  
*(Interviewee 1)*

*“If you take a GPT model for example, which has been talked about internally, then it should come from the outside as it is so universal, and could be used a little bit for everything, e.g. for coding or as a facilitator of any other mechanical work. Then if you make a bigger machine learning model, you have to do it in-house when all*

*that data comes in a certain format and from certain places, there is no ready-made solution for that.” (Interviewee 3)*

It was also discussed that a clear strategy would be helpful for the further development of AI solutions within the organization. This is, because organization A is big, and there is siloing happening between different units, even though they work around similar topics. In order to increase strategic readiness within organization A, communication, guidelines, collaboration and culture were pointed out to be helpful for the effort. Communication would help to show the direction and the guidelines that the organization’s management is planning to go with its AI solutions and which solutions are already under development. Collaboration on the other hand was pointed out to make it possible to work with separate teams and business units with projects that would give mutual benefit. All of this falls under the culture that the organization has to empower and encourage the employees to look for and come up with ideas for AI adoption and to lower the barriers in doing so with clear strategy

*“If you think about the whole organization, it is very important that the company has a strategy, or whatever AI strategy it is, and that it is informed to all employees in very plain language, because otherwise as this technology is developing so quickly some people are faster to adopt new solutions and then you can also use them wrongly. This is why it is important that the company has some organization unit that is responsible for getting information about these new solutions, what could be used in our business, make a guideline on how they should be used, how we want to use them in future, and whether you can use them or not. So the only way actually to improve the strategic readiness is really to include AI into our strategy and communicate it clearly” (Interviewee 1)*

*“We definitely need to make our culture better in terms of collaboration. I really feel the best way we would get these AI initiatives forward would be to collaborate between different planning units.” (Interviewee 2)*

*“Some common sense it should have (discussing about the AI strategy) that of what tools are used, and that it remains in control. But then again, when there is a lot of in-house software that is not used then by only maybe 10% of the whole organization and then again the other half uses just another ten percent of the software we have, it leads to a situation where the relevant software should be able to communicate with the same AI blocks and so that we would not repeat*

*same things... someone needs to be in control of the AI relevant IT infrastructure and know the strategy to keep the thing under control” (Interviewee 3)*

#### **4.1.1.2 Organizational Readiness**

People in organization A has strong overall IT knowledge and skills as the company is technology focused. This means that all employees are involved in operating several IT systems that are needed to execute their daily work tasks, but also that the organization’s products are technologically intensive. In addition, the organization as a whole has still a strong remote working environment due to the aftermath of COVID but also due to the global presence within the teams. This is thought to improve their readiness factors regarding AI adoption especially on the technological side. They also pointed out the possible IT skill gap between different generations.

*“Generally I see that IT skills are clearly the most important thing with artificial intelligence. To varying degrees, my subordinates too have a fairly large age range and then to varying degrees I know that people's ability to take on completely new technologies is different, but I would think that on a larger scale we have a good readiness level because everyone does remote work so for example the basic skills with the computer and technology are really good. I would like to say that even better than average.” (Interviewee 1)*

The knowledge of how to operate an AI solution is not enough to fulfil the people’s IT skill readiness according to the interviewees. In order to have real AI readiness they pointed out that people need to understand the technology that they are operating – how it produces the output and how reliable it is. In addition, they need to really understand their own role and what is required from them. Even though a sophisticated generative AI model can solve complex problems, and generate content for people outside of their business unit and expertise area, it does not mean that the content is necessarily correct or suitable for the problem at hand. This is, because depending on the AI solution and its training data, the prompt or input that employees insert into the system might have flaws or might not describe the whole situation which can lead to wrong outputs.

*“Anyone, basically, who can ask that AI the right questions, can produce the kind of content, for example, code, that they want. However, I don't think it's going to do any good if you don't understand what's going on in that piece of code. It becomes quite impossible to maintain the software or block that is being coded, if the guy who copied the code from the GPT for the first time, then doesn't understand what's going on in that block and why, and they then go and attach it to the rest of the code.” (Interviewee 3)*

*“In addition to IT skills, I see that in the expert work that my team does it is at least as important to be source critical with AI outputs. Depending on what data is used and what data should be used versus what data should not be used. The expert needs to understand the AI output. They cannot just take the AI output as a fact, and they need to be critical of the answers they get” (Interviewee 1)*

The people's readiness was raised as an integral part of the organizational readiness by the interviewees. Knowledge and skills associated with AI was discussed the most with the interviewees. The expert pointed out the training needs that they saw the most important for those that worked in similar positions. On top of training, they saw that there should be separate AI experts within business units that could mentor and help the business units with their AI relevant needs. These people would be internal experts with the solution and could be responsible for the product and advise others on using it. This would be relevant both to support operating the technology but also to know how to handle the data properly.

*“Well skill development with AI tools would be a good starting point on my behalf as well. A new tool always requires a moment so one can learn the tool, has time to review and get familiar with it in order to understand what can actually be done with the tool. Surely in our case the tool will be external so we will need an external person from the company that sells the tool to teach us what is possible and what is not. - - In addition, I actually see that organization of our size needs a person who would be responsible for the tool and who would know better how it can be used and they would then act as internal advisors for that solution.” (Interviewee 2)*

As organization A is a large company with several business units, the importance of collaboration between people and different business units was seen as an important readiness factor. As AI is a complex solution it requires people from different business units

with different aspects of expertise around the solution. In addition, as there are several business units within organization A that work in similar roles, but who work in different business units and with different products, they do share similar processes together. Thus, involving these parties in relevant AI adoption projects was seen as a beneficial thing to do in future as the siloing within the organization was seen as a aspect that currently lowers their AI readiness. At the moment it would be possible that another business unit would make the AI tool adoption and the other unit with similar processes would not know about it.

*“I really feel the best way we would get these AI initiatives forward would be to collaborate between different planning units. There are different supply planning teams working with different products and we should be able to discuss with them...and share information about the solution... But at the moment I think we could not do that because we have no idea of what they do and how they do their planning so we need to solve that first.” (Interviewee 2)*  
*(Interviewee 2)*

Furthermore, the involvement of IT and legal department was seen as a integral part of the AI adoption process. The business units wanted to involve IT department in every step of the adoption process to get them to really understand what are the use cases in the business. Also, the manager emphasized that there should be clear limitations for the access rights regarding certain information available from their future AI model. They were concerned that if people within the organization would get access to information that is not relevant to their role it would cause unnecessary confusion. They were also concerned that without proper access rights there would be a risk of unintentional and intentional information leakages. Thus, the presence of the legal department was also seen as an important thing. Therefore, including the correct stakeholders into the project was seen as an organizational readiness factor.

*“The AI adoption would require legal department, IT department, business unit leaders, and the main group of end users to see who can benefit from the solution - - Once we have identified the main user group for the solution we must make sure that their voice is heard as well. IT department would be the one to lead the development and legal department would be there to produce the guidelines about who*

*should be able to use the system - - It should be internally limited who can access what information with the AI. A good example is that we (the supply chain) do not want sales to know our strategic sourcing contracts. Otherwise the sales people could sell totally wrong things to our customers if they started to interpreting out sourcing contracts with the AI” (Interviewee 1)*

Reflecting to the internal GPT model that was already released within organization A, none of the interviewees were aware of how the model could really be used the best way and what it was capable of. In addition, there were internal communication about the release of this AI model, but it had not reached everyone. One of the Interviewees were aware of the internal guidelines but now about the trainings, and one was unaware that they had any internal trainings available about their internal AI model. This was the main reason why the interviewees were highlighting the importance of training and communication relating to new AI solutions. The lack of clear and profound communication and training has led to a situation where they have not used their internal model very actively or are not aware of what they could really do with it and how they could benefit from it.

*“I think it is very limited what I can do with our internal AI in my job. - - We do not have any AI training available in our organization or at least they are not mandatory so the information flow depends solely on whether people read the internal communication or not - - I see that the lack of trainings significantly lowers the user adoption of our AI model because we do not know what we can do and what is allowed to do with the AI.” (Interviewee 1)*

*“Our IT has made guidelines regarding our internal GPT model and external ones on how to use them and what not to do with them. - - I have not really thoroughly read the guidelines and have actually used the internal model so little that I have not bothered to do so. I have not enrolled myself to any trainings and it would feel strange that we would not have any trainings on the matter (referring to their Internal AI model) - - Now that I am checking from our intranet there actually is a lot of training options regarding AI but none of them are mandatory.” (Interviewee 2)*

The processes within organization A seemed to be quite versatile and flexible in the business area when it comes to adapting them to the AI solution. The sourcing unit, where the sourcing expert works, had very flexible processes, especially on the strategic

sourcing side which focuses more on negotiating supply agreements with suppliers. This flexibility within their processes has allowed them to completely modify their processes to their needs and they have only little similarity with the other sourcing units within their organization. The process flexibility is a beneficial readiness factor when it comes to AI adoption within their business unit. However, as discussed earlier, the interviewees mentioned that there are many other sourcing units within their organization, and it would be easier to get permission to source a AI solution from the markets if there were more users to it rather than just their unit. Thus, if the processes greatly differ between different sourcing teams, it could cause difficulties and change resistance when adopting a shared AI solution.

*“I would say that our processes are quite flexible. As I said earlier, our sourcing unit’s order process is very different from other order processes within our house. If we want to do things differently within our team, we can do so. - - Our process map has been drawn with free hand so to say and it has only a few similarities with the basic order process. - - If we were to involve other units with a shared AI solution project I would say that the other teams would have a much much more change resistance compared to our team because they have very well established and clear processes that have come with little if any changes along the way” (Interviewee 2)*

At the same time, the manager who works mostly with the contract negotiations and is responsible for their sourcing strategy, argued that on a higher level AI solution would be easier to implement. It was discussed during the interview that when compared to more traditional sourcing activities to contract negotiations the situation is very different. In the traditional sourcing, the processes are very strict and rigid with a little to none flexibility. These sourcing activities are mostly done with ERP software, and they are very limited to what each employee is allowed to do. Whereas on the contract negotiations side, AI solutions would be much easier to adopt as the process is very abstract. On the other hand, however, the AI solution required on a contract negotiation level is far more complex than what it would be when automating and adjusting traditional sourcing activities.

*“Process readiness is not an issue for us and it would be very easy to adopt the AI into contract negotiations and potential supplier sourcing. Our processes are not done within the ERP so we do not repeat the same things over and over again which is done on more basic sourcing... - - Of course it would mean that the chat GPT we would be using needs an access to all of our previous contracts so it could support us in negotiations. It could tell us what kind of contract would be aligned with our strategy and that it could do the market analyses for us... It would be mind blowing and the potential would be huge but it comes with many new problems” (Interviewee 1)*

On the IT side they had a recent example project they had executed together with sales and procurement regarding robotic process automation. In this project they had created a machine learning algorithm that automatically suggests spare parts for procurement and sales that the customer would need. This machine learning algorithm was based on data on what the organization had sold to their customers, what was their life cycle, what was the average time for service needs and which parts were supplied in which service request. The algorithm then automatically suggested to the sales that this customer will most probably need service for their equipment and once sales had confirmed this from the customer, procurement was able to pre-order the parts. In this project, the process readiness was taken care of in all perspectives. Technological needs were mapped beforehand to know what technologies were needed based on the process. The change requests originated from the sales team so they already knew how they needed to change their way of working. In addition, after the implementation they blocked access from the salespeople to the system so they had to use the new algorithm.

*“Well first we needed to know the manual process and what could be done to it so that we know what we need to take into consideration. Only then we are able to see what technology is needed and where the data needs to be pulled from. - - In this case the way of working for the sales and procurement changed quite profoundly because they used to have to be reactive, but now they have to be proactive and contact the customer themselves that service need is coming... they seemed to be quite happy to receive this big change even though we had to block their entry to the old system to make sure they use the new one” (Interviewee 3)*

#### 4.1.1.3 Technological readiness

There were really different viewpoints about the actual technology regarding technological readiness. The interviewees had very different ideas about how AI actually works as a technology and what it consists of. The manager and the expert said in the very beginning that their understanding regarding AI as a technology is somewhat limited. The manager constantly referred to AI as “ChatGPT” or “OpenAI” without the intention to refer specifically to the company called OpenAI or its product ChatGPT but rather meaning an GPT model overall. Whereas the expert only referred to AI generally and did not want or did not know how to specify the technology their solution used. Furthermore, the manager and the expert level did not know the specifics of the adoption processes or projects, and what their solution would mean technology wise. Nevertheless, they did argue that more complex solutions would cost more and be harder to implement.

*“It would be really simple to do our weekly tasks with OpenAI or with ChatGPT because our weekly tasks on contract negotiations are not done in ERP and are thus not repetitive process. - - I would say that the project could fail if we do not understand the technology or if the scope is too wide it will become very expensive...” (Interviewee 1)*

On the other hand, the IT level had a very clear idea of the technological side of the adoption process. They could specify which AI technologies they had used in their spare part management solution and how their internal GPT based AI operated. In addition, they were able to estimate what different levels of AI adoption would require technologically from their organization, and how to evaluate whether AI technologies would bring any added value to the solutions they were looking for. Most of the technology they needed for their previous spare part management solutions and for future AI solutions was related to data handling and storage. For this purpose, they were able to freely choose either to use local servers or cloud servers, whatever suited them better. It became clear that the technological capabilities were really good and there were many alternatives to the needs.

*“Basically, all capabilities already exist (technology and infrastructure wise) - - For our project we had chosen to use cloud storage because it was easily accessible for everyone and it made the project easier.” (Interviewee 3)*

During the interview, interviewees had quite differing opinions on how broad the understanding should the AI adoption project participants have regarding the technological solution itself or AI overall. The expert thought that they should bring the process expertise into the project and that IT should lead and act as translators for their needs. The manager said that management should actively scan their area of operations regarding best practices and new technologies and push the development onwards. In addition, the manager argued that once such development projects start, they should be led by the IT. Whereas the IT thought that, where they of course will bring the IT expertise into the project, the manager side should ideally have more deepened understanding regarding the technological solutions. This way the management level would be able to analyze the complexity and overall suitability of the projects for their team and the organization as a whole. Thus, basic understanding could be used to avoid common IT project problems and projects that eventually end up as IT would be realistic.

*“It does not matter if we (at management level) do not understand the technology. Our IT has their project processes in place and they should understand the technology so well to avoid any problems (talking about making technical requirements). (Interviewee 1)*

*“Every IT project needs approval from the management, so they need to have at least basic level understanding about the technological side as well to make at least some sensible decisions” (Interviewee 3)*

Overall, all of the interviewees shared the same idea that for their organizational development it is more important to think about the added value of the new information system rather than just to include AI into the system in some way. Even though the interviews were AI centric, the interviewees did not think that AI should be adopted just for the sake of it. For the spare part management project that they had previously had, they were even ready to drop the machine learning algorithms out of the project as it

seemed to be far too complicated. However, the algorithms were later on developed when the base product was functional.

*"...we would input the data and the parameters in the software, and it needs to make decisions for us and whether it uses AI or something else to do the logical thinking, I do not really care. As our supply chain becomes more and more complex it would just be important to minimize the human errors and get the basic stuff given by the system." (Interviewee 2)*

*"First, we had very big and ambitious plans for the (spare part management) project. We had planned to build this beautiful machine learning algorithm but the technological solutions for the data collection became a problem - - We decided to make filtering algorithm instead where we could later add the machine learning algorithm on top of the beautiful thing that moves the data from one place to another" (Interviewee 3)*

All of the interviewees also agreed that the technological readiness within their organization is already established. However, even though the technological readiness was there, the data readiness was seen more as an issue. The spare part management project had already faced issues with the data storage even though they had freedom to choose their data storage methods. The reason was that as the organization is large, there are so many different software in use that stores their data to different places in different formats, it is troublesome to collect all this data and use it in the new solution.

*"The technological solution for data collection became a problem. It turned out to be a bit more challenging to gather the relevant data from fourteen different data sources in one place and in such a format that it can be processed and analyzed in any sensible way. And then the fact that it is able to spin it through the whole data flow automatically" (Interviewee 3)*

Furthermore, the expert and the manager were concerned regarding their data management capabilities and protocols. This concern was due to concern of letting the data get to the wrong hands within the organization. As discussed earlier, the manager was most afraid that sales would access sourcing organization's data and interpret that with the AI, which would in turn lead into sales of wrong things. However, the concern also revolved around on how it will be limited on who can access and what data. The AI system should

be able to know what information can be safely passed for people in their certain roles and when to tell them that they should contact the subject area expert for further information. Nevertheless, as the LLM models are currently programmed to answer all questions and their safety mechanisms can be partly avoided with correct prompting. This was an clear unsolved issue for organization A relating to data management with AI. The system should be able to use all the data, even sensible data, as training material to avoid people from making costly mistakes but without revealing them too much.

*“If we compare us to for example our workers in factories. I would say that they should also be able to have access to the system, but their access should be very limited. But still, I think the training data should be there so it can tell them when to contact other expert about the issue and at the same time it should restrict them from doing things wrongly even though they do not have straight access to a certain technical or logistics document” (Interviewee 1)*

When discussing data readiness in relation to people and processes within organization A, the readiness was seen to be on a good level. The manager and the expert said that they already have strict data protocols in place. For example, on the expert’s line of work there are only a few free text fields through which they can insert into their ERP, whereas the rest are format limited fields, thus lowering the error margin. The data needs to be already correct for their current supply and demand planning activities so there was no big change seen whether they use AI or not. It was pointed out that of course if the data input were to be done by AI the human error margin could be mitigated even further. On the other hand, the manager said during the discussions that as they deal mostly with contracts with different stakeholders, the review process each contract goes through lowers the error margin significantly. They said that they put maximum effort to avoid there are any wrong words in their contracts. Hence, their employees at least on manager and expert level are already dealing a lot with data and taking care of data correctness on daily basis.

*“Portfolio management and contract negotiations is what our firm does. We constantly source suppliers and negotiate prices and terms with them and draft*

*contracts based on those discussions... We have a very highly tuned process for our contracts.” (Interviewee 1)*

*“We have all our historical data already stored and our current processes supports data handling. The issue currently is that we would need that data to be more easily accessed but that is not our job to do. - - Without correct data our supply and demand planning would not do any good even without AI” (Interviewee 2)*

As mentioned, in organization A the data infrastructure has been quite scattered previously, but the organization had already taken action in order to renovate their data handling infrastructure as a strategic initiative. There was a project ongoing to transfer all of their data handling into one data storage under one supplier’s product. This means that in future their data is stored in one place and in one format which makes it much easier to use the data for AI training purposes.

*“We do have a bigger data model change project ongoing where we are collecting all the data from 14 different relational databases into one dataset and under one data model” (Interviewee 3)*

Finally, a point that really stood out between the responses from the manager and from IT was external data security. The manager was clearly very worried about data security against external threats regarding AI solutions, in addition to the internal ones discussed earlier, whereas the IT was not worried at all. IT pointed out that the data is already in the system and in the storage and adding an AI on top of the current infrastructure does not increase the data security risks. They argued that building a solution into their current system that only operates internally does not change the threats from the current level at all. Furthermore, it was argued that even adding external APIs to access internet with the AI model does not cause any bigger issues than their current solutions.

*“It does not change from the current situation if we add an AI into our system. Everyone already has their access to different places and even if the needed work flows then make few more transactions between servers and so on adds a couple more extra steps to the data flow, I do not see how it would increase the security risks at all... There should not be any changes to the data transfer protocols such as SFTP that we currently use a lot” (Interviewee 3)*

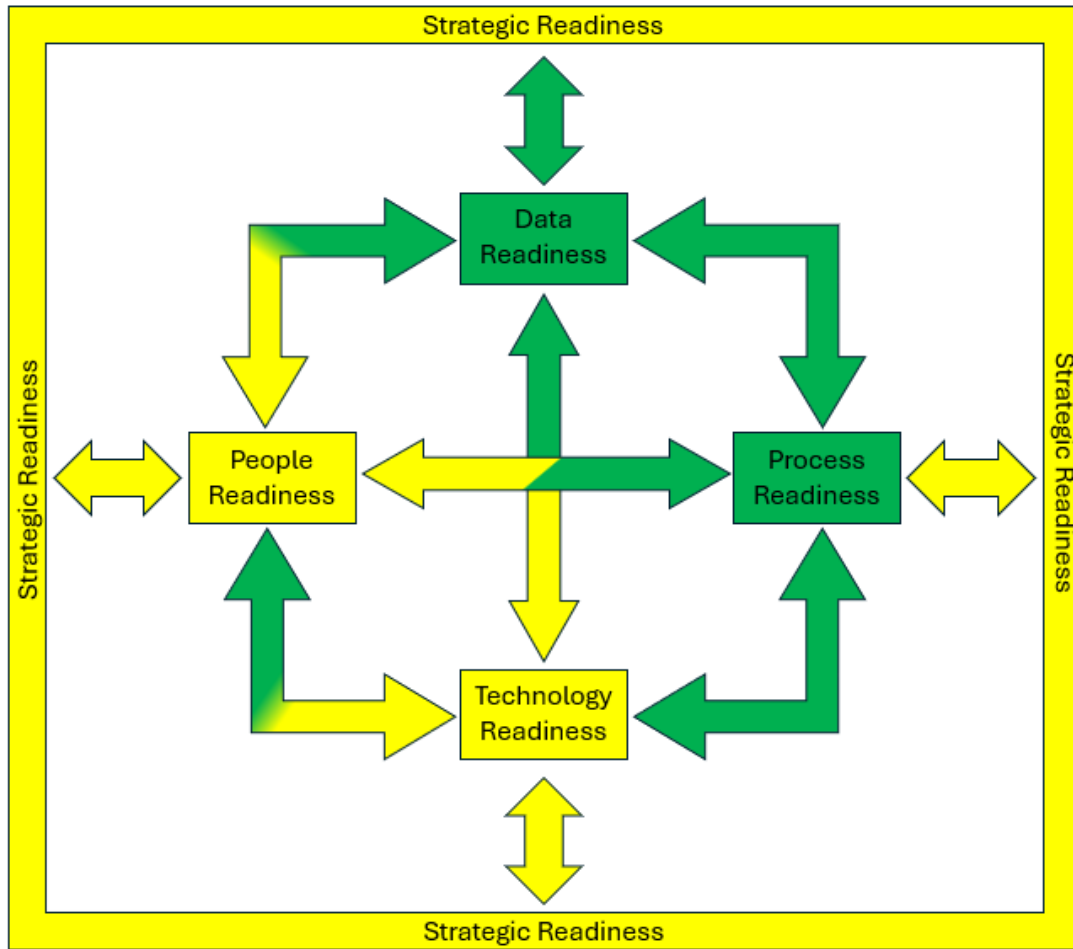


Figure 9 AI Adoption Readiness In Organization A

| Dimension                             | Organization A | Key Findings                 | Effects on adoption   |
|---------------------------------------|----------------|------------------------------|---|
| Strategy $\leftrightarrow$ People     | Intermediate   | Unclear communication        | Uncertainty makes adoption less effective and influences attitudes      |
| Strategy $\leftrightarrow$ Process    | Intermediate   | Siloing between departments  | Hinders the process alignment and causes extra work                     |
| Strategy $\leftrightarrow$ Data       | Intermediate   | Under development            | Aligned data infrastructure makes AI adoption easier organization wide  |
| Strategy $\leftrightarrow$ Technology | Intermediate   | No organization wide goals   | Creates a possibility for the formation of a fragmented AI entity       |
| People $\rightarrow$ Process          | Good           | Flexible processes           | People are willing to change processes if needed                        |
| People $\rightarrow$ Data             | Good           | Meticulous work required     | The people in sourcing are already meticulous and data oriented         |
| People $\rightarrow$ Technology       | Intermediate   | Lack of AI knowledge         | Could lead to poor decision making and resistance to change             |
| Process $\rightarrow$ People          | Intermediate   | Lack of AI knowledge         | People might lack required AI knowledge to change their processes       |
| Process $\rightarrow$ Data            | Good           | Strict data protocols        | Limited options and controlled data entry protocols keeps data clean    |
| Process $\rightarrow$ Technology      | Good           | Sufficient IT infrastructure | IT infrastructure is sufficient for planned AI enhanced processes       |
| Technology $\rightarrow$ People       | Good           | Sufficient IT infrastructure | IT infrastructure is sufficient to support the people's requirements    |
| Technology $\rightarrow$ Process      | Good           | Sufficient IT infrastructure | IT infrastructure allows freedom for process design                     |
| Technology $\rightarrow$ Data         | Good           | Sufficient IT infrastructure | IT infrastructure is capable of storing and processing data as required |
| Data $\rightarrow$ People             | Intermediate   | Data access protocols        | Can cause role confusion and even compliance violations                 |
| Data $\rightarrow$ Process            | Good           | Data maintenance in place    | Current processes support data maintenance needed for AI                |
| Data $\rightarrow$ Technology         | Intermediate   | Under development            | Incompatibility of legacy data models can cause problems                |

**Table 3 Breakdown of Readiness Factors in Organization A**

#### **4.1.2 Organization B**

Organization B is a large Finnish corporation that operates in Finland. This organization operates in the financial sector in which they focus on consumer and corporate finance. The financial sector has become increasingly digitalized in recent years, and this has also affected organization B making its services also mainly digital. All of the interviewees were from the corporate finance side, and they all operate within the same product category. As the financial sector is mainly service based where money is the product the organization is under pressures to automatize and digitalize its services in order to stay competitive in their relative market. The organization has already installed some of Microsoft's Copilot services, but they did not implement large-scale deployment to end users. In addition, they have made some recruitments regarding AI and have started to look for potential AI partners from Finland to plan and prepare for more wholesome AI adoption. They were in the midst of planning an automatization project for their customer funding decision-making process with AI and robotics. Interviewee 4 is a manager, interviewee 5 is a corporate finance specialist, and interviewee 6 is an IT expert and product owner. All of the interviewees are employed by organization B.

##### **4.1.2.1 Strategic readiness**

Organization B is currently in the process of creating and publishing a new organization-wide business strategy as their previous strategy period is soon ending. The current strategy does not hold AI in it as it was formed five years ago. In fact, it does not mention technology separately at all on any level. However, technology is embedded within the other parts of their strategy. This is, because the financial sector has become so digitized, the technology has grown to be part of how the business is done. In order for businesses within the finance sector to create competitive advantage and to improve their services it has to do something with digital improvement. Still, the interviewees said that they wish that technology, and especially AI, will be specifically mentioned in their new

strategy because it would benefit the development of their competitive advantage within the markets.

*“As per my understanding, our current strategy does not mention technology on any level, but I do hope that our new strategy will. The new strategy will be published within two weeks or so and I think that it should mention it. No only for our internal use and improvement but to help our customers as well” (Interviewee 6)*

*“It is not mentioned specifically in our strategy... - - However, we do talk a lot about digitization and how to utilize it in order to continuously improve our core business functions and so even we do not say it straight the technology is this way embedded in our strategy” (Interviewee 4)*

When discussing further with the interviewees about their strategy, there were eventually a lot of things hinting that there would be a larger plan in place for technology and AI. First, there were data and AI specific recruitments within organization B. They had recruited a person with “Data and AI Lead” title few months ago to begin the groundwork for AI development within their organization. Also, they had already bought and installed the latest licenses for those Microsoft tools that uses their Copilot AI. The manager said that there has been some discussions about the plan to take Copilot to wider use in the near future. Lastly, when discussing more about AI as a technology and how it works and which technologies fall under it, the interviewees said that robotics and automation is what they do the most to improve their processes. They had, for example, several different machine learning algorithms in place to execute different tasks and some of them were even very sophisticated.

*“It was not long ago when they introduced the new data and AI lead position that they had previously fulfilled in a townhall call” (Interviewee 5)*

*“Oh yeah we have a lot of robotics algorithms in out house and we use them all the time to automate different tasks so in that sense we are using a lot of technologies that fall under the sub categories of AI technologies. For example when I was working in credit risk management they had just created this big an complex credit engine for us.” (Interviewee 4)*

Even though there was eventually a lot of different factors showing that the technology was heavily present within everything they did the interviewees still saw that AI especially should be clearly mentioned in their future strategy. The reason for this was that as the financial sector is so heavily digitized, AI was seen as a necessary factor in future to keep them competitive. At the moment, all of the interviewees said that at the moment none of their competitors are using AI. They saw this as a clear opportunity to build competitive advantage. Furthermore, they also said that by mentioning AI in their strategy they could change their culture and way of thinking about AI. Currently especially the IT expert saw that if they do not openly speak about AI as an opportunity, people will see it as a threat that will take everyone's job in future. Furthermore, the expert mentioned that currently they are not encouraged to try and find ideas how they could make their work better by using AI. As organization B is smaller when compared to their rivals they do not have as big development budgets as compared to others. Thus, this type of strategic alignment could create additional resources for their product development and compensate for this budget difference.

*"It is very odd that we are not encouraged to try and think different ways to use AI in our work. If we compare our development budgets to our competitors who have endless IT budgets it is exactly what we should be doing." (Interviewee 5)*

*"The way how I see it, is that AI is seen as some sort of threat in our industry. Mostly due to data security reasons. People for some reason fear that once you start using AI all of your data will magically leak somewhere... - - We could change this and remove this bottle neck by broadcasting AI to everyone through our strategy." (Interviewee 6)*

The most important factor, why AI must be included in the strategy, was the development speed of AI. The interviewees saw that if the new strategy period does not have any focus on AI, they will fall back in the development. This is because adopting AI now could give them competitive advantage, whereas if they do nothing in their five-year strategy period, they would fall far behind in the industry. The interviewees saw that AI will quickly develop into commodity technology due to the development speed and have a similar role within five years as ERP systems and cloud services have now.

*“The AI is developing so quickly and the faster we get onboard and learn to use it the better position we have in the markets” (Interviewee 4)*

*“The strategy period in our sector tends to be five years. God help us if we sit and wait around for five years and watch as our competitors go and do cool stuff with AI” (Interviewee 6)*

When discussing how the organization is planning to adopt the AI solutions into their business, they had already clear ideas. First was the Microsoft Copilot that they basically already had but which they had not taken into use yet. Copilot would help them in operating their Microsoft-based software much more efficiently and it would help everyone in the organization. More specifically because they are in corporate finance, they had already started looking for external AI partners as they do not have any viable resources within the organization yet. They had planned to use these external companies to source the best practices that are already in use abroad in similar industries. The interviewees also said that due to budget constraints they do not think that they will do anything more inhouse than to just configure these solutions from external markets.

*“Well as we are not an IT house I do not think that we could ever do anything ourselves. What I have heard and understood is that they are always looking these IT solutions through our IT partners because we have basically outsourced our whole IT function” (Interviewee 5)*

*“We do not have such resources in house to build our own AI systems. And so far what I have understood our IT partners do not have either. The system must come from completely another party that our IT party is able or licensed to then install further and which we would then configure. Just like we are doing with the Copilot” (Interviewee 6)*

#### **4.1.2.2 Organizational readiness**

The level of technological readiness that people currently hold in organization B was seen to be at an average level. The manager argued that in their organization at least, the technological skills go quite much hand in hand with people's age, but that there are exceptions. They argued that among their subordinates the average age is lower and that most of the people do have quite good IT skills. The IT expert shared quite similar views, but they specified that in AI adoption cases business experts are not expected to have too deep knowledge about AI solutions technically. Rather their value for AI adoption is to bring forth the development ideas and expertise regarding their processes. The IT department said that they are there to help with the technical side of the development. However, they did emphasize that management is expected to have both business and technological skills. This is, because they make the decisions about the development projects and if they do not have at least the minimum level of understanding about technology, their decision-making comes harder and there could be misjudgments. Overall, the consensus was that basic rules of required knowledge applies the same in any other IT development project.

*"This might sound quite harsh, but I do think that there is a generational division in our company's IT skills. Of course, there are exceptions in both ways but overall I would say that the younger people have better readiness to work and talk about AI solutions for example" (Interviewee 4)*

*"Well with AI I think that for our business side it is enough to understand how to use AI, but I do not think that they should understand what happens under the hood too much. - - The management on the other hand must understand both the business side and what happens under the hood at least to some extent to make viable decisions. But I have to admit that it is quite a shame that more and more I face managers that do not understand either of them." (Interviewee 6)*

When discussing how to increase the level of people readiness the interviewees highlighted the role of self-development and trainings. The role of self-development was raised especially by finance specialists and IT expert. The finance specialist argued that they should be encouraged to try and test different AI solutions with safe data to explore new ways of utilizing AI in their day-to-day work. This way they could get specific use cases and pile them up for a larger solution to be employed. Furthermore, they said that

they have been discussing this with their colleagues, and they have agreed that in every team there should be one person who has AI expertise. Thus, this person could teach and aid the rest of the team in efficient and safe use of AI.

*“We have actually discussed the usage of AI quite much in our team. Because some of us are more interested in AI and more capable with new technologies than others, we have agreed that it would be beneficial to have one or two AI enthusiasts in every team. - - It would say that it would make IT’s life easier in AI implementations if the management would let us try and learn these new solutions and find new things from AI on our own” (Interviewee 5)*

The training, on the other hand, were seen as a necessity for AI development. Currently, the lack of training was seen as a major limiting factor in readiness for organization B. The interviewees said that the level of internal AI training is currently zero. The IT expert was the only one who said that their department has some access to external training organized by their IT partners or by different organizations they belong to in their private life. The importance of training for AI adoption readiness was seen so important by the interviewees, because it is a new thing and according to them, everyone who is currently employed by their organization has not been taught about AI in school. Thus, their current knowledge level is close to zero and the training was seen to be the only way to increase the awareness of everyone in order to increase their readiness on the area.

*“The latest we have to start the AI trainings for everyone is when we start implementing the solution. By educating our employees beforehand we can prepare them for the implementation and make it go smoother. - - Although AI is a new and complex technology, I believe that its use and soul life can be taught to anyone just like any other new thing.” (Interviewee 4)*

*“We do not have any other option than to train our people (regarding AI). This is a matter that has not been taught in school to anyone in our organization. No one could five years ago foresee this coming. After we have got AI included in our strategy we must start educating our employees about AI. This way they could learn the basics of it and it would lower their fears about it because we humans always fear everything new.” (Interviewee 6)*

The role of culture was highlighted by the interviewees in several instances, and it was also tied to processes and people. As organization B operates in the financial sector they are facing a lot of regulation in their operations. Thus, there are many roles within their organization specific to fulfilling these regulatory aspects. This causes costs for the organizations in the sector and hence they are constantly looking for solutions to automate these tasks. Therefore, AI and robotics has been discussed a lot as potential solutions to fulfill these regulatory processes. However, this has created change resistance within their organization as people are afraid of losing their jobs due to the fear that their jobs would be automated. This change in resistance has caused cultural issues regarding the adoption of AI.

*“Due to the business that we do we face a lot of regulatory processes that are externally supervised. This of course creates bureaucracy in our organizations, if you can call it so, and we want to get rid of it by automating these tasks. - - Yes, we do have people employed specially for these roles and of course this technological development causes fear in them. I can only imagine how much it sucks to know that you would be the first ones whose role would be replaced by a robot.” (Interviewee 5)*

The actual business processes that organization B has are complex and there are a lot of different factors and steps to consider. There are a lot of parts of these processes where robotics could be used to automate some parts of the processes but where more sophisticated AI solutions would be needed to complete the whole process. This is, because none of their cases are identical and require logical thinking. In addition, these processes require a combination of following regulatory rules while thinking about customer relationships in terms of future sales. An example process was brought forward from their customer funding activities and the decision-making process relating to it. In this process they need to first analyze the customers' financial data in business and regulatory terms. After this, they need to discuss with the customer in order to form a better understanding about the customers' current situation and future outlook. Then they need to create customer specific analysis and calculate tenders based on the analysis. Then they need to negotiate the terms with the customer and if they agree with the terms then they need to start the crediting process, which is highly regulated. Overall, the process

structure is very complex, and they need to take a lot of different aspects into consideration. This is a crucial process for them that they should be able to automate as it takes too much time. However, the consensus was that the process is able to transform for the needs of technology, but the process itself is so complex that the current technology might not be able to solve it.

*“In each separate case where we go through the decision whether we fund the customer or not we go through a process with awful lot of steps. If we were to do this process with AI we would need to define crystal clear and strict parameters for it that it would become a technical nightmare to implement. - - Even if we were somehow able to define the parameters we would anyway end up in a situation where would accept cases that we do not want to have in our balance sheet and reject cases that we would want to have with us - - This is the process that we would very much need to include the AI in but it just seems to be too much and we end up in situation where we have to think is it worth it if does not work in the first place” (Interviewee 4)*

On the other hand, the IT argued that the example process of customer funding decision-making should be divided into several pieces. Thus, each part of the process should be considered independently on which technology would be the best to be used for automating the process step. They argued that gradual adoption of robotics to automate the process step would be needed and that AI would be deployed on top of them. Overall, robotics would include technologies such as transformers and different depth levels of machine learning algorithms and neural networks to first automate the individual process steps. Only then, the AI would be adopted on top of this to replace the human logical decision-making process. However, they said that with the current IT budget and their organization’s relationship towards AI is hindering this process. They would have to start with basic robotics and take the quick wins by automating the first tasks from the process.

*“Depending on the process steps, we would need to first find right robotics tools for moving data from place A to place B and automate the fillings of certain fields. We would need to build this on top of the old funding decision-making data and train the algorithm to fill the right things into right places. And only then we could put the AI to operate on top of that. - - ... and especially within these breakdown*

*process steps we first need to make the quick wins with the robotics and algorithms.” (Interviewee 6)*

When discussing the transformability of processes in organization B the interviewees said that certain conservatism within their organization makes these changes challenging. They did tell that the processes can be changed but the hard part is to get the people to change. They argued that too drastic changes to these processes would cause change resistance in people and bigger changes would be hard to get through due to the bureaucracy. Part of this change resistance comes from the strict regulation that they face but most of it comes from the people. The expert argued that the change resistance for people is created through the culture that their organization has and that they recruit people based on certain risk aspects that people have and which supports the organization’s culture. Furthermore, this can be connected to what the IT expert said about the importance of adding AI into their strategy in order to change the way how they think about new technologies and so that new things would not be seen as risks and bad things.

*“It is well known that the companies in financial sector are highly conservative and we are no exception. We might as well be one of the worst ones and actually now that we are discussing this I really believe that we recruit only certain types of people who already suit our conservative culture.” (Interviewee 5)*

Even though regulation plays a big role in organization B’s sector and controls what they can do and how they can do their funding processes, there are still possibilities in bringing AI into their processes. As the interviewees mentioned earlier, the AI is not yet used amongst their competitors. At the same time, the regulation they face does not include anything AI specific yet. This was seen as an opportunity to become a forerunner in AI and this way the interviewees saw an opportunity where they could affect the regulation.

*“The regulation processes are very slow and as we saw for example in 2008 the regulation only caught up once something bad had already happened. In a way this creates a possibility with AI as there is a chicken and egg situation where we do not have any precedents yet from the Financial Supervisory Authority regarding AI. There could be an opportunity for us to make the first moves and be the one based on whose initiative re regulation would be built on” (Interviewee 4)*

#### 4.1.2.3 Technological readiness

Technological readiness in organization B is on a good level. This is due to the technological intensity that is characteristic of the industry. For companies in the financial sector to stay and be competitive they need to constantly look for ways to digitize and automate their operations and centralize their functions in order to save on costs. For this reason, organization B also has relatively high yearly investments in their IT software and hardware. Even though AI is not specifically mentioned in their strategy, they possess the required technological readiness in terms of IT infrastructure.

*“Well as we discussed earlier, the digitization applies strongly to our technical side as well and I know that we are constantly developing our IT. - - If we look at our competitors, we know that they are doing the exact same thing and thus investing in IT is a lifeline for us as well as it is for them” (Interviewee 4)*

*“The level of our IT infrastructure is decent, and we have a lot of good things in there. Of course, there are parts that are quite scattered at the moment and some things that are not quite finished yet but I really think that if and hopefully when we bring the AI into the picture it will finally unite the rest of the IT together.” (Interviewee 6)*

*“I know that we put quite a lot of effort and money into our IT and you can see in the day to day work life. I cannot say that I know a lot about our physical IT infrastructure as it is not part of my work. But what I can say is that the effort is there and there are certain software that I think are quite outdated but there are plans ongoing to make them better.” (Interviewee 5)*

In order to make their technological readiness even better and to ensure that it serves the organization in future, the role of strategy was highlighted again. Especially the IT expert underlined that even though the current level is good, there is a lot of work to be done. This is because in history there has been some mergers and acquisitions which have lead into a quite scattered IT infrastructure as each company has had their own IT infrastructure. Although most of the IT has already been combined and united, overlapping software and hardware still exists. Therefore, IT should be highlighted in the

strategy in order to ensure investment flow in the future to finish up the current IT infrastructure but also, as the expenses will likely increase when AI is included.

*“We need to make sure that the people on the upper floor (referring to management) knows our needs IT wise as it is them whose blessing we need for everything. If they do not know them, and do not provide us with the budgets needed in future it is useless to knock on the roof when it is already too late” (Interviewee 6)*

Another factor that was raised to improve their technological readiness was to increase their internal skills regarding AI. The finance specialist argued that when they are adopting Copilot or other AI tools, they would require an internal specialist who could support different teams in using it. Currently, as their IT development is outsourced, they are depending on external resources. The issue with the outsourced IT function is that they do not always have the required resources available. The IT expert for example told that they have been postponing a system update in one project just because they have been waiting for external resources. Therefore, internal AI specialists would be required in the future because external support can take its time and be quite expensive. The internal specialist could make the internal learning curve steeper, and cheaper.

*“I was discussing with our IT lead regarding a IT project I am part of, and we started talking about our Copilot project. He said that there is a slight problem with it as our IT partners are seemingly lacking AI resources to support us. We started thinking then that we should hire one or two Copilot experts or train them ourselves so that we can ensure internal support in the future and do not need to sit around and wait whether our IT partners are able to support us over their bigger clients” (Interviewee 5)*

All of the interviewees had a good general understanding about AI and also about which technologies would fall under the term AI. Especially the manager and the IT expert were able to differentiate robotics from more generative AI models. It was told to the interviewees that robotics are included in AI technologies as a subcategory in this thesis. The manager and IT expert both argued that it is more important for them to adopt those technologies that bring them the greatest value with the least effort, which in their case means robotics mostly. Furthermore, the IT expert argued that even though they do keep

it very important, that their future strategy is mentioning AI specifically, they do not see any reason to adopt AI just for the sake of having an AI model.

*“I do see that the difference between robotics and AI is that AI is able of drawing conclusions and produce answers that deviate from the script, whereas robotics are only capable of moving stuff from point A to point B. - - In our processes we are more keen of having quick wins with robotics in short run.” (Interviewee 6)*

*“The models that we are currently using are more based on robotics and machine learning rather than AI specifically... - - In that case (including robotics and ML as a sub-category for AI) we do use these AI technologies already quite broadly in other business segments.” (Interviewee 4)*

Organization B had just gone through an extensive data reform project where all of their old databases were combined into one. This reform project was seen to significantly increase their AI readiness as now all of the data was in usable format in one single location. However, they had at the same time faced an issue, as the new data was operated in a different way than the old ones. Hence, they faced a significant lack of internal talent who were skilled enough to make more complex data queries from the new database. The IT expert argued that they would quickly need to find one or two skilled data analysts that had specific skills with the new database they had started using. Therefore, even though the technological data readiness improved significantly, the relation of data to people was at the same time decreasing.

*“The data transition has improved our data readiness significantly, but you need to find the right people to get the data queries from the system. - - If I wanted to get a certain set of data into reporting at the moment, it would not be done within a year. So, in other words we do have the wood and the tools in the workshop, but the carpenter is still missing and thus we are not making any chairs at the moment” (Interviewee 6)*

The data that organization B needs for their AI adoption has already been collected. Their processes were designed so that all of the data produced by the process was saved in the database. However, even though the data is being collected, it is not complete. The manager told that even though they have processes mapped and documented, and they

have created process guidelines, they are not being followed in every instance. This is mostly because different people are accustomed to doing the processes in their own way. This has not created issues before because everything has been done according to the guidelines, but now that they have gone through the data for the AI adoption, they have seen that there are pieces missing and the data is not homogenous. However, they did not see that streamlining the process from the data perspective would not cause a lot of trouble because they could easily just change the process guidelines and requirements.

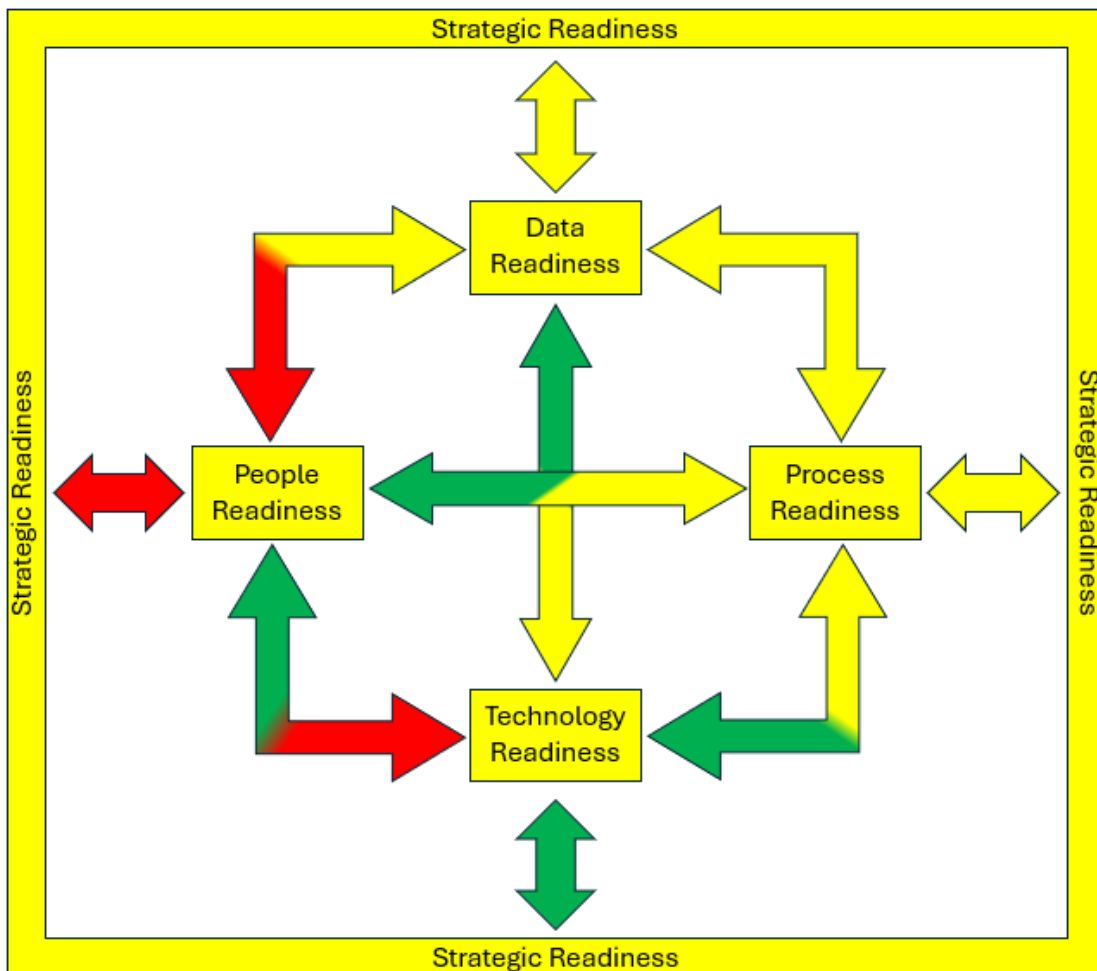
*“Overall, we are collecting a lot of data house wide, but we are still missing pieces from the puzzle if we think of using it to train some AI model. - - We do of course document everything we do regarding our customers as it is mostly obligatory for us, but if had to pull all of this data into one place and use some parameters to go it through you would not find the same things from the same places” (Interviewee 4)*

*“Well changing our processes data wise is super simple – just do the changes in the documentation and tell the people who are the next step in the process to start declining the inputs of the previous people in the process if something is not according to the process documentation. That is exactly how it has been done before in such situations. ” (Interviewee 6)*

Finally, when discussing data security, IT did not see any increase in the risk of data loss when adopting AI into their system. The main argument was that as long as the AI operates only in a safe internal environment and has only such connections to the internet that their current systems already has, there are no increased risks in data security. All of the data is already in their system so if someone is able to breach their IT system they will have access to their data whether they have AI or not. The manager said that they are not able to comment on this, but the finance specialist had similar views with the IT. The finance specialist also added that the AI that they really need is really only operating internally with internal data. In addition, the data security concerns that people within their organization have is mostly relevant for using external tools such as Gemini or ChatGPT. They think that people easily mix up things when talking about AI because their view of AI is built around OpenAI and ChatGPT because they are highly visible in media and many people sees ChatGPT as an equivalent for the concept of AI.

*"I do not see any added security risks or threats with out internal AI. I think that some unaware person can do much more harm for us by using Google Chrome browser than by someone who is trained to use their internal AI tools." (Interviewee 6)*

*"I find this data security discussion quite amusing because I just do not get it why our data that we already have in our system would be under any more threats with or without AI that just operates internally. I feel that the media has got people mixing the term AI with OpenAI and especially ChatGPT. Some of my colleagues refer AI overall with ChatGPT or other LLM's they are using." (Interviewee 5)*



**Figure 10 AI Adoption Readiness in Organization B**

| Dimension                             | Organization B | Key Findings                 | Effects on adoption  |
|---------------------------------------|----------------|------------------------------|--|
| Strategy $\leftrightarrow$ People     | Weak           | Lack of training             | Without having any training in place successful AI adoption is unlikely      |
| Strategy $\leftrightarrow$ Process    | Intermediate   | Regulation                   | Strict regulations is a driver for change but can cause design issues        |
| Strategy $\leftrightarrow$ Data       | Intermediate   | Lack of skilled employees    | Current data infrastructure is not easily usable which could affect adoption |
| Strategy $\leftrightarrow$ Technology | Good           | Nature of industry           | Industry requires IT intensity to remain competitive                         |
| People $\rightarrow$ Process          | Intermediate   | Change resistance            | Fear of losing jobs causes change resistance which could affect adoption     |
| People $\rightarrow$ Data             | Intermediate   | Data handling                | Lack of understanding the relevance of data weakens the data                 |
| People $\rightarrow$ Technology       | Weak           | Lack of training             | Lack of internal talent and resources can prolong the AI adoption project    |
| Process $\rightarrow$ People          | Good           | Process knowledge            | Subject matter experts for each process enhances AI process design           |
| Process $\rightarrow$ Data            | Intermediate   | Heterogenous input           | Heterogenous data input can compromise AI outputs                            |
| Process $\rightarrow$ Technology      | Good           | Sufficient IT infrastructure | IT infrastructure is sufficient for planned AI enhanced processes            |
| Technology $\rightarrow$ People       | Good           | Sufficient IT infrastructure | IT infrastructure is sufficient to support people's requirements             |
| Technology $\rightarrow$ Process      | Intermediate   | Resource issue               | Lacking IT personnel resources can prolong the AI adoption project           |
| Technology $\rightarrow$ Data         | Good           | Sufficient IT infrastructure | IT infrastructure is capable of storing and processing data as required      |
| Data $\rightarrow$ People             | Weak           | Lack of training             | Lack of understanding the importance of data weakens the data readiness      |
| Data $\rightarrow$ Process            | Intermediate   | Data maintenance             | Current processes does not support data maintenance                          |
| Data $\rightarrow$ Technology         | Intermediate   | Data readiness               | Overall lack in data readiness can compromise AI outputs                     |

**Table 4 Breakdown of Readiness Factors in Organization A**

## 4.2 Cross-case analysis

In this section the two cases are being cross analyzed in the light of AI readiness literature with the framework. Each theme is discussed separately and in the same order as they were in the interviews. The cross-case analysis starts from the strategic readiness after which it moves to organizational readiness and finally to technological readiness. This gives an overall view of what different aspects are affecting an organization's readiness to adopt AI and what measures can be taken to improve different AI readiness factors.

### 4.2.1 Strategic readiness

The relevance of strategy for AI adoption readiness was recognized by both of the case organizations. Both organizations noted benefits from having clear digital strategy in place that incorporates AI in it, but they had different reasons. For organization A it was due to the corporate culture and siloing thus linking it more to organizational readiness factors. Whereas for organization B, it was due to competition and securing sufficient resources for development linking it more to technological readiness. Similar reasons are pointed out by Fornasiero et. al (2024), as they argue that the strategy is needed to support the AI adoption along the way as the lack of relevant strategy will wither unorganized attempts of AI adoption. However, theory around the topic does not specifically mention siloing as an issue but rather discusses culture in terms of people readiness and how people are accepting changes and are innovative (e.g. Fornasiero et al., 2024; Jöhnk et al., 2021; Tehrani et al., 2024; Weiner, 2009). As shown in organization A's case, especially in larger organizations, siloing could significantly hinder the success of AI adoption. Thus organizations should consider different stakeholders during AI adoption and use it as a chance to fix also underlying organizational issues.

The business criticality of AI was viewed differently between the case organizations. The interviewees from organization A seemed more comfortable with their lack of specified

and clearly communicated AI strategy. This was due to the stronger presence of AI in their day-to-day activities and internal communications that gave references to the existence of an AI related strategy even though it was not clearly communicated. Meanwhile in organizations B the interviewees seemed more stressed about their lack of clear strategy incorporating technology and AI. However, it is important to note that the strategy period in organization B was ending, and their new strategy was under development, and they were unable to share anything related to the new strategy. Yet, in their current organization-wide strategy, there was only a few references to strategic AI activities. For example, they had recently appointed Head of AI to their organization as a completely new position. Especially their IT seemed the most concerned about the lack of clearly communicated AI strategy, when comparing their organization to their competitors. Communication is a key to establishing AI readiness in organizations. Without clear communication of the strategy and goal setting the probabilities of successful AI adoption are decreased significantly (Frick et al., 2021). Thus, this lowered the strategic readiness for organizations B more in comparison to organization A, in relation to other readiness factors.

One clear cultural difference between the case organizations was that in organization A the interviewees seemed more proactive with AI and believed they could take initiative in bringing in new AI solutions. They also gave the impression that it is more on them to be on the lookout for new AI solutions and best practices. Whereas in organization B the interviewees seemed more passive and waited for the management's guidelines with the new overall business strategy that was under development. However, as the sample was limited in size this cannot be generalized. Organizations need to be able to foster a culture that embraces the possibilities of AI and promotes the importance of knowing how to use the AI to make the best of it (Tehrani et al., 2024; Weiner, 2009). To assure a more accepting culture, and to fulfill the information need of people, this will require very decisive and transparent communication throughout the adoption process to ensure that people understand the benefits of the new technology (Jöhnk et al., 2021). This is also why the strategic readiness in organization B was seen to be on a lower level.

#### 4.2.2 Organizational readiness

Both of the case organizations still had a strong remote working culture due to the aftermath of the COVID pandemic. In addition, both organizations operate in intensive technology industries which also increases the technological insensitivity of their employees. This was thought to establish the basic readiness level in terms of people and processes for both organizations. Yet, an important issue related to people's readiness that was brought up by the interviewees was that different depths of knowledge is needed by different stakeholders in AI adoption. Both organizations pointed out that decision makers need to possess more theoretical information regarding the solution and technology itself whereas the experts need more practical skills and knowledge. IT department was brought up as a department requiring both practical and theoretical skills and knowledge. This is an important point considering to the complexity of the AI as technology. Previous studies have shown that lacking knowledge regarding the technology being adopted can lead to misalignments with the needs when making adoption decisions (Alet, 2023; Holmström & Hällgren, 2022). In order to increase their AI skills, both organizations pointed out the need of super users who would support and teach the use of AI during and after the adoption. This was though also to upkeep the AI skills.

People as a readiness factor was the greatest difference between the case organizations. The most important way to increase the people readiness level according to both organizations was thought to be training. However, as both organizations lacked a clear strategy or it was not efficiently communicated, also the training options were lacking in both cases. Training is one of the easiest and most effective ways to prepare employees for organizational IT change such as adoption a new AI model (Jöhnk et al., 2021). However, as can be seen from the organization A, having the trainings available is not enough as their importance and availability needs to be also communicated to employees to increase the AI readiness (Frick et al., 2021). In organization B's situation there were no AI related training available. This situation applied throughout the organization as IT department was not offered training options either. This was considered to lower their

people's readiness factors in relation to strategy, data and technology especially. Strategy did not support the AI adoption for organization B at all. In data readiness perspective as people are not being trained about AI, they cannot be aware of the importance of data related to AI solutions. Finally for the people readiness from a technological perspective, as there is an overall lack of AI knowledge, successful AI adoption would be unlikely. Furthermore, as organization B outsourced most of their IT functions, the lack of resources from their IT partner also lowered their people's readiness. This caused an asymmetric relationship between people and technology as technology infrastructure was considered to be able to support AI adoption but where people were seen unable to implement the chosen AI solution. When compared to organization A, they did not have as clear asymmetric relationships between readiness areas. Their currently available training and internal IT function caused the biggest differences in their current readiness level in people perspective.

From process readiness perspective, the organizations were different. Where organization B faced a lot of heavily regulated processes, but also processes that were created due to regulation, organization A had more flexible processes. When an organization has more freedom in their processes and the processes are more abstract, they are easier to adapt for the needs of AI adoption (Frick et al., 2021; Holmström, 2022). Whereas more regulated processes are stiffer and not as easily configured. Yet, it can be that more abstract processes require much more complex AI solutions to aid the people to execute these processes. Meanwhile, more controlled and regulated processes can be fully automated in some situations. All in all, both of the organizations had considered their core value creating processes and they were considered to be suitable to be operated together with AI. This is considered to be the cornerstone of AI related process readiness (Holmström, 2022; Uren & Edwards, 2023). Even though their processes differed, both organizations had thought about the possibilities of either altering their processes or the AI solution for better fit.

### 4.2.3 Technological readiness

Both of the case organizations operated in industries that required technology insensitivity from them, and this was also reflected in their good technological readiness. Both organizations had good IT infrastructure established, and they saw their current infrastructure as a commodity allowing them to stay competitive in their relative markets. As the theory suggested, previous technologies tend to transition to so called commodity technologies even if they have once been strategic resources for organizations (Mendes et al., 2024). Therefore, it is important to note that the applied framework is time sensitive and current readiness levels only apply for the moment when the analysis was made. Thus, current readiness levels do not guarantee good readiness in future if the AI evolves in the current phase. One outcome can be that current simple AI innovations can quickly transition into commodity technologies in the future. Aligning with literature either of the case organizations saw that AI would increase their cyber security risks. Both organizations argued that including AI into their closed systems does not threaten their cyber security levels if the people involved in adoption are skilled enough and if the data protocols are in place.

During the interviews all of the interviewees outside the IT department repeatedly referred to AI as a technology with terms “Chat GPT” and “OpenAI”. One of the interviewees also stated that AI as a technology was developed and launched somewhere during the COVID pandemic. This supports the theoretical finding that organizational units, especially outside the IT unit, has limited knowledge about AI as a technology which causes distortion between the actual solution and their idea about the solution (Afjal, 2023). However, apart from the theory, the interviewees seemed to be quite realistic with their expectations towards AI and how their organizations would benefit from it. In the theory it was argued that the fast development phase of AI have created unrealistic expectations around AI (Vinsel, 2023). However, as the sample was small it is not enough to deny this argument but shows that it might not apply to every case.

From a data perspective, both organizations had changes to their data infrastructure. In Organization A they were undergoing a data reform project in order to combine their current data platforms into one location. Similarly, organization B had already gone through this transition and had implemented their one data platform principle already. In both cases, this was considered to increase their data readiness. These reforms made it possible to store and process the data in one place. For AI data readiness, the usefulness of data culminates in an organization's ability to collect, store, and process data (Kalinaki et al., 2024).

However, the sufficient data infrastructure to process and store data is not enough as the data as a readiness is affected by influence patterns. In organization B's situation the lack of AI relevant training for employees and weaker control over process data quality affected their overall data readiness. These factors led to a situation where their current data readiness was seen to possibly compromise their AI output in future. The data needs to be high in quality and there needs to be enough of it for the chosen purpose (Jöhnk et al., 2021). This is, because the usefulness of data is not measured by the quantity or quality alone, but rather by its ability to produce insights for organizations (Kalinaki et al., 2024). These aspects were not completely met in organization B whereas for organization A these aspects were already considered. It is important to note also that the nature of work supported organizations A in the data readiness aspect.

## 5 Discussion

The purpose of this thesis was to study organizations' readiness factors for the strategic adoption of artificial intelligence. This study began by exploring the relationship between strategy and technology adoption through the existing view of digital strategy literature and emerging literature on AI strategies. An organization that is engaging in AI adoption needs to have a strategy in place so that the adoption supports their current strategy and strategic goals (Mendes et al., 2024; Sting et al., 2024; Tehrani et al., 2024). This view got support during the interviews as both case organizations recognized strategy's importance in their AI adoption. Furthermore, depending on the complexity of the AI solution the strategy should consider required readiness in decision making process (Lokuge et al., 2019; Sting et al., 2024; Sun et al., 2024). Especially in case organization A this was recognized, as in larger organizations siloing was seen to cause overlapping in AI solutions. Then, the role of AI knowledge for successful adoption was examined. The overall complexity of AI as a technology requires decision makers to understand also the technological aspects of AI in order to have realistic expectations for the adoption process (Holmström, 2022; Jöhnk et al., 2021). This also got support from both case organizations. Due to this complexity, AI cannot be approached in the same way as previous major new technologies but rather requires more preparation (Duan et al., 2019; Jöhnk et al., 2021).

The study then moved to explore new technology adoption and how different readiness factors need to be considered in AI adoption. The people, process, technology and data model by Uren & Edwards (2023) was presented. This model visualizes the four main factors of AI readiness and their relationship, which applies to every organization. However, after reviewing more topic in the literature it was concluded that the model does not consider strategy as a readiness factor. Digital strategy literature has examined the role of strategy in relevance of adopting new technologies into organization as has shown that strategy has a central role in forming readiness (e.g. Rêgo et al., 2022;

Tehrani et al., 2024; Zhou et al., 2024). Strategy is also presented as a capability in maturity models that examine technology development over time in organizations, as presented by Fornasiero et. al (2024). Based on reviewed literature, strategy was added into the theoretical framework presented in the literature review. By using the framework, organizations' current level of AI readiness could be analyzed thoroughly. This addition was found meaningful during the case analysis as unclear strategy was found to affect the other areas of readiness in both case organizations.

It was found out that both case organizations had similar views regarding organizational and technological readiness factors. They shared a lot of similarities in terms of readiness factors and had similar views on how to develop their readiness even though the case organizations naturally differed from each other. Supporting the literature, both organizations held strategy in high value as a readiness factor and saw it as a key factor in supporting other areas of readiness. Neither of these organizations had an AI included deliberately in their current strategy but agreed that it should be included to increase their AI readiness. The reasons pointed out were different, as the other organization was concerned about their internal alignment with AI solutions and the other organization was concerned about competition. Both of these factors were also found out during the literature review as AI has been recognized as a source of competitive advantage (Mendes et al., 2024) but also that internal alignment is imperative for successful AI adoption (Sun et al., 2024). In addition to having an AI strategy in place, efficient strategy communication and culture supporting innovation was also raised as important factors by both case organizations. Without efficient communication people are unlikely to be motivated throughout the adoption process if they do not understand the benefits of the AI solution (Frick et al., 2021).

AI relevant skills and knowledge was found to be the center of people's readiness. Both organizations saw that training was the most cost-effective way to increase their people's readiness. However, in the case of organizations the training was not yet established yet or the existing training was not communicated to employees. The shortcomings in

offering sufficient AI training was found to be connected to the lack of AI in their strategy and significantly lower their AI readiness in literature reviews as well (e.g. Jöhnk et al., 2021). Another way to increase people's AI readiness was by training super users for the AI solutions across the organization to develop and upkeep the AI skills which was bot clearly found out during the literature review. Finally, the depth of AI knowledge was found to be meaningful especially for decision makers. Both case organizations argued that decision makers need to also understand AI as a technology to a certain extent so that they can make correct adoption decisions that align with their readiness.

From the process readiness perspective, the cases differed more, as they operated in different industries. This offered insight into how the nature of different industries affect the process of readiness. Still, both case organizations considered their processes suitable for AI adoption. Cross analysis of these cases indicates that organizations facing more regulation can have harder time in adapting their processes for AI whereas more abstract processes are more easily adapted to be operated with AI. However, abstract processes might require more sophisticated AI solutions that could increase the readiness requirements on other factors (Mendes et al., 2024).

Technological readiness was found to be well established in both cases. The technological infrastructure for the case organizations was seen more as a commodity, keeping them competitive on the markets. As shown in literature reviews, legacy technologies act as a basis for AI solutions and for older and larger organizations the technology basis is an essential for being on moder markets (Ali et al., 2022; Lokuge et al., 2019; Sting et al., 2024). However, the relevance of data infrastructure was seen as more important. Both organizations were going through a data platform transfer aiming to create one data platform. This was seen essential for AI readiness as the data needs to be collected, stored and processed in one place. Otherwise, poor data readiness would compromise AI's output. The relevance of data for AI solutions is widely recognized in the literature (e.g. Kalinaki et al., 2024; Ojanperä, 2023; Uren & Edwards, 2023). Yet, having data and IT infrastructure is not enough as data readiness is heavily influenced by the readiness

of processes that store and operate the data, but also by people's readiness to work with the data. This is, because the usefulness of data is not measured by the quantity or quality alone, but rather by its ability to produce insights for organizations (Kalinaki et al., 2024). In data security perspective, aligning with literature, neither organizations saw increased risks in applying AI as their data protocols were in place and AI that operates in internal environment does not differ from their current protocols.

### **5.1 Theoretical contributions**

This thesis expands the research on strategic AI adoption and AI readiness by combining these two aspects. As the research on these topics is only establishing the combination of these research areas reveals their interconnectedness. This study confirms the importance of analyzing organization's readiness for AI adoption and expands the research area to include strategy's importance in supporting the overall readiness. This theoretical contribution is culminating in the framework that was used to analyze the case organizations AI readiness. This framework can be used in future studies in analyzing organizations' AI readiness and can be further developed as a ready model.

### **5.2 Managerial contributions**

This thesis offers several managerial contributions to consider. Most importantly it offers a view on how the AI readiness is established, developed and analyzed in two large Finnish organizations. The framework and analysis can be used by decision makers to assess their own organization's current AI readiness level. Furthermore, it offers insight into decision makers on how AI adoption should be approached and what needs to be considered.

When deciding on adoption of AI, decision makers should consider their strategy and how the AI model that they are aiming to adopt supports their strategy. They need to make sure that they have the required knowledge to understand the technology that they want to adopt. This technology should support their long-term goals and the organization's AI readiness should align with the technology's requirements. To ensure this, they need to then apply the framework to their organization in order to confirm that their current readiness level either support the adoption as it is, or that they recognize the development areas. When deploying this framework, different organizational levels should be included in the analysis. This is, because managers, IT department and expert level have different views on different readiness levels.

This way the organization can be sure that they have a realistic view on their readiness and that they have a transparent and realistic view on their current readiness level. Only then can they realistically set goals for adoption and increase their chance of achieving their set goals for adoption. By recognizing the development areas of their readiness, managers are able to prioritize their investments to develop their readiness. Thus, they avoid wasting resources on pointless adoption projects that are too early for their readiness, and are able to improve those readiness areas needing development. Additionally, this also improves risk management in organizations as better assessment of AI readiness lowers the risk of unsuccessful adoption projects. In other words, the ROI is increased as the risk of failing adoption and mismatched requirements is lowered.

### **5.3 Limitations and suggestions for future research**

This thesis focuses on analyzing organizations' readiness levels statically thus presenting their readiness by the time of the analysis. It is highly likely that the readiness factors are changing over time within the organization, and they will gain different weighting during the adoption depending on the technology being adopted. One suggestion for future research would be to review the presented framework and adapt a new version that could examine the readiness factors over time during the adoption dynamically. In

addition, as this thesis does not examine the adoption process over time, or focus on the process steps specifically, this perspective could generate different findings and through them it would be possible to find which readiness factors to underline in different stages of the process. Thus, one avenue for future research is to examine empirically which readiness factors are highlighted in different stages of the adoption process.

Another limitation is the relatively small sample size of interviewees per organization compared to the size of the organizations. This makes broader and more detailed organization wide assessment impossible. Including more interviewees per organization from different organizational levels could generate more points of view for AI readiness and produce more insights for the organization. Thus, the insight per case is relatively small, even though different organizational levels were considered, and several interviews were done per organization. Future research could use the framework to analyze one organization thoroughly by including several interviewees from different organizational levels and from different departments to see if the insights are different with larger sample size.

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## Appendices

### Semi structured interview

#### Background information

- Background information about the interviewee
  - Tell me about your role in the organization and your professional history.
- Knowledge and experience about AI
  - How do you understand AI as a technology?
  - Has your organization adopted/planning to adopt AI?

#### Strategic Readiness

- Tell me about your current organizational strategy.
  - How is/should technology/AI included in it? Why?
- What are your organization's short-term and long-term goals for AI adoption?
- How do you see your organizations strategy in relation to AI adoption?

#### Organizational readiness

- People readiness
  - How would you describe your organization's people's readiness for AI adoption?
  - Should different parties be involved and considered in adoption of AI?
  - How is your organization developing readiness factors in this area?
  - Describe how people's readiness should be developed.
- Process readiness
  - Describe the process that is/will be enhanced with AI.
  - How would you describe your organization's processes' readiness for AI adoption?
  - How do you think that your organization's personnel perceive possible process change?
  - How do you think an organization should address the process readiness?

#### Technological readiness

- Technology readiness
  - How do you view your organization's technological readiness for the AI adoption?
    - ...people wise?
    - ...process wise
  - How will the AI adoption affect your IT architecture?
  - What new technologies are presented?
  - How is your organization developing readiness factors on this area?
- **Data readiness**
  - How do you see your organization's data readiness regarding the AI adoption?
    - ...people wise?
    - ...process wise?
    - ...technology wise?
  - Could you describe the data sensitivity of the AI solution?
  - How is the data governance taken care of?
  - How is your organization developing readiness factors on this area?