

Vegard Ressem

Implementing AI in Organizations: The Role of Leaders and Its Impact on Leadership

Master's thesis in Economics and Business Administration

Supervisor: Daniel Casoinic

May 2023

Vegard Ressem

Implementing AI in Organizations: The Role of Leaders and Its Impact on Leadership

Master's thesis in Economics and Business Administration
Supervisor: Daniel Casoinic
May 2023

Norwegian University of Science and Technology
Faculty of Economics and Management
NTNU Business School



Abstract

Artificial intelligence (AI) is predicted to cause a technological revolution and impact organizations and society in ways which are not yet fully known. The implementation of AI in organizations is important because it is thought to offer increased productivity and efficiency.

This study aimed to investigate the implementation of AI in organizations and the role of leaders in this process, and how implementation of AI impacts the role of leadership itself. Organizational capabilities and leadership competencies needed for successful implementation were investigated. Through a qualitative research method, five leaders of large Norwegian organizations were interviewed, and the empirical data was supplemented with a secondary data source.

The findings present how AI is implemented in organizations and why. This research highlights what AI contributes to in organizations and found that tasks are augmented in practice. The analysis revealed several skills that leaders need in facilitating successful implementation of AI, namely the understanding of change, having a general understanding of AI technology, and to see possibilities with implementation of AI to create business value. The role of leaders in implementing AI is to drive change, and the thesis suggest that an authentic-transformational leadership approach is advantageous for dealing with AI in organizations. The analysis revealed the attitudes of leaders toward AI technology and challenges that follow implementation. Ethical considerations, bias in data and difficulty in trusting AI are found to be challenging but does not hinder the experimentation and implementation of AI in organizations.

The study sought to investigate a proposed research model derived from the literature. Based on this study's empirical findings, the AI capabilities of the organization needed for successful implementation were identified as IT personnel, knowledge of AI technology across the organization, ability to adapt, quality data, AI trainers, and in-house development. In the model, the role of leaders is suggested as facilitators of change, being the link between AI capabilities and successful implementation.

In conclusion, theoretical and practical implications are discussed, as well as limitations of the study and suggestions for further research.

Sammendrag

Kunstig intelligens (AI) er forventet å skape en ny teknologisk revolusjon og påvirke organisasjoner og samfunnet på måter som til dels er foreløpig ukjent. Implementering av AI i organisasjoner er viktig fordi det er forventet å skape økt produktivitet og effektivitet.

Denne studien tok sikte på å undersøke implementering av AI i organisasjoner og rollen ledelse spiller i denne prosessen, samtidig som å undersøke hvilken påvirkning implementering av AI har på ledelse selv. Organisatoriske kapabiliteter og ledelseskompetanse som behøves for vellykket implementering ble undersøkt. Gjennom en kvalitativ forskningsmetode, ble fem ledere fra store, norske organisasjoner intervjuet. Den empiriske dataen inkluderte også en sekundær datakilde som supplement.

Funnene i undersøkelsen viser hvordan AI er implementert i organisasjoner og hvorfor. Undersøkelsen belyser hva AI bidrar til i organisasjoner og fant at oppgaver er augmentert i praksis. Analysen avdekket flere ferdigheter som ledere trenger for å tilrettelegge vellykket implementering av AI, nærmere bestemt forståelse av endring, generell forståelse av AI teknologi og evnen til å se muligheter med implementering av AI for å skape verdi. Rollen ledere har i implementering av AI er å drive endringsprosessen, og studien foreslår at en autentisk-transformell ledelsestilnærming er fordelaktig for å drive med AI i organisasjoner. Analysen avdekket holdningen ledere har til AI og utfordringene som følger implementering. Ethiske betraktninger, bias i data og vanskeligheter med å stole på AI ble funnet som utfordrende, men hindrer ikke eksperimentering og implementering av AI i organisasjoner.

Studien etterstrebet å undersøke en foreslått forskningsmodell basert på litteraturen. Basert på funnene i studien, er AI kapabilitetene som organisasjoner trenger for vellykket implementering identifisert som IT-folk, forståelse av AI-teknologi på tvers av organisasjonen, evnen til å tilpasse seg, kvalitetsdata, trenere av AI og utvikling av AI internt. I modellen er rollen til ledere foreslått som tilretteleggere av endring, og er lenken mellom AI kapabiliteter og vellykket implementering.

Avslutningsvis er teoretiske og praktiske implikasjoner diskutert, i tillegg til begrensinger av studien og forslag til videre forskning.

Foreword

The interest in AI in an organizational and leadership context sparked during my Experts in Teamwork (EiT) course at NTNU. Although this course was about explainable artificial intelligence (XAI), it made me think of how I could research AI for my masters' thesis. I want to thank everyone that has supported me during the process of writing this thesis, especially my supervisor Daniel Casoinic, who has given me thorough critique, encouragement, and support all the way from start to finish. I also want to thank the participants that took part in this study, and everyone that helped me reach these participants. It would not have been possible without you.

Vegard Ressem

Trondheim, Mai 2023

Table of contents

Abstract	1
Sammendrag	2
Foreword	3
Table of contents	4
1. Introduction	1
1.1 Structure	2
2. Literature review	3
2.1 Artificial Intelligence	3
2.1.1 Definition of AI	3
2.1.2 Typology of AI	4
2.1.3 Responsible and Tustworthy AI	5
2.2 Implementation of AI in Organizations	6
2.2.1 The role of AI in organizations	6
2.2.2 Automation and augmentation	8
2.3 Leaders and their role as facilitators of AI implementation	10
2.3.1 Definition of leadership and the role of leaders and managers in AI	10
2.3.2 Leaders as agents of change	12
2.3.3 The Leadership Approach in Relation to AI	13
2.4 Leadership competencies: The skills and attitudes of leaders	15
2.4.1 The skills leaders need for successful implementation of AI	15
2.4.2 Leaders' attitudes toward AI	18
2.5 The AI capabilities of the organization	20
2.5.1 The resource-based view and dynamic capabilities	20
2.5.2 AI capabilities	21
2.6 Summary and research model	23
3. Methodology	24
3.1 Scientific framework	24
3.2 Research design and methodological choice	25
3.2.1 Research strategy	26
3.3 Data collection	27
3.3.1 Sampling and recruitment of participants	27
3.3.2 Data collection method	29
3.3.3 Interview procedure	31

3.3.4 Secondary data	32
3.4 Data analysis.....	32
3.5 Reliability, Validity and Generalizability.....	35
3.5.1 Reliability	35
3.5.2 Validity	36
3.5.3 Generalizability	36
3.6 Ethical considerations.....	37
4. Findings and Discussion.....	38
4.1 How AI is implemented in the organization and why	38
4.1.1 Leaders' definition of AI.....	38
4.1.2 Why organizations are implementing AI.....	40
4.1.3 How organizations are implementing AI: automation or augmentation	42
4.1.4 Limitations to implementing AI	46
4.2 The role of leaders in implementing AI and how AI impacts leadership.....	47
4.2.1 The current impact of AI on leadership	48
4.2.2 The future impact of AI on leadership.....	48
4.2.4 The role of leadership in implementing AI	50
4.2.5 Leadership approaches for implementing AI	51
4.3 The organizational capabilities and leadership competencies needed for successful implementation of AI	52
4.3.1 Organizational capabilities	54
4.3.2 Leadership competencies needed for successful implementation of AI.....	56
4.3.3 Understanding ethical and trustworthy AI.....	59
5. Conclusion.....	62
5.1 Summary and theoretical implications	62
5.2 Theoretical implications	64
5.3 Practical implications	65
5.2.1 General technological understanding and knowledge of strategic implementation	65
5.2.2 Focus on data.....	65
5.2.3 Focus on interpersonal skills when AI enters the workplace	65
5.2.4 Understand change and change leadership.....	66
5.4 Limitations of this study.....	66
5.5 Future research	66
References	68
Appendix	82
Appendix A: Mind-map of themes and sub-themes from the thematic analysis.....	82

Appendix B: Approval from NSD.....	83
Appendix C: Information and form of consent	84
Appendix D: Interview guide English.....	86
Appendix E: Interview guide Norwegian.....	89

1. Introduction

Technological development is constantly transforming the environment in which organizations operate. Artificial intelligence (AI) is the latest set of technologies and is predicted to cause a new “industrial revolution” which will change the way organizations and people work (Titareva, 2021). AI is a set of technologies which supports human intelligence by understanding, learning, and acting on the basis of data, and does so with minimal human intervention (Kolbjørnsrud, 2017; Wijayati et al., 2022). AI as a research discipline dates back several decades, but practical AI applications as we know them today emerged in the early 2000s (Peeters et al., 2020). AI is increasingly implemented in the workplace today, mostly supporting automated tasks and analyzing big datasets, but it can also assist in more complex tasks, and even more so in the future (Kolbjørnsrud, 2017; Petrat, 2021; Kolbjørnsrud & Sannes, 2022). A consequence of increased use of AI may be a change in the human aspect of business. When machines take up more space in the workplace, the relational aspect of leadership arguably becomes more important (Kolbjørnsrud, 2017; Mikalef et al., 2019a).

Artificial intelligence is predicted to drastically change how organizations do business, and leaders and managers will face a new set of challenges (Anagnostou et al., 2022; Peifer et al., 2022). Implementing AI systems in the workplace requires leaders to have some understanding of how the technology works but also how it changes the way leadership is done (Wijayati et al., 2022). AI is already implemented in banking, finance, real estate development, the automotive and logistics industries, and several other sectors (Peeters, 2020; Kolbjørnsrud & Sannes, 2022; Wijayati et al. 2022). Currently, the literature on this topic is limited and it is necessary with more insight into implementation of AI, and the relationship between AI and leadership (Mikalef et al., 2019A; Tsai et al., 2022). Thus, the aim for this thesis is to explore how AI is implemented in organizations and the role of leadership in this new environment. This has resulted in the following central research question:

How do leaders implement and work with AI in organizations?

Following the central research question, three research questions (RQ) emerged:

1. How is AI implemented in organizations and why?
2. What is the role of leaders in implementing AI, and how does AI impact leadership?
3. What organizational capabilities and leadership competencies are needed for successful implementation of AI?

1.1 Structure

With the topic, research question, and sub-questions presented in the introduction, Chapter 2 presents the theoretical framework for this thesis. After reviewing the literature and presenting the theoretical framework, Chapter 3 describes the methodological choices made. Chapter 4 explores the empirical findings for this thesis, and discusses these in relation to the literature. Chapter 5 concludes the findings of the research project, presents theoretical and practical implications, and closes with limitations of the study and suggestions for further research.

2. Literature review

This chapter presents the critical review of the relevant literature used in this thesis. The chapter is structured around different concepts which are defined and reviewed. The key concepts are Artificial intelligence, implementation of AI in organizations, leaders and their roles as facilitators of AI implementation, the leadership competencies in relation to AI, and the AI capabilities of the organization. The chapter is concluded with a summary and the theoretical framework for this thesis.

2.1 Artificial Intelligence

This section will first define AI, then examine the different types and typology of AI. Finally, responsible and trustworthy AI in organizations is explored.

2.1.1 Definition of AI

Artificial intelligence (AI) has been a hot topic the last couple of years and has certainly faced controversy with the debate concerning how it will replace millions of jobs and outperform humans in complex tasks (Arrieta et al., 2020; Willcocks, 2020; Titareva, 2021). The development of AI technology can be understood as an extension of the digitalization that has been known over the last decades (Peifer et al., 2022). However, AI arguably holds more challenges to implementation and use than previous technologies (Frick et al. 2021; Petersson et al., 2022). There are multiple ways to define AI, but for the purpose of this thesis AI can be defined as a set of technologies which supports human intelligence by understanding, learning, and acting on the basis of data, and does so with minimal human intervention (Kolbjørnsrud, 2017; Wijayati et al., 2022). AI has also been defined as disruptive technologies that affects management and leadership (Titareva, 2021). This second definition implies that AI changes how organizations and leaders understand leadership and is important in this thesis to highlight this phenomenon. Although the definitions are broad, it covers most aspects of what makes AI different from other technologies. Further in-depth analysis of what AI entails will follow in this chapter.

The way AI technology is perceived and understood can impact the way it's incorporated in the workplace, and in society as a whole. According to Peeters et al. (2020), how AI is understood can be divided into three general perspectives: the technology-centric perspective, the human-centric perspective, and the collective intelligence perspective. The AI systems

that are applied in industry today are not able to supersede human intelligence, but still performs some tasks better than humans (Peifer et al., 2022). Because of this, the thesis uses the third perspective, the collective intelligence perspective, where human intelligence and AI are both limited. True intelligence can only be found in the collective intelligence of AI and humans, which emerges when these entities collaborate over longer periods of time. Enabling a collective intelligence perspective should still be careful not to overestimate the knowledge or capabilities of one entity, relying too much on the other (Peeters et al., 2020).

2.1.2 Typology of AI

AI can be divided into further categories, depending on the complexity of the technology. This is represented in Figure 1. The first category, machine learning, is training an algorithm on existing data sets, where an artificial neural network identifies patterns in the data and make predictions based on them (Petrat, 2021; Peifer et al., 2022). The difference between this and traditional algorithms is that machine learning can develop new algorithms based on the data to solve problems and make decisions (Kolbjørnsrud & Sannes, 2022).

The next category within AI is deep learning, a type of machine learning that uses neural networks of high complexity and mimics the way the human brain works. Deep learning systems are further differentiated by how they learn, be it supervised, unsupervised or reinforcement learning (Peifer et al., 2022). Often these neural networks become so complex, with millions of parameters, so that it's impossible for humans to gain full insight into the operations of the AI system and becomes so called "black-box models" (Arrieta, 2020).

Another way to distinguish these technologies is by referring to weak and strong AI. Weak AI is algorithms targeted at a specific problem with fixed boundaries, while strong AI refers to systems that mimic the human brain (Pennachin & Goertzel, 2007). A critique of these definitions of AI is that there's no clear divide between the different typologies and no unified area of research. Furthermore, AI that attempt to mimic the human brain are questionable since we do not even understand the human brain fully (Petrat, 2021).

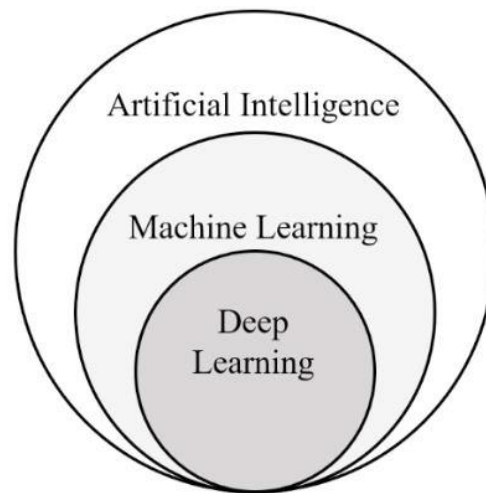


Figure 1 - Systematization of AI (Peifer, 2022, p. 1026)

The purpose of this thesis is not to investigate these differences in AI systems further, albeit possible differences may occur for use in business and leadership with various impacts. When talking about AI systems, or AI technology, this thesis is referring to self-learning algorithms of different complexity. This thesis is consistent with the argument of Einola and Khoreva (2023): what matters most in studying AI in relation to humans, is not the specific type of AI, but how it is understood and experienced by leaders, employees, and organizations.

2.1.3 Responsible and Trustworthy AI

Human intelligence is biologically constrained and suffers from biases, limited memory, stress, and external pressure (Peeters et al., 2020; Haefner et al., 2021). Artificial intelligence overcomes many of these limitations, especially in the amount of data it can process and how it analyses this data (Parry et al., 2016; Titareva, 2021; Kolbjørnsrud & Sannes, 2022). Additionally, the absence of personal bias will make many processes fairer, such as in recruitment and promotion of employees (Charlwood & Guenole, 2022). There are however many challenges regarding AI and the use of data, many of them concerning ethical issues (Leslie, 2019; McDermid et al., 2021). If the data that is used contains errors or bias, then AI could strengthen these errors and biases (Davenport & Foutty, 2020; Kolbjørnsrud & Sannes, 2022). Black-box models are uninterpretable, and subsequently makes for ethical issues when it comes to decision making in many industries (Rahwan, 2018; Anagnostou et al., 2022). These considerations are especially important considering the role of AI in leadership (Parry et al., 2016; Peifer et al., 2022). Different industries have different requirements for the use of

ethical AI. Medicine, the automotive industry and other high-stakes industries needs to be especially sophisticated in their application and use of AI (de Bruijn et al., 2022).

When it comes to organizations in both the public and private sector, leaders and managers need to thoroughly understand this side of AI technology because it concerns humans. The way AI works should be understood when making business decisions, and is something that businesses are concerned with today by developing protocols and guidelines (Arrieta et al., 2020). Encouraging trustworthy and ethical use of AI have a direct impact on how and where AI is implemented in business (Anagnostou et al., 2022). Explainable artificial intelligence (XAI) is the field within artificial intelligence research that aims to address some of the problems of black-box models and uninterpretable AI (Mittelstadt et al., 2019). The goal is to make AI transparent, trustworthy, and able to explain its decision making. Different stakeholders require different explanations, and leaders and managers without technological understanding should still know how their system functions (Langer et al., 2021).

2.2 Implementing AI in Organizations

This section explores the role of AI in organizations and the impact of implementing AI in organizations. It also shows how AI is implemented in organizations, and whether it's done by automation or augmentation.

The concept of implementation in this thesis can be understood as how innovation and technology is diffused throughout organizations and sustained in daily practices.

Implementation focuses on the strategies, processes and context that facilitate the successful use of new technologies (Schoville & Tiller, 2015). Therefore, successful implementation of AI examines what capabilities in the organization facilitates its success that ultimately leads to increased business value.

2.2.1 The role of AI in organizations

AI can outperform human intelligence in several tasks, but mainly in structured routine tasks that can be easily automated (Parry et al., 2016; Haefner et al, 2021; Titareva, 2021). AI is already being implemented in the workplace today, mostly supporting automated tasks and analyzing big datasets, but it can also assist in more complex tasks (such as decision making, creativity, and emotional intelligence), and even more so in the future (Kolbjørnsrud, 2017;

Petrat, 2021; Kolbjørnsrud & Sannes, 2022). The technology does not replace humans but can make their work more efficient; AI becomes a leadership and management tool. There is also a rising number of companies that use AI for leadership and management tasks (Petrat, 2021; Wijayati et al., 2022).

Human decision making is limited, and especially in complex and uncertain situations (Kolbjørnsrud & Sannes, 2022). There is already a development towards using automated decisions in more complex, unstructured tasks (Parry et al., 2016). AI is therefore not only for automating routine tasks but can also outperform humans in generating new ideas and creative solutions (Haefner et al., 2021; Kolbjørnsrud & Sannes, 2022). Regarding the collective intelligence approach mentioned above, systems that aid decisions under such circumstances fits right under this perspective.

Improvements in productivity, employee engagement, and work performance is the result of AI implementation in organizations today, both in HR, marketing, recruitment, and decision making (Peeters et al., 2021; Raisch & Krakowski, 2021; Titareva, 2021; Wijayati et al., 2022). One challenge for AI is to have enough data to train on, as it takes a lot of effort to “learn”. But once the AI is trained, further predictions are very cost-effective, offering value for organizations (Agrawal et al., 2019).

One challenge with applying AI in HR is the amount and quality of data, as most HR data has been labeled bad data (Buckingham, 2015). Personal qualities and performance can be hard to measure, and people can lie. The difficulty of measuring human performance, cultural fit, and “soft skills” is not easily accounted for in an algorithm. Humans are not perfect in doing this, but an algorithm may just amplify these problems (Tambe, 2019). To reconcile the bias of decisions when it comes to people, the algorithm can be trained on noisy data to account for it when applied (Cowgill, 2020). In a recruitment process, such an AI model could pick up on soft skills better than human recruiters would. In either case, leaders and HR managers need to be trained in the way AI works, so that the output is understood (Tiwari, 2020).

A study by Pessach et al. (2020) further explored the role of AI in the recruiting process. The machine learning model was trained on recruitment data, and provided a higher level of precision on hiring and placement than human recruiters. In addition to an overall improved success rate, the system improved diversity in hires. Although it is argued that the AI system

could overtake the role of human recruiters, they suggest a human-AI collaboration to avoid eventual bias. In the end, implementing such a system would maximize return on investment on hires, and could be used by leaders and HR to make accurate hiring decisions.

Decision making with AI is important for innovation management. Innovation and information processing regarding new innovations could contain hundreds of decisions (McNally & Schmidt, 2011). Processing data for new innovations could therefore be much more efficient with AI. Instead of managers reviewing all the input, AI technology could automate or augment this process (Haefner et al., 2021).

There are different tasks within organizations, which some are easily done by AI, whereas others are not. A synchronization of these tasks is required for full implementation of AI systems in the workplace (Snell & Morris, 2021). Leaders and HR professionals are the ones who need to explore these solutions, so understanding the technological and ethical side of AI is critical for leaders (Einola & Khoreva, 2023; Davenport & Mittal, 2023). A major critique to companies that claim to develop such technologies is the exploitation of the confusion about what AI is and can do (Narayanan, 2019). AI is not a “fix-all” solution. AI can aid with leadership tasks in many cases, but it must be thoroughly investigated to be implemented effectively. De Cremer (2020) further strengthens this argument by reviewing why many organizations implement AI: *“Today most (leaders) are influenced by surveys showing that as a business you have to engage in AI adoption because everyone else is doing it. But how it can benefit your own unique company is often less well understood.”* (Section 3).

2.2.2 Automation and Augmentation

The collective intelligence perspective, also referred to as the augmentation perspective has greater potential to organizations’ performance than just automating according to a study by Raisch and Krakowski (2021), who examined the differences between automation and augmentation. Automation implies that machines take over human tasks completely, while augmentation refers to human-machine collaboration on performing tasks (Raisch & Krakowski 2021; Kolbjørnsrud & Sannes, 2022). However, the study also revealed that both automation and augmentation have their place in the management domain, but there is always a tension between the two. Their research focused on relieving this apparent paradoxical tension and concluded that neither automation nor augmentation should be overemphasized.

Einola and Khoreva (2023) examined this paradoxical tension further but found no support for this claim. Both automation and augmentation are always in place and constitutive of each other because AI technology is implemented in organizations with human actors in control.

The number of businesses using and implementing AI is rising and are mainly used in two ways according to Kolbjørnsrud and Sannes (2022): by automating tasks and completely removing humans out of the task, or by supporting in decision making and problem solving. The latter is also referred to as augmentation (Raisch & Krakowski, 2021; Kolbjørnsrud & Sannes, 2022). Compared to standardized routine activities, in tasks that demand creativity, emotional intelligence and complex problem-solving, AI is most suited for augmenting human tasks rather than automating (Kolbjørnsrud, Amico & Thomas, 2017). Automation and augmentation can be viewed as two different paradigms for the design of AI. Currently, developers of AI are mostly positioned towards automation, but there should arguably be more stakeholders involved in how AI is used (McDermid et al., 2021; Charlwood & Guenole, 2022). Leaders, HR-professionals, and employees influence on how an AI system is developed may reap larger benefits in the organizations it will be implemented. Raisch and Krakowski (2021) discuss augmentation and define its role in organizations:

Instead of performing mechanical work, machines now take on cognitive work, which was traditionally an exclusively human domain. However, machines still have many limitations, which means we are entering an era in which the human-machine relationship is no longer dichotomous, but evolving into a machine “augmentation” of human capabilities. [...] managers should acknowledge that AI has the potential to augment, rather than replace, humans in managerial tasks. (p. 193).

Full automation, without the interference of humans have several challenges, and in certain environments becomes a severe ethical issue. Choosing automation or augmentation depends on the nature of the task. Whereas routine and well-structured tasks can be automated, complex tasks often require some human interaction, making augmentation the preferred method (Parry et al., 2016). Raisch and Krakowski (2021) argued that the combination of automation and augmentation will always be interdependent, because a human will always stay “in the loop”. Thus, a critique to the divide between automation and automation is that any use of AI will have a human in-the-loop, which per definition is augmentation (Zanzotto, 2019; Einola & Khoreva, 2023).

The difference between automation and augmentation may not make any difference to stakeholders using AI. The important thing for humans working with AI-solutions is the way it enhances their work, not the underlying specifications of the technology. Einola and Khoreva (2023) describes this relation between AI and humans as co-existence rather than a relationship, as relationships are reserved for thinking and feeling humans. The co-existence notion describes how different organizational agents work together, be it with automation or augmentation. Leaders who have their work assisted by technology may not care for the specific technology, as long as it's helpful in their role.

2.3 Leaders and Their Role as Facilitators of AI Implementation

This section will define leadership, investigate the role of leadership in AI, and examine leaders as agents of change for implementing AI in organizations.

2.3.1 Definition of Leadership and The Role of Leaders and Managers in AI

Leadership can be defined as the ability of an individual or group to influence and guide organizations towards a common goal (Barney, 2023). However, leadership can be defined in several ways (Hoch et al., 2018; Petrat, 2021; Peifer et al., 2022). One way is individual-centric theories that emphasizes the unique talents and abilities of a leader, and how they influence the organization to reach its goals (Cunliffe & Eriksen, 2011). This individual-centric conceptualization of leadership may not be sufficient in complex environments of technology and digitalization (Dhamija et al., 2021). Therefore, another definition of leadership is useful in relation to technologies such as AI, which defines it as a function, carried out by one or several people to manage, lead and motivate (Peifer et al., 2022). This means that leadership is executed by more members of the organization than the executive leaders, such as middle managers, HR-employees, and project leaders.

Leadership style is defined as the behavioral pattern of a leader, as perceived by employees, which differ depending on the situation (Herold et al., 2008; Dhamija et al., 2021). The distinction of different leadership styles dates back to the divide between transactional and transformational leadership, where transactional leadership exchange reward depending on the performance of employees, and transformational leadership focuses on increasing the motivation of followers (Herold et al., 2008; Joo & Nimon, 2014).

Leadership can also be defined as a process; an emergent concept, meaning the interactional dynamics that are important to leadership (Acton et al, 2019). Relational leadership styles are positioned under this view and for the purpose of this thesis, several of these leadership theories will help shed light on the role of leadership in relation to AI. Transformational leadership, authentic leadership, and relational leadership are all theories that look at relationships within a leadership context, and have similarities to such a degree that they can be grouped together (Joo & Nimon, 2014; Onyeneke & Abe, 2021; Petrat, 2021).

Transformational leadership is about inspiring and motivating employees to achieve the organizations goals and considers the situational aspect of leadership (Joo & Nimon, 2014). Transformational leadership in relation to AI enables leaders to inspire change and handle each situation with care, both in relation to the change that follows implementing AI, and how it impacts different individuals (Parry et al., 2019). Transformational leadership arguably holds more creative and abstract aspects, which is more difficult to delegate to an AI system (Parry et al., 2019; De Cremer, 2019). The transformational leadership style is found important in dealing with AI for both employees and managers since it focuses on motivating and caring for the employees (Petrat, 2021).

Authentic leadership is a theory of leadership that combines both authentic and ethical leadership (Joo & Nimon, 2014). Authentic leaders are viewed as self-confident and trustworthy, allowing themselves to be their true selves as leaders and in relation to employees (Walumbwa et al., 2008; Joo & Nimon, 2014). The authentic leadership construct may not offer anything beyond the already established transformational leadership style (Hoch et al., 2018), but was specifically tested in the AI literature, and is therefore worth mentioning as it relates to this thesis. Hao et al., (2020) found that authentic leadership worked well for employees and teams working with AI in their business. The leader being at the same level as other group members stimulated psychological safety in a complex environment. Authentic leaders inspire employees to be their true selves and develop a level of trust needed to succeed with change processes such as implementing AI in the workplace.

Significant overlap exists between different leadership theories, and Avolio (2016) noted the lack of integration between theories. Many theories are often created without comparison of existing models, and different theories may in fact represent the same phenomenon. Yukl et

al. (2002) tried to integrate these different overlapping theories into three different groups, namely *task-oriented behaviors*, *relational-oriented behaviors*, and *change-oriented behaviors*. Relational-oriented behavior is most effective for personal development in followers, while change-oriented behaviors is most effective in predicting job satisfaction of employees (Borgmann et al, 2016). The next section delves further into the importance of change leadership in organizations working with AI.

2.3.2 Leaders as Agents of Change

According to Kotter (2011), change leadership is about leading a process through different steps, from accepting the change to succeeding with change throughout the organization. A strategy and vision for change is essential for influencing employees to accept change processes. The behaviors of change leaders range from providing a plan and vision for planned change, monitoring the implementation of change and creating capacity for employees to enact change (van der Voet, 2016). Frick et al. (2021) defined change leadership as an event-based construct and examines the engagement and responsiveness from leaders in complex change processes. Change leadership is great at influencing employees to accept change, and subsequently commitment to change, which in turn makes change more likely to be a success (Onyeneke & Abe, 2021).

Change leadership could be associated with transformational leadership: change leadership is the link between the forementioned leadership theories and leaders facilitating a change process (Higgs & Rowland, 2011). Change leadership is suited to understand digitalization, change, and technology: which is all part of implementing AI in organizations (Parry et al., 2016; Wijayati et al, 2022). According to Higgs and Rowland (2011), executing change leadership may offer significant success in more complex situations, which organizations implementing AI technology may experience.

Wijayati et al. (2022) examined the role of change leadership in an AI oriented workplace on work performance and work engagement. It was found that change leadership positively moderates the influence of AI on these constructs. AI arguably represents a more disruptive way of change than previous technology (Frick et al., 2021; Petersson et al., 2022). This makes change leadership especially important in organizations that implement AI technology,

and Wijayati et al. (2022) stressed the importance of change leadership in an ever- more rapidly- changing world, which the implementation of AI in society will create.

Technology positive leaders may implement AI solutions in basic tasks for their employees, without being users themselves. AI is “forced” on employees because it’s the new thing, but leaders and employees will experience the use of AI differently (Einola & Khoreva, 2023). The employees that work daily with the AI solution, can have a dramatically different experience than the leaders that force them on. Understanding employees’ attitudes towards implementing change is important, and even more so with AI, which comes with a set of ethical challenges (Davenport & Foutty, 2020; Petrat, 2021).

Leaders’ role in the face of change that accompanies implementation of AI is understanding how employees feel when change occurs. This means compassion and empathy is needed, areas where AI fall short (De Cremer, 2020). AI can detect surface-level emotions and respond to those, but it does not understand authentic emotions like humans. An important aspect of relational leadership styles are the purely authentic human qualities, like making mistakes and errors, but providing unique value in complex environments with integrity and honesty. AI can give a “perfect” answer to standardized questions, but cannot offer authenticity in organizational settings (Geddes, 2017).

A technological understanding and interest in AI may be crucial for any leader that aims to implement AI in their business. On the other hand, emotional skills, empathy, and understanding human relationships are well as important. Understanding both technology and humans is the way to lead going forward (Huang et al., 2019). Geddes (2017) put it as humans needing to become even more human, in a workplace increasingly shared with non-human “colleagues”.

2.3.3 The Leadership Approach in Relation to AI

Leadership as a function must be understood to enact change in a given context and is indifferent to who this leader is. One must also understand the interactional, interpersonal aspects of leadership as a process.

Joo & Nimon (2014) confirmed the similarities between transformational leadership and authentic leadership approaches, and the dimensions of relational leadership appear to be similar enough that they can be grouped together (Petrat, 2021). For simplicity, the conceptualization of leadership in this thesis will be an extension of Authentic-transformational leadership approach, a term coined by Burns (1978), as it covers all main aspects of these theories, but includes change leadership. This means that the extended model of the authentic-transformational leadership approach is a combination of relational- and change behaviors (Yukl et al., 2002; Higgs & Rowland, 2011).

However, grouping leadership theories together may face validity issues (Borgmann et al., 2016). This thesis is not concerned with the validity of the model, but rather operating with an extended, inclusive framework that combines a set of leadership styles. The authentic-transformational model and its related leadership styles are represented in Figure 2.

How managers approach leadership (leadership approach) may change with the implementation of AI in organizations. As summarized above, a multitude of leadership approaches might be suitable in environments where humans and AI co-exist, including aspects of authentic-transformational leadership (Geddes, 2017; Hao et al., 2020). What seems clear is that change management and technological awareness make up the AI readiness of leaders (Frick et al., 2021; Haefner et al., 2021). Executing augmentation in the organization is a combination of the leaders' technological understanding, human understanding, and understanding where in the decision-making chain AI can promote productivity (De Cremer, 2020).

Authentic-transformational leadership



Figure 2 – The extended model of authentic-transformational leadership used in this thesis.

2.4 Leadership Competencies: The Skills and Attitudes of Leaders

This section explores the competencies leaders need for successful implementation of AI, namely their skills and attitudes. The competencies of leaders are situated under the AI capabilities framework which will be examined further in the next chapter (Mikalef, 2019a).

2.4.1 The Skills Leaders Need for Successful Implementation of AI

A decline in employment in routine jobs, done more effectively by AI algorithms, has been shown empirically by Frey and Osborne (2013). For leaders too, the tasks that are replaced are standardized, administrative tasks (Parry et al., 2016). However, when AI improves on routine tasks it allows humans to focus more on the tasks which still to this date requires human expertise, such as interpersonal and creative skills (Charlwood & Guenole, 2022). In addition, it is freeing up more time for interpersonal and creative leadership tasks, such as inspiring and motivating employees (Kolbjørnsrud, 2017; Petrat, 2021; Wang, 2021).

Relational aspects of leadership become even more important when administrative tasks get automated, and more time is spent on creativity, social skills and collaboration (Kolbjørnsrud, 2017; De Cremer, 2020). Interpersonal and empathetic skills are a necessity in organizational environments where AI takes over many of our human tasks (Huang et al., 2019). An

important part of this new work environment is to motivate and listen to employees concerns about using AI. Organizations will not get the benefit if they are not ready to co-exist with AI: while some managers are aware of the distinctly human characteristics needed in the AI-human environment, the employees may not view it this way, and some employees may still appreciate doing routine tasks themselves (Einola & Khoreva, 2023). Leaders who inspire change have a positive impact on implementation of AI in organizations (Effendi & Pribadi, 2021).

AI will assist in more complex tasks in the future, and subsequently revolutionize how business is done (Kolbjørnsrud, 2017; Petrat, 2021; Kolbjørnsrud & Sannes, 2022). Therefore, the AI competency of leaders become increasingly more important, as they need to understand how human-AI interaction functions in the organization (Davenport & Foutty, 2020).

The successful implementation of AI in an organization will largely depend on the role of the leader (Frick et al., 2021). Davenport and Foutty (2020) describe seven attributes that leaders working with AI should have. The first one is knowledge about the technology they use. Several leaders lack IT knowledge, especially outside of IT-businesses. AI is more complex than previous IT and can affect multiple areas of a business and has also ethical challenges to it. Leaders working with AI should know enough about the technology to successfully maneuver its many challenges, but also opportunities. The second AI attribute, or skill leaders need relates to the former; they need to know what they are using AI for. Why and where AI systems should be implemented needs to be strategically founded. The third attribute is for leaders to not overly rely on AI to improve their business. In most cases AI, at the level the technology is at today, can assist in core operations and improve already existing systems. It is easy to think that AI systems will revolutionize the organization in some grand way, but that's less often the case.

The fourth attribute is that leaders must see the value AI will create for their existing business, and not only take on AI projects on the side of core operations. The fifth attribute is getting the whole organization onboard. This means AI leaders must drive change and transformation (Davenport & Foutty, 2020; Wijayati et al., 2022). The new interaction between man and machines, be it with augmentation or automation will be a highly data-driven transformative process according to Davenport and Mittal (2023): *"The greatest challenge leaders face is*

creating a culture that emphasizes data-driven decisions and actions and is enthusiastic about AI's potential to transform the business.” (p. 124).

Leaders must understand the technology, but also facilitate technology training for all employees (Davenport & Foutty, 2020). After all, every part of an AI driven business will be affected by implementing the technology fully. Data is at the core of AI technology, and so the sixth attribute of leaders must be a focus on data quality and gathering of data. The final attribute of AI leaders is understanding that successful implementation requires not only the executive leadership team, but division managers, mid-level managers and HR employees to implement and work with the technology.

Sousa and Rocha (2019) surveyed managers across different levels, and their prediction of future skills needed in disruptive businesses (where AI was included). The different skills were grouped by innovation, leadership, and management skills. Leadership and management skills are the two groups of skills that managers perceive to need the most development in future, disruptive environments. These skills include knowledge of organizational change, social and relational knowledge, motivation and satisfaction of employees. In addition, the managers identified the need to learn emergent technologies and how these will impact decision making and strategy. A summary of the skills leaders need for successful implementation of AI, as found in the literature, is presented in table 2.

Table 2 – The skills leaders need for working with AI as identified in the literature.

Skills of leaders working with AI	Selected literature
Technological knowledge	De Cremer (2019) Langer et al. (2021) Davenport & Mittal (2023)
Understanding how AI should be integrated to create value	Brosig et al (2020) Frick et al. (2021) Haefner et al. (2021)
Not overestimating what AI can do	Davenport & Foutty (2020) De Cremer (2020)
Integrating AI with the rest of the business	Mikalef et al. (2019a) Petersson et al. (2022) Einola & Khoreva (2023)

Change leadership	Effendi & Pribadi, (2021) Wijayati et al. (2022)
Focus on data	Balaraman et al. (2018) Varian (2019)
Understanding that change is made by multiple stakeholders	Wilson et al. (2017) Miller (2019) Davenport & Mittal (2023)
Interpersonal skills	Kolbjørnsrud (2017) Sousa & Rocha (2019) Huang et al. (2019) Petrat (2021)
Understanding ethical challenges and trustworthy AI	Arrieta et al. (2020) Langer et al. (2021) Anagnostou et al. (2022)

2.4.2 Leaders' Attitudes Toward AI

The attitude towards AI varies among leaders; some are more hopeful about AI technology, while others doubt its usefulness and has problems trusting output from AI (Kolbjørnsrud, 2017; Peeters et al, 2020; Tiwari, 2020). There is also a divide in the tasks leaders and managers think AI could assist with (Parry et al., 2016; Titareva, 2021; Kolbjørnsrud & Sannes, 2022). Petrat (2021) showed that most managers believe that interpersonal skills should definitely not be replaced by AI. However, they believed that AI would become increasingly important for organizations in the future. Some managers even believe that AI will become a part of a company's board of directors in the near future (De Cremer, 2019).

Leaders and organizations encourage trustworthy and fair implementation of AI, developing protocols for ethical use (Parry et al., 2016; Arrieta et al., 2020). Glikson & Wooley (2020) found a lack of trust from managers toward AI, which in turn corresponds to a lack of implementation. Jarrahi (2018) argued that implementation itself could foster extended trust, by adapting and readapting to the technology. This means that organizations which implemented AI could trust it more than those who have not. Tiwari (2020) found that HR professionals are generally positive to the implementation of AI, and that organizations that had implemented AI found it to be an asset of the company. The most positive HR professionals were the ones that had already implemented some solution. Most leaders expect that AI could make their work more effective as well (Kolbjørnsrud, 2017). Petersson et al.

(2022) surveyed leaders and found that their concerns about implementing AI is in integrating AI systems with the rest of the organization.

Einola & Khoreva (2023) notably found that top level executives were more positive than their employees towards the implementation of AI, and that it worked as a branding tool for the company. Organizations may use the development and use of AI as a means to show that they are competitive and future oriented. Leaders showed an over-enthusiastic attitude towards AI technology, even though it played a small part in the overall business strategy. This goes contrary to the recommendations from the literature, which states that one should understand the business value AI can bring and where it should be integrated in the organization (Davenport & Foutty, 2020; De Cremer, 2020).

In the next instance, the debate whether leadership could be fully automated or not brings about various attitudes (Parry et al., 2016; De Cremer, 2019). Automated leadership means delegating leadership responsibilities or tasks fully to an AI system (Parry et al., 2016). Automated leadership is in theory leadership done without the involvement of a human agent. There are both positive and negative aspects of fully automating decision-making. Parry et al. (2016) argues that when it comes to envisioning a compelling story, as is one of the main tasks of a leader, AI based systems are able to tell this story on the basis of complex data, without personal bias and beliefs getting in the way. A second positive is the ability to resolve agency problems which often is the result of conflict between leaders and shareholders. Automated decisions regarding this matter would ensure transparency from a purely data driven approach. An AI-based decision system would also distance unpopular decisions away from leaders, mitigating trust issues between employees and leaders. There is evidence, however, that this solution also has its limitations. Input from an algorithm may be less preferable by employees than human input, even though the algorithmic input is better (De Cremer, 2019). This is because some employees value the purely human aspect of human input.

One negative aspect of automated leadership is AI's challenge to compute qualitative data, meaning that data which humans typically excel at, could be regarded as not influential in making a decision, when in fact these data are important for leadership decisions. There is however an increasing belief that AI can get to the level of humans or even surpass human ability in this kind of decisions (Kolbjørnsrud, 2017; Kolbjørnsrud & Sannes, 2022). Another

negative aspect is, as mentioned earlier, that AI algorithms can enhance existing bias in data, and is therefore unsuited to act in a fully automated way without human “in the loop” (see Rahwan, 2018 for a discussion about the human in-the-loop concept). The same goes for removing humans from the decisions where ethics are concerned. In complex situations that affects humans in some way or another this becomes an important issue (Parry et al., 2016; Habli et al., 2020; McDermid et al., 2021).

Another question is how people would react to having an AI algorithm as their leader. Petrat (2021) surveyed leaders in their view of having such a leader themselves. Employees are skeptical as leadership loses its human aspect. Algorithms are more suited to management roles according to De Cremer (2020). Leadership requires more than decisions based on data for specific contexts. It requires emotional, empathic, and relational skills, and allows leaders to navigate management decision on a broader scale (De Cremer, 2019). The leadership aspect is therefore important when investigating the implementation of AI in organizations.

2.5 The AI Capabilities of The Organization

This section describes the notion of AI capabilities and defines the resource-based view of the firm, dynamic capabilities and finally what is meant by AI capabilities. The section explores which capabilities are needed to succeed with AI in organizations. This is different from the capabilities leaders need to harness regarding AI and looks at the organization as a whole. However, many organizational capabilities include leadership skills. The knowledge of AI capabilities is important for leaders and managers to have, as the level of implementation can identify current capabilities and future strategic use (Brosig et al., 2020; Chen et al., 2022).

2.5.1 The Resource-based View and Dynamic Capabilities

What capabilities organizations should develop regarding AI, and where they should spend their effort is an increasing concern, as implementing AI in organizations to gain a competitive advantage requires an effort across the organization (Pavlou & El Sawy, 2006). An organization’s capability regarding AI could be defined as its ability to mobilize and utilize AI-based resources in combination with already existing resources and capabilities (Bharadwaj, 2000). One theoretical foundation for examining capability is the resource-based view (RBV), often used to investigate IT-capabilities, but has also been used in the context of AI (Mikalef et al., 2019a; Mikalef et al., 2019b). The RBV looks at the resources which gives

an organization its competitive advantage. The innate capabilities of the resources themselves is what makes them advantageous, specifically these are resources that fall under the VRIO framework (Barney, 1991; Palmatier et al., 2007). In order to gain a competitive advantage with AI, organizations will need to combine it with existing resources.

Capabilities can be divided into operational and dynamic capabilities. While operational capabilities typically are stable and present across long time-periods, dynamic capabilities are new combinations of resources or completely new resources needed to maneuver change and complex environments (Mikalef et al., 2019b). Dynamic capabilities include the organizations' ability to change, apply new ways of doing business and implementing new resources. Dynamic capabilities are further moderated by internal and external factors such as leadership, organizational culture, and intellectual capital (Bowman & Ambrosini, 2003) A dynamic capability view has notably been effective in Big Data and AI implementations (Mikalef et al., 2019a; Wamba et al., 2020). As implementing AI requires change and implementation of a new resource, dynamic capabilities will be the main focus of the RBV in this thesis.

2.5.2 AI Capabilities

AI capabilities are the specific capabilities that organizations need to have regarding AI, and this framework is also based on the RBV. Successful implementation of AI depends on the organizations' AI capabilities and their AI-readiness (Mikalef et al., 2019a; Frick et al., 2021). The AI capabilities of an organization indirectly contribute to performance as successful implementation facilitate better products and processes (Brosig et al., 2020).

When talking about AI capabilities specifically, this includes tangible, non-tangible and human resources (Grant, 1991). One of the main tangible AI resources that organizations need to have is data (Mikalef et al., 2019a). AI without large amounts of data is unable to train, and small amounts of data subsequently gives little accuracy in its output. Data management and understanding data analysis goes alongside the asset that is the data itself. Being able to integrate data from several systems require a sophisticated technological infrastructure and experts on data analysis (Balaraman et al., 2018; Varian, 2019; Brosig et al., 2020). Haefner et al. (2021) argued that an organizations core capability in the digitalized age was its digital capabilities.

Additionally, the context in which AI is implemented matters, and is made up of both the physical environment, human assets, organizational assets, and lastly financial resources (Nilsen & Bernhardsson, 2019). Petersson et al. (2022) argued that implementation of AI technology within organizations does not rely on the individual leader, but various organizational capabilities which make up the total context of implementation. Understanding how different employees and stakeholders experience the co-existence with AI is key to successful implementation and long-term success (Einola & Khoreva, 2023).

The human assets related to AI is the forementioned data and analysis skills, as well as the ability to develop and train AI-systems and the effective application of these systems in the business (Mikalef et al., 2019a). Wilson et al. (2017) identified three human assets that will emerge as AI-capabilities in the future. The first category is trainers. AI needs to be trained on how to perform, either by creating algorithms or train through text in the relevant environment. The development of an AI-system is not limited for technology-savvy people and data engineers but can be implemented in the business and trained on data by no-coding based solutions (Iyer et al., 2021; Kling et al., 2022). This allows businesses to create their own AI-system based on their needs.

The second category is explainers. These are people with the skills to explain AI to business leaders and other users. The emerging field of XAI aims to fill an explanatory role for AI systems (Miller, 2019). Decisions without explanation can cause leaders and decision-makers to question its validity. People with XAI skills could help explain decisions when needed. The last category of human assets needed for AI capability is sustainers. This skill is important because it makes sure that the AI system works as intended, without getting out of hand when it comes to performing the job and keeping within ethical boundaries. Sustainers will also see to that the business gets the benefits promised with AI.

The non-tangible resource of organizational culture is the third AI capability. As with any change, getting the whole organization aboard is key for succeeding. Technology in itself offers little value without the change needed to succeed with it (Vial, 2019). Overcoming resistance associated with implementation of AI is needed. Davenport and Mittal (2023) addresses the importance of a data-driven culture in order to succeed with AI. The whole organization must be excited to work with AI solutions in order to fully implement it. Change

leadership may be one solution to inspire organizations towards change with AI (Wijayati et al., 2022).

2.6 Summary and Research Model

This section will summarize the literature review and propose a research model for this thesis. The theoretical framework is visualized in the model to help elucidate the research question.

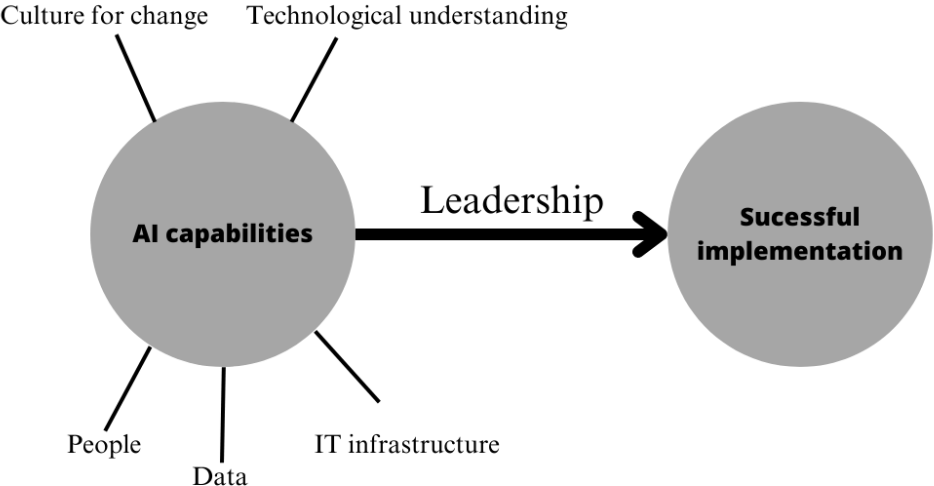


Figure 3 - Research model

The literature broadly identifies five AI capabilities, which facilitated by the leadership role, lead to successful implementation of AI in organizations. AI also impacts leadership, and has its own set of skills identified in relation to AI (as described in Table 2 above).

The model's design is inspired by Mikalef et al. (2019a) and borrows some of its AI capabilities but combine and suggest new ones from the literature. In this thesis, the leadership competencies required for AI are conceptualized and understood as part of the *role of leaders*, as leaders are seen as change agents facilitating the relationship between AI capabilities and the successful implementation. Strengthening an organization's AI capabilities can lead to subsequent successful implementation, if facilitated by leadership. Humans and AI adapt to each other over time, making capabilities and successful implementation an iterative process (Jarrahi, 2018; Peeters et al., 2020).

3. Methodology

The chapter describes in detail the methodological choices selected for this thesis. This includes the epistemological framework and research design, recruitment and selection method of participants, the sampling methods, data collection, and the methods for the data analysis. I will also discuss the validity, reliability, and generalizability of the thesis project, as well as the ethical considerations for the project.

3.1 Scientific Framework

The scientific framework of any research project is affected by the researcher's own assumptions about the world (Johannesen et al., 2017). While this view admits to the possibility of noise in the data, and bias from the researcher, it is impossible to conduct research without considering its epistemological perspective (Tjora, 2012; Saunders et al., 2019). Therefore, it is important that the researcher admits to the possibility of biases and explains his position and worldview. These assumptions will guide both the object of study and the methodological choices.

Ontological and epistemological differences determine how the researcher relates to reality and science (Gehman et al., 2018; Bell et al., 2022). Ontology refers to what we can know about the nature of reality, while epistemology is theories about what we can know, and already know. Ontology has two aspects, objectivism, and subjectivism. Saunders et al (2019) describes that objectivism argues that the social reality we research is external, meaning that phenomena exist independently of individual viewpoints. Social and physical phenomena exist externally to us and others, leaving one universally objective truth to be researched. Subjectivism argues that social reality is made from individual's own perceptions. In its extreme form subjectivism assumes no underlying reality of the world beyond what people perceive and experience about the world, meaning that for each person there is a different reality. This thesis takes a less extreme approach being social constructivism, which argues that reality is constructed through social interaction. People create shared meanings and experiences, and reality is constructed intersubjectively. This approach enables a social reality where interactions are in a constant state of revision, and different interpretations make up the phenomena being researched.

In consequence, this thesis follows an interpretivism approach to research philosophy. This research paradigm is concerned with understanding the way humans attempt to make sense of the world (Saunders et al., 2019). Humans are different from physical phenomena because they create meaning and should therefore be studied differently. The purpose of interpretivism is to create new and richer understandings of the world, looking at the perspectives from different groups of people.

Furthermore, an abductive research design was chosen. This opens the possibility of revision of theory and data along the way, using the best explanation to describe the phenomena (Mantere & Ketokivi, 2013). This way of understanding theory and data as a continuous process that affects each other along the research process is commonly referred to as a hermeneutics, as research is fundamentally about the dialogue between data and theory (Bell et al., 2022). The abductive approach to research is a practical way of collecting and analyzing data and is commonly used in business research as it is flexible and allows the back-and-forth process that research often is (Saunders et al., 2019).

3.2 Research Design and Methodological Choice

The research design of a thesis decides, in simple terms, what is to be studied and how it should be studied. The design of a thesis should consider every step of the research process, from thesis question to area of study, to data collection and analysis (Johannesen et al., 2017). On the basis of these considerations the design is chosen. Specifically, a research design is the framework for which data is collected and analyzed (Bell et al., 2022).

As noted in the literature review, research on AI in relation to leadership and organizations needs more attention from scholars, and the number of empirical studies is limited (see Mikalef et al., 2019a). Based on this fact, an exploratory research design is used in this thesis. The exploratory research design is well suited for subjects where there is a lack of theory, literature, and empirical studies (Saunders et al., 2019). Although the exploratory design often accompanies quantitative data, nuances can be explored in qualitative data when collected from different sources (Abildgaard et al., 2019). This allows for a broader starting point for the thesis, with more narrowing as it progresses.

Qualitative research is often deductive or inductive in nature, but this thesis settles on an abductive analysis. This allows the researcher to have a broad familiarization of the theory, but does not require in-depth knowledge to a specific area before analyzing the data (as with deductive analysis). This also helps the researcher fit surprising data from the analysis to existing theory (Timmermans & Tavory, 2012; Bell et al, 2022). This matches the hermeneutic, interpretivist framework and finds the best explanation of empirical data, broadly grounded in existing theories. It is important to note that surprising data does not constitute an inductive approach and the development of new theories. It can simply be that the phenomena is examined in a different context, with additional dimensions, or with misguided preconceptions (Timmermans & Tavory, 2017).

This thesis utilizes a qualitative research design, making it possible to delve deep into the research question and explore details about the participants' experience (Bell et al., 2022). As opposed to quantitative data, which typically deals with data in numbers, qualitative research deals with various, ambiguous data, often text (Gehman et al., 2018). A qualitative design naturally follows from the interpretive research philosophy of this thesis (Saunders et al., 2019). Furthermore, the qualitative research enables an abductive approach to data and case study research, which is suitable to study organizations.

3.2.1 Research Strategy

A cross-sectional case study was chosen as strategy, as the objective for this thesis was to investigate the research topic within a specific context. Specifically, multiple cases were used, to gain an understanding of the topic across contexts. In this study, the topic is the link between AI, implementation, and leadership, and the context is different organizations that work with AI. A cross-sectional case study means collecting data from the multiple cases, at a single point in time (Saunders et al., 2019).

The case study research is often used for an exploratory research design, because it can answer a multitude of questions to gain a rich understanding of the context (Saunders et al., 2019). The case study uses interviews, observation or questionnaires as its main data collection method, and the data collection method for this thesis will be described in more detail below. An overview of the methodological choices used in this thesis is represented by "The research onion" derived from Saunders et al (2019) and is presented in Figure 4.

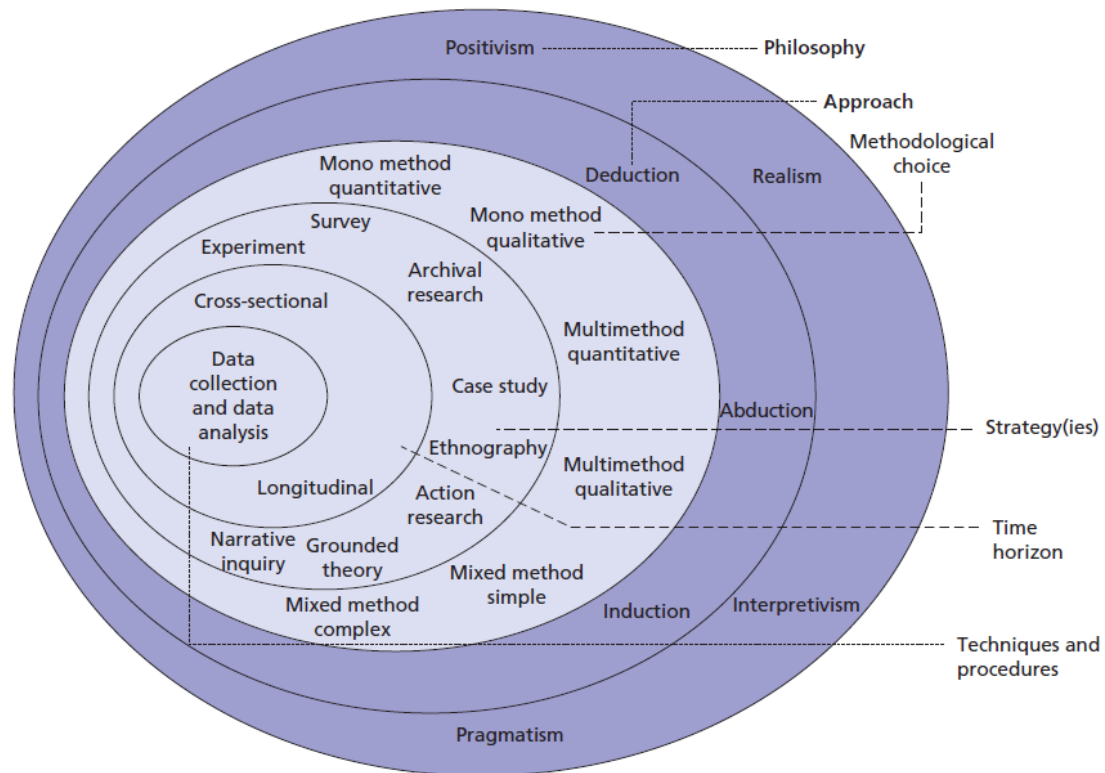


Figure 4 - The research "onion" (Saunders et al.,2019).

3.3 Data Collection

In this chapter the sampling method, recruitment of participants, and a description of the sample will be presented. Then the data collection method and interview procedure will be described.

3.3.1 Sampling and Recruitment of Participants

The notion of AI is relatively new in organizational contexts. Therefore, a challenge for this thesis was finding suitable participants. The recruitment of participants started by contacting a major research organization by e-mail. They provided a list of possible participants as well as a link to another research institute that is collaborating with organizations on AI. This was a good way to start, because it provided assurance that these organizations were working with AI to some degree. E-mails with detailed information about the project were sent out to relevant parties, and asked for further contact information of leaders or middle management who worked with AI in some way in their organization.

The sampling method used was purposive sampling, in order to attract participants relevant to the research question (Bell et al, 2022). There were two selection criteria for the participants; that they were leaders in their organization, and that they were working with AI to some degree. Cases or individuals meeting these two criteria satisfies purposive sampling (Palys, 2008; Bell et al., 2022). The first round of recruitment fell short. In order to increase the sample size, additional emails needed to be sent out. In the second round of recruitment, large Norwegian companies were contacted with the same information.

The full sample ended up with five participants. The participants were a mix of leaders with different leadership roles, educational background, and experience, from five large Norwegian organizations. Four out of the participants are employed in the private sector, and one participant was employed in the public sector. A consideration whether to compare these facets were made, but the lack of comparable participants made it unsuitable. Upon reviewing the data, there are no relevant differences between the public and private sector in the analyses. The participant's ages ranged between 35 and 55 years old, with three men and two women.

Most of the participants worked with AI on a project basis. During the recruitment process I discovered that most leaders who work with AI, were also working on developing AI for their respective companies. This was also the case for the existing literature: AI and leadership is highly normative, "should" driven, and more about looking ahead than current practices. Although the participants worked with implementing solutions for their organization, they were not using AI in many aspects of their daily work. The leaders main focus is to develop AI for their companies, test solutions and implement best practices. They were asked to describe AI in their daily work, and a combination of this and future considerations is explored.

The data was aggregated and anonymized in compliance with the current GDPR regulations on data protection. As a result, no participants could be identified, and participants will be referred to in later chapters using coded names. Table 3 illustrates the participant's demographics.

Table 3 – Demographics of the participants

Participant (P)	Job position	Sector	Industry	Experience in current role	Technical background
Participant 1 (P1)	Head of research	Private	IT	1 year	No
Participant 2 (P2)	Department director	Private	Insurance	2 years	Yes
Participant 3 (P3)	Department director	Private	Media	3 years	No
Participant 4 (P4)	Head of research	Public	Archiving	5 years	Yes
Participant 5 (P5)	Department director/Project manager	Private	Construction	1 year	Yes

3.3.2 Data Collection Method

The collection of primary data for this thesis was done using a semi-structured interview. This is a useful method for collecting data when the nature of the study is exploratory (Saunders et al., 2019). The strength of this type of interviewing is following an interview guide in order to ensure quality in the research and to map similarities between the participants (across cases). However, the semi-structured interview allows the researcher to diverge from the guide, should there be a need to ask follow-up questions on interesting themes (Saunders et al., 2019; Bell et al., 2022). The questions asked in the interviews was not always the same as in the guide, and the participants often answered multiple questions in their elaboration.

The semi-structured interview provides information about a subject, the way participants experience it in real-time (Gioia et al., 2013). This is because the participants are not familiar with the questions beforehand, and the answers takes on a more spontaneous nature. In this way, the researcher can note other qualities than just the answer in itself, be it tone, hesitation, or body-language (Bell et al., 2022). In this multiple case study, the semi-structured interview provided in-depth knowledge about the topic in the most suitable manner.

The interview questions were developed based on continuous feedback from the thesis supervisor and by reviewing the relevant literature on AI and leadership. According to Agee (2009), developing research questions for qualitative research could be seen as a dynamic, reflective process. The first draft aimed to develop questions which answered three sections of the literature, namely the general understanding of AI and the uses of AI, AI in relation to leadership, and finally what organizational capabilities and leadership competencies are needed for working with or developing AI (Figure 5). These concepts were amply positioned under the overarching research question for this thesis (Agee, 2009). The final goal of the interview questions was to collect primary data that would be answer to the research questions.

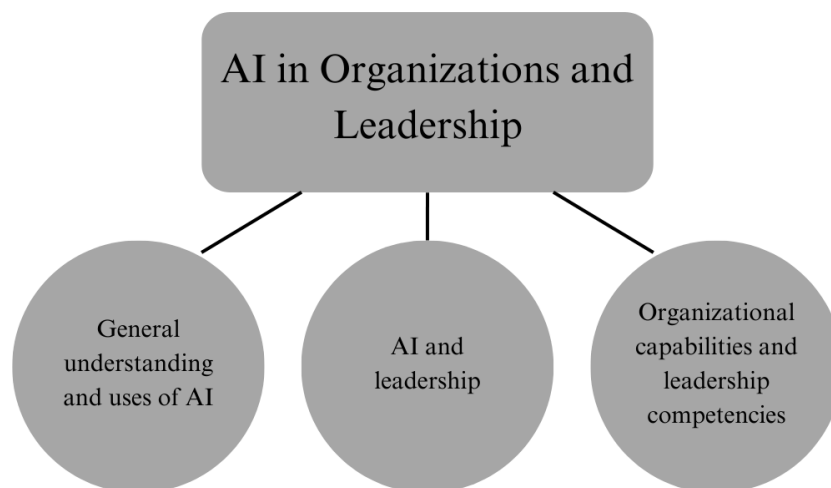


Figure 5 – Three concepts of AI in organizations and leadership identified in the literature

To explore these concepts, some questions were inspired or directly borrowed from the existing literature, which is a good way to both test and challenge assumptions (Marx, 1997). Developing research questions will always be influenced by the researchers own background, but should satisfy the following criteria (Bell et al., 2022): Research questions must be clear and neither too broad or too narrow, researchable, connect with established theory and research, logical and conceptually linked together, and contribute to knowledge. After a lengthy iteration process the final questions were formed and included in the interview guide (see Appendix D).

3.3.3 Interview Procedure

One interview was conducted in English, by request of the participant, while the rest were conducted in Norwegian. Before starting the interviews, both an English and Norwegian version was developed, and made as similar as possible (See appendix D and E). All interviews were done by video, specifically using MS Teams, which has both advantages and disadvantages (Bell et al., 2022). The main advantages of interviewing the participants over MS Teams were significant time saving, as most participants were located in a different area than the researcher. According to Akyirem et al. (2023), the use of online interview tools, such as MS teams, are suitable when recruiting participants with different geographical locations. Flexibility, time savings, and advantages of the recording-tool influenced the decision on doing no face-to-face interviews. The ability to pick up on non-verbal cues and body language may not be significantly reduced compared to traditional interviews (Bell et al., 2022).

One of the main disadvantages to video interviews are internet connection, which makes interruption in the recording likely. The cases where connection was interrupted, the participants were asked to repeat their answers. Another issue is the ethical considerations, as the researcher can't control the environment in which the participant is located in, for example a shared office space (Bell et al., 2022). Conducting interviews per video has become a widespread method for qualitative research over the past years, and the validity of collecting data in this way has few practical limitations, most of them being issues with the technology itself (Conlon et al., 2023). Therefore, it is just as reasonable to have collected data for the thesis in this way compared to traditional face to face interviews.

When the participants were contacted, they were given an informed consent form to participate in the thesis. Additionally, all participants agreed to the interview being recorded before it started, and they were encouraged to express any concerns both before and after the interview. The interviews lasted between 29 and 40 minutes, which made for full concentration during the process. It was decided to take minimal notes, to fully engage in the interview. Both video recording and the built-in transcription software in MS Teams would ensure I could capture everything and analyze the data subsequently.

3.3.4 Secondary Data

For stronger validity of the data, a secondary source of data was included in the analysis. Secondary data can provide additional knowledge to the analysis (Saunders et al., 2019). The data was collected from a podcast named “AI – fra ide til produksjon” (PwC, 2020). The secondary source of data is an interview with the Data Science Manager of online grocery store Kolonial.no (now Oda). The interview was conducted by PwC in 2020, was 29 minutes long and was transcribed before using it in the analysis.

The interview was included in the data sample because it satisfied the sampling criteria and answered similar questions to the primary data. This is by no means a comprehensive data source but offers value by drawing comparisons to the primary data on implementation and capabilities. This is a method called data source triangulation, which aim to give a broader understanding of the phenomena (Carter et al., 2014). Data source triangulation increases the sample size with a time efficient, and valid data collection method (Carter et al., 2014; Bell et al, 2022). Table 2 describes the demographics of the interviewee as a means of comparison to the rest of the sample.

Table 4 – Summary of the secondary data source

Data type	Job position	Sector	Industry	Experience in role	Technical background	Time of recording
Secondary data / interview	Manager	Private	Retail	1 year	Yes	2020

The secondary data was not coded in the same manner as the primary data. The secondary data was used as a supplement, and quotes will be presented in Chapter 4 where it is useful for comparison.

3.4 Data Analysis

The primary data collected via semi-structured interviews was partly transcribed by the built-in transcription function in MS Teams, in addition to a more thorough, manual transcription

of the recordings. Finalizing the transcriptions was done after all interviews were completed, as the interviews transpired closely together. Especially interesting notes were written down after each interview, but the full transcriptions were only done after all the interviews were conducted. As mentioned above, non-verbal cues from the video recordings were also noted during the transcription, as well as ways of expression, pauses, and uncertainty in the participants voices. This all makes up the meaning of the information conveyed and lays the groundwork for the next step in the analysis.

The next step was to analyze the data, and the method of choice for this thesis was the thematic analysis. Thematic analysis is one of the most common methods in qualitative research and can be used in most instances, allowing flexibility and simplicity, which subsequently makes it a popular method in research (Bell et al., 2022). Thematic analysis explores different themes in the data which are coded into different categories or groups of categories. The goal is to find similarities, differences, and patterns in the data, as well as outliers and specifically important themes. It is an appropriate method of analysis when seeking to understand experiences, thoughts, or behaviors across the data set (Kiger & Varpio, 2020).

Braun & Clarke (2006) recommend approaching the thematic analysis as a continuous process, where establishing codes and themes is an iterative process. The analysis can be divided into six phases; familiarizing oneself with the data, initial coding, searching for themes, reviewing themes, defining themes, and finally producing the report, but in practice one moves back and forth between these phases as one works with the data. This is shown in Figure 6. This has also been the mindset when working on this thesis. The decision to do a thematic analysis was ideal for this thesis since the literature is limited, and there are very few similar studies. This is consistent with the explorative and abductive framework for this thesis (Saunders et al., 2019). Both established themes from the literature were found, and new unestablished ones.

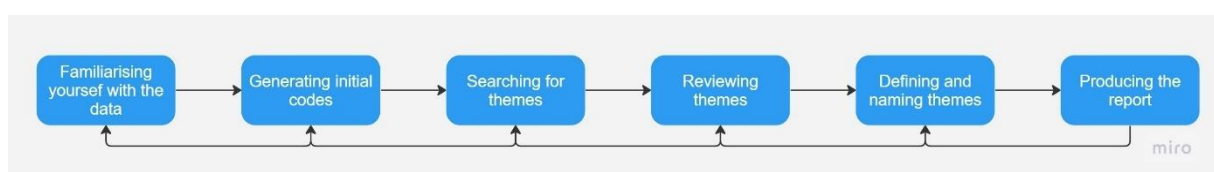


Figure 6 – Six phases of thematic analysis (from Braun & Clarke, 2006).

The transcribed material was imported into NVivo, an analysis tool for qualitative data. Here, coding is made relatively simple by highlighting the relevant parts of the text one wishes to code. The different codes are established by the researcher who is free to make codes in whatever way one chooses, but often based in the research questions (Bell et al., 2022). The flexibility of thematic analysis is both the strength of the method, and its main critique, allowing the researcher with too much personal choice according to some researchers (Antaki et al., 2002; Braun & Clarke, 2006). An overview of the data was gained when transcribing the material, which made the initial coding easier. The analysis will be affected by prior familiarization of the data through interviews and transcription, and the researcher will most likely have identified some patterns within the data beforehand (Braun & Clarke, 2006).

The first codes were often large paragraphs of the text which concerned similar topics. As I worked with the codes and established themes, some of the original codes were merged or moved to different codes. Similarities and differences were noted, and also parts of the data that resonated with the established literature. A mind-map was created to get a visual representation of the codes, and the overarching themes were made up of groups of similar codes (Braun & Clarke, 2006). The mind-map is attached in Appendix A. Similarities, differences and particularly interesting data were established in addition to relevant data that aligned with the research questions and existing literature.

The next step was to review the themes, in accordance with Braun and Clarke's (2006) six step process. All extracts for the different themes were re-read and edited. Some codes were moved from one theme to another, and some codes were removed altogether. The important thing was to create a coherent theme with internal logic. Part two of this phase was to review the themes against the entire dataset. I read the entire transcripts again and questioned if the themes accurately reflected the meaning in the data.

A second round of searching for themes were also done, both to identify meaning and if it made sense in regards to my theory chapter. This process resulted in the final themes; *Definition of AI*, *Capabilities*, *Leadership*, *Implementation*, and *XAI*. Upon reviewing the themes against the literature, it made sense to create sub-themes to the overarching themes. This helps to make sense of larger and complex themes (Braun & Clarke, 2006). *Implementation* is made up by "Implementation of AI", "Use of AI: Automation or Augmentation", and "Limitations". Two sub-themes were created for *capabilities*:

“Leadership capabilities” and “Organizational capabilities”. *Leadership* was divided into “The current landscape of AI and Leadership”, “Leadership qualities” and “The future of AI and leadership”. I was satisfied with my themes and sub-themes and were ready to write and convey the meaning of the empirical data. The sixth and last step in thematic analysis is producing the report, and I found that some finalization of the analysis was done when writing the next chapter (Braun & Clarke, 2006).

3.5 Reliability, Validity and Generalizability

This section addresses the quality of the study, and discusses the reliability, validity, and generalizability of the research. These criteria for quality are especially important in qualitative research with its interpretive nature (Tjora, 2017). The overarching objective for these criteria is ensuring trustworthiness in research (Rose & Johnson, 2020).

3.5.1 Reliability

Reliability, in its traditional sense, is concerned with the problem of whether replicating the study is possible (Bell et al., 2022). This criterion is difficult to meet in qualitative research since the phenomena is studied in a particular context that would be impossible to replicate fully (LeCompte & Goetz, 1982). Following this critique, alternative criteria is established for evaluating qualitative research.

Guba and Lincoln (1985) propose two primary criteria for assessing qualitative study: *trustworthiness* and *authenticity*. Several researchers support these criteria as being valid in qualitative research (Sinkovics et al., 2008; Nowell et al., 2017). A component within trustworthiness is what Guba and Lincoln (1985) refers to as *dependability* which is parallel to traditional reliability. Dependability is achieved by making the research traceable and clearly documented: the methodical choices in this study are described in detail and shows the process as the study progresses, making readers the judges of its dependability (Nowell et al., 2017).

Data collected through interviewing were first recorded and later transcribed. This process is described in detail, ensuring dependability, and relevant documentation is attached in the Appendix. Additional dependability is achieved through an *audit trail* by discussing the study

and its progress with a supervisor (Merriam 1995; Sinkovics, 2008). Regularly discussing theoretical assumptions and methodical choices will increase the reliability of a study.

3.5.2 Validity

There are several ways to measure validity in research and is concerned with the integrity of conclusions that the study generates (Bell et al., 2022). Validity aims to answer if we actually get an answer to what we measure (Tjora, 2017). Internal validity, or to use Guba and Lincoln's (1985) definition, *credibility*, can offer considerable trustworthiness to qualitative research.

This study uses two techniques to ensure credibility, the first being respondent validation. The thesis used a semi-formal interview for gathering data, and validation can be ensured by asking participants if their answer is correctly understood by the researcher (Nowell et al., 2017; Bell et al., 2022). This was done by repeating answers back to participants or asking follow-up questions where answers were unclear.

The second technique used is triangulation, namely data source triangulation, which ensures that data is explored from multiple sources, which gives a better understanding of the phenomena (Carter et al., 2014). Data was transcribed from an interview with a participant that met the initial sampling criteria. This offered a confirmation that the primary data was solid compared to secondary sources.

3.5.3 Generalizability

Generalizability is concerned with whether the results of a study can be relevant in other contexts or settings (Sinkovics et al., 2008; Tjora, 2017). It can be difficult to generalize a specific context in qualitative research, since it often uses cases and small samples (LeCompte & Goetz, 1982). Guba and Lincoln recommend uses the *transferability* criteria in qualitative research (Guba & Lincoln, 1985).

Ensuring transferability in qualitative research can be made through sufficient information of the study, enabling the readers to judge for themselves the quality of its findings (Nowell et al., 2017). In this study, a thick description, as suggested by Lincoln & Guba (1985) is

conducted to ensure transferability. A thorough description of the phenomena, sample and context is given, enabling a comparative ground for future research across different cases.

3.6 Ethical Considerations

Research ethics is concerned with the standards of behavior that governs research. Fair and respectable collection of both primary and secondary data must be considered, as it often involves human participants (Saunders et al., 2019).

As part of this thesis work, an application was sent to the NSD to ensure that the correct ethical standards were followed for this research. The application described the scope and purpose of the study, and requested collecting personal information from participants, but of no sensitive nature. The application was approved, and the interviews could begin (see Appendix B).

An informed consent form was sent to the participants on initial contact, informing them about the study and their participation rights (See Appendix C). The participants were asked a second time for their approval for being recorded and having their interviews transcribed, before the interview started. If the participants gave their verbal consent, the interview was conducted. The participants were given the opportunity to state their concerns both before and after the interview.

The data collected was stored on the NTNU servers for extra security, and no data file would be accessible elsewhere. The recordings and transcriptions were deleted after use, and no personal information about the participants were saved. After the thesis is finished and submitted, the handling of personal data will follow the prescribed procedures of the NSD and cease to exist.

4. Findings and Discussion

This chapter presents the findings from the thematic analysis. The empirical data is presented and discussed in light of the literature, in order to answer the research questions established in this thesis. Particularly interesting quotes are presented to illustrate important findings. Both primary and secondary data is presented.

Table 5 – Reminder of the research questions.

Research question (RQ)	
RQ1	How is AI implemented in organizations and why?
RQ2	What is the role of leaders in implementing AI, and how does AI impact leadership?
RQ3	What organizational capabilities and leadership competencies are needed for successful implementation of AI?

4.1 How AI is Implemented in The Organization and Why

This section presents and discusses how AI is implemented in the participants' organizations and why. First, the participant's own definition of AI is presented and discussed. Secondly, both how AI is used and why is discussed, and whether it is done by automation or augmentation. And finally, this section concludes with limitations to implementing AI.

4.1.1 Leaders' Definition of AI

The participants were asked to define AI; to deliver their first thoughts upon thinking of AI, and their personal definition. Artificial intelligence as a concept has been around for decades, but the version we know of the technology today is relatively new (See Peeters et al., 2020). Another thing to consider is that AI entails a number of things and draws definitions from several fields of research such as cognitive science, psychology, computer science, robotics, engineering and artificial intelligence (Tsai et al., 2022). As a result, different definitions of AI emerged from the interviews, as expected. The purpose of asking this question was to establish the participants' own view of AI, which would lay a foundation for the rest of the interview and subsequent analysis. The conceptualization of AI can help explain the

participant's view of why they need to implement AI in their organization (Nilsen & Bernhardsson, 2019; Peeters et al., 2020).

The participants are broadly defining AI as digital tools that aid with decisions and processes. AI is technology that serves a function for the organization. AI is further described by the words dataset, algorithms, machine learning, automation, and generative technology. Some respondents have used terminology found in popular media such as ChatGPT (see OpenAI, 2022; Waters, 2023), machine learning, and intelligent robots, while others were more precise in their definition. Participant 1 (P1) described AI with more precision and seemed to be aware of the multifaceted nature of AI and the confusion around the term. This confusion is identified in the literature, as confusion in the AI landscape may be connected to its many typologies and definitions (Petrat, 2021).

P1: *“So, let’s first define what AI is, because there is a lot of confusion in the market. It could be data tools that help companies, business leaders and decision makers to make better decisions based on their thoughts. That’s decision support based on data. And the second use of AI is tools that help us to automate processes. For me, AI is [...] both a decision support tool and automation.”*

AI is described in both positive and negative terms. Some participants were more positive while others were more conservative about the future of AI. Participants with a background in technology delivered the most conservative view of AI. The conservative view is honest about the current state of AI and perhaps more realistic, as described by participant 5 (P5).

P5: *“...I mean, for a long time I’ve been thinking that it’s all (AI) a big hype. The word artificial intelligence is thrown around a lot, and it’s very tabloid by those who don’t work directly with it.”*

AI is no miracle technology, and riding the hype, many organizations can be deceived into investing in the technology and push it on its employees with little success (Narayanan, 2019; Einola & Khoreva, 2023). The participants are in large part aware of the current state of what AI technology can do.

Differences in industry and resources can make up the divide in viewpoint, as well as personal differences and background (Peeters et al., 2020). The fact that AI encompasses different technologies and can be used for multiple tasks, supports a broad definition to understand it in this context; that AI is a tool, a set of technologies to support human tasks (Kolbjørnsrud, 2017). An exact definition is not important for the participants, but how they can benefit from it is. This is also noted in the literature (Einola & Khoreva, 2023).

4.1.2 Why Organizations are Implementing AI

This section explores to what degree AI is implemented in organizations and the reasons for implementing AI. A considerable attention in the literature about AI and leadership, and AI in organizations, is positioned towards implementation (see Frick et al, 2021; Einola & Khoreva, 2023). The participants were asked how they use AI technology in their organization, and in their role, and why they choose to implement AI technology.

One major finding is that the level of implementation varies greatly. The level of implementation is important to identify because it directly determines how much AI impacts the organization. Some of the participants rely on AI-technology in their daily work and have AI as an integral part of their business, while others are currently working with AI on a project basis, as something “separate” from the rest of their business. The question that follows is to what degree leaders and organizations rely on AI, and if this changes how AI is implemented. It was identified that, for the most part, leaders don’t use AI much in their daily work. Not working with AI in their own tasks is a commonly underdeveloped area for leaders and managers working with AI (Davenport & Mittal, 2023).

The literature argues for taking a leap with AI, and not keeping AI projects on the side of core operations: A full integration is needed, a pilot program on AI can only take you so far (Davenport & Foutty, 2020; Davenport & Mittal, 2023). A full integration of AI may be useful to gain all the advantages it can bring, but benefits are still found in the empirical data by experimenting. Experimentation hopefully leads to further implementation, and the degree of implementation can vary by how it fits the organizations’ business process.

Implementing AI is in the early stages for some participants, but with the clear intention to test solutions for possible application in business. This is described by participant 2 (P2), who

has not yet implemented AI in their daily work but is developing a solution from an external provider to replace certain tasks for their employees. The system is currently being trained on the organization's data.

P2: *“Our caseworkers will have some of their standardized tasks replaced by [...] this program. We are currently seeing how we can best train this program to handle our tasks. Testing and training are being done by our employees who will use the system”.*

Participant 3 (P3) was hesitant to answer whether they have actually implemented any AI solutions but mentioned that they use and rely on technologies that are AI-driven. P3 states that while a lot of the technology they use is weak AI (Pennachin & Goertzel, 2007), they have some experimental initiatives on AI that will be relevant for their business.

P3: *“Implemented, I don't know about that, but this is a set of technologies we work with and rely on in addition to [...] experimental initiatives. We try different technologies and create different proof of concept that can be relevant for our business. Everything from text-summary to article-summaries, text to speech in video and podcast, and then we have curated recommendation-algorithms. We use external suppliers for a lot of our AI, but train it on our own data locally to make it better. [...] other than that AI-technology is integrated in a lot of the services we already use, like Gmail and writing email and stuff like that, google translate is a pretty sophisticated translating technology relevant for producing content.”*

Generally, the reason for implementing AI technology is to enhance existing processes, automate certain tasks, extract information from their data, and the belief that AI will be increasingly important for their industry in the future. The reason for implementing resonates with the literature, as well as the belief that AI will become more important for their business in the future (Kolbjørnsrud, 2017; Petrat, 2021; Kolbjørnsrud & Sannes, 2022).

P3: *“We want to learn about the technologies that will be very defining for our industry. It (AI) has a very immediate relevance for the processes we have in our business and similar businesses. ... There's a lot of examples where we can make processes more effective, deliver a stronger value-proposition and deliver content in many more ways with relatively low cost. That's why AI is relevant for us. You can use generative AI for a lot of tasks, but I want to say*

that, for the main part, in a perspective of efficiency, if in the end you can save money by not spending time on doing something, we want to do it.”

Why the leaders of the different organizations implement AI solutions are further exemplified by P1 and P5.

P1: “We share knowledge about AI, we are running AI projects [...] and inspiring all leaders of our company to invest in AI technology and competency. We build in-house AI or buy products from external partners because I think we will work more with AI eventually. How can we use this technology to better our business models and efficiency?”

P5: “There are a lot of aggressive goals that we need to meet, everything from optimizing how we build things to what we build. It gets increasingly difficult to extract the last pieces of the puzzle to reach our goals, but we’re starting to gather more data and we can use AI to optimize these increasing needs. [...] we can use machine learning to train the program on specific projects to optimize our processes.”

As exemplified, why organizations are implementing AI ranges from testing and optimizing processes, to larger strategic goals. How AI can be implemented to reach strategic goals are one of the main promises of experimenting with AI (Frick et al., 2021; Haefner et al., 2021).

4.1.3 How Organizations are Implementing AI: Automation or Augmentation

In the literature, AI is mainly implemented in two ways (Kolbjørnsrud & Sannes, 2022): By automation or augmentation. The current state of AI suggests that most tasks are automated, but in practice a leaning towards augmentation may be closer to the truth (see Raisch & Krakowski, 2021 for further discussion). The AI systems seek to automate processes, but human input is almost always present, making the implementation augmented rather than automated. The rationale for asking how AI was implemented was to map out if the tasks were mostly automated or augmented. The first part of this section identifies the specific uses of AI in the participants’ organizations.

Some of the uses that were identified were decision support, optimizing processes, predictions, extracting data, detecting patterns in data, marketing, HR, recruitment, reading of

documents, and automatic classification of documents and incoming requests. Most of these are identified within the existing literature and is consistent with what the AI technology that exists today can do (Peeters et al., 2021; Titareva, 2021; Wijayati et al., 2022). The areas where AI is used in the participant’s organizations are summarized in Table 6.

Table 6 – The areas where AI is used in the participants organizations.

<ul style="list-style-type: none">- Decision-support- Optimize processes- Make predictions- Detect patterns and extract data- Marketing- HR- Recruitment- Automatic scanning and reading of documents
--

Some of the participants did not work much with AI in their own role but gives examples from how it is used in their organization. The focus is on experimenting and testing AI solutions, and some solutions provide more value than others. This is exemplified in the excerpts from participants P3, P4 and P5.

P3: *“Using AI to write summaries of documents, text to speech, experimenting with (AI) to assist with some tasks, using automatic writing support, translating services...”*

P4: *“Automatic detection of handwritten documents, reading of codes in our documents to place it correctly in our systems, and extracting meaning of our data.”*

P5: *“A lot of what we use in our daily work has traces of AI technology, but this is very generic and not something we specifically get business value out of [...] but where we see the most possibilities are towards our specific projects. We control some of our machines by tracking (with AI), so they can do things automatically, and we use AI to see patterns in our data.”*

The secondary data (S1) describes the following use of AI in their business. This excerpt highlights how AI is used in an organization with a high level of implementation.

S1: *“We use optimizing algorithms to find the best routes to deliver our products by. Another thing is recommending items to buy based on what you have bought before. We use historical data on your purchases to recommend what you might need to buy now. [...] In many cases, the implementation of AI is to incrementally improve existing processes. For any process that humans typically do, there is a prediction problem [...] and if the data to solve the problem exists, you can train it (AI) to do the same. It can in the least work as decision support for the person doing that task.”*

P4 describes a fully automated process in their business. As exemplified, automating a task with AI outperform humans, and is done unless the documents are sensitive in nature. In practice, a human is “in-the-loop” for critical cases, because it could possibly harm people or operations. This shows an awareness of responsible AI use from leaders, which arguably every leader should have (Langer et al., 2021; McDermid et al., 2021).

P4: *“... and we use AI to automatically censor some documents, so that our people don't have to. It's a boring job and not time effective, so we automate it. [...] we have a 98,9% success rate, better than humans, so we automate it completely if the documents do not contain sensitive information [...] then we need humans for quality assurance.”*

Participant P4 then goes on to describe more of their business and explains that most of the task they use AI on is a combination of automation and augmentation. They seek to automate processes as much as possible, but some tasks require human-machine collaboration. When the complexity of the task increases, or it is a critical task, then AI is augmenting rather than automating for the participants. This is in keeping with the literature on augmentation (Parry et al., 2016; Kolbjørnsrud & Sannes, 2022).

P4: *“... most of what we do is a combination of man and machine, in that we need someone to read and understand the results. AI is mostly a supplement. We have an automated feedback-loop for our automated systems, so if something is wrong with the model we can go in and fix it, but this is not a daily task.”*

The excerpt from P1 shows an awareness of the divide between automation and augmentation, describing the different applications of the technology in detail. P2's organization uses AI in a similar way.

P1: *“We automate our call center, so that the right type of calls goes to the right agents. Based on this insight we are able to differentiate traffic and segment our customers a lot better. The consequence of this is that we can put agents with different qualities on the right calls [...] so this is an automation and augmentation process. Automating tasks enables our employees to focus on more complex tasks, more meaningful tasks. That increased, of course, their motivation and willingness to learn.”*

P2: *“We want to classify incoming requests, either by email or call. We want to identify the prioritization that these inquiries require automatically. [...] this enables us to prioritize those needing urgent assistance and get rid of a time-consuming, repetitive task for our employees.”*

Shown in the excerpts above, employees have their repetitive tasks replaced, which opens for more urgent, complex, and meaningful tasks. This resonates with the literature in what automation will do (Frey & Osborne, 2013; Kolbjørnsrud, 2017; Petrat, 2021). Eionola and Khoreva (2022) showed that resistance to having routine jobs replaced, even if this means freeing up time for more complex work, also exists. This is because some employees prefer their routine tasks. Huang et al. (2019) argued for a middle ground in the replacement of jobs. Not all standardized jobs will be replaced, and not all new tasks will be of creative and emotional aspects. AI does replace some tasks, but augmentation, a human-AI collaboration, is the reality of how AI is implemented in most organizations, as the empirical data suggests.

The divide between automation and augmentation does not seem clear for the participants, and they use the words interchangeably. The difference may not matter for leaders, as the important thing is the value it creates (Eionola & Khoreva, 2023). Both automation and augmentation are always in place, constitutive of each other, and leaders foster a human-machine collaboration in accordance with the collective intelligence approach (Peeters et al., 2020; Raisch & Krakowski, 2021). Even in the most automated cases for the participants, there is human assurance, someone doing the final check. Following the argument from

several sources, the use of AI in organizations always apply augmentation (Zanzotto, 2019; Raisch & Krakowski, 2021; Einola & Khoreva, 2023).

4.1.4 Limitations to Implementing AI

How organizations implement AI has some limitations. The participants were asked if they saw any limitations with AI, both regarding implementation, and for their role as leaders. Implementing AI solutions in business proves to be difficult. The participants describe a lot of trial and error and different levels of success for different solutions. Having enough data, and quality data to train your AI models on is a big challenge. Scalability is another challenge, taking it from the project phase to actual widespread use in the organization.

P1: *“The big problem is scalability. We are struggling to automate the workloads and really understand what this technology means for us. Something can work in testing, but scaling it to automate our processes is difficult when you have to train the AI on limited data. [...] so, deploying the technology throughout our business is an issue.”*

P4: *“My impression is that actually implementing AI is something very few do. It’s easier to test something and have it work, than to have it work in production. We try to focus on implementing it in our production and we have an understanding that it will not work 100%, but if it works 70% it’s better than nothing, but we have to inform (our employees) that this solution is based on AI and will only give a certain level of accuracy.”*

Implementing AI into existing workflows is the real test of how applicable AI will be to the organization (Davenport & Mittal, 2023). As P4 described, actually implementing developed solutions will give the best results. The secondary source S1 pinpoints the necessity to have data for implementing AI.

S1: *“On of the main reasons AI-projects fail, is that you’re unable to solve a problem well enough based on the data you have available. [...] if you have data that describes the input and output of a process, you have a good prerequisite to use AI to solve the problem. [...] you need enough data, and representative data for your problem.”*

On the other hand, Participant P3 addresses issues concerning the use of data, both for his employees and for his role as a leader.

P3: *“If we all end up relying on the same technology and the same datasets, conformity and homogeneity will become a problem. If everyone gets the same recommendations and definitions, or how to handle a certain situation we can get a huge problem with conformity.”*

Hinders in the early stage of AI is typically, as described, having enough data to train on and having people that can train the AI (Agrawal et al., 2019; Mikalef et al., 2019A). Having enough quality data is one of the main limitations identified, and resonates with the literature (Agrawal et al., 2019). This might be less of a problem for larger companies (Davenport & Mittal, 2023), but all of the organizations in this sample is of relatively large size. Another way to ease the structure and application of data is to build in-house solutions. Fitting AI technology to already existing systems might be a greater challenge for external solutions (Brosig et al., 2020). Some participants use both external solutions and in-house developed AI. Implementing an external solution “just because” is more likely to fail (De Cremer, 2020).

4.2 The Role of Leaders in Implementing AI and How AI Impacts the Role of Leaders

This section presents and discusses the role of leaders in implementing AI in organizations, and how AI impacts the role of leaders. The findings are discussed in light of the literature on AI and leadership. The section first presents and discusses the impact AI has on the role of leaders, and then secondly the leadership role in implementing AI. The participants were asked to describe how their leadership role was impacted by AI, and how they thought it would impact them in the future. They were also asked in what way AI impacted their understanding of what leadership is.

The first part explores how AI impacts leaders, both in the present and in the future. The second part discuss the role of leaders, and in the final part of this section, leadership approach is discussed.

4.2.1 The Current Impact of AI on The Role of Leaders

Since the direct use of AI technology varied amongst the participants, most of their thoughts are positioned towards future use, but the excerpts below exemplify in more detail how leaders are currently impacted by AI. Using AI to automate tasks enables P3 to prioritize what to focus on, and to see the possibilities that can be used across the organization.

P3: *“There are little things, where AI technology is implemented in some of the systems we use, like text selection and translating etc. It (AI) impacts my priorities, both in what I should focus my time on by automating tasks, but also spending time experimenting with AI and considering the possibilities that emerges.”*

4.2.2 The Future Impact of AI on The Role of Leaders

The participants shared their views on the future of AI and leadership. The participants were asked to reflect on what tasks they would have AI automate or augment in the future, and how it would impact their role. These were standardized tasks, routine tasks, and administrative tasks, which resonates with the literature: AI will take over these tasks, so that leaders can focus more on interpersonal, strategic and creative aspects (Kolbjørnsrud 2017; Petrat, 2021). The excerpts from P1, P3 and P5 show what tasks leaders prefer to have AI take over.

P1: *“Automating my travel bills, financial reporting, invoices... I think that type of unnecessary reporting should be handled by software. And when it comes to my responsibilities towards my employees, like setting up time for follow-ups, training and development, setting goals... there’s a lot of manual work that can definitely be handled by AI.”*

P3: *“Replying to emails, plan meetings, schedule my day, create documents and to-do lists. Draft a project plan or mandate for a team What remains is following up individuals, the interpersonal leadership role, work with what we call “the why”, and motivating my team.”*

P5: *“Pay my invoices, approve invoices, write statements [...] Not necessarily leadership tasks, but I would have it take over more boring tasks”*

Kolbjørnsrud (2017) surveyed hundreds of leaders and found that administrative tasks took up around half their time. Leaders from this survey want and believe that AI can take over administrative and routine tasks in the future, and the participants shared this view. The impact AI has on administrative tasks is represented in Figure 7.

AI automates administrative tasks, resulting in more focus on interpersonal tasks

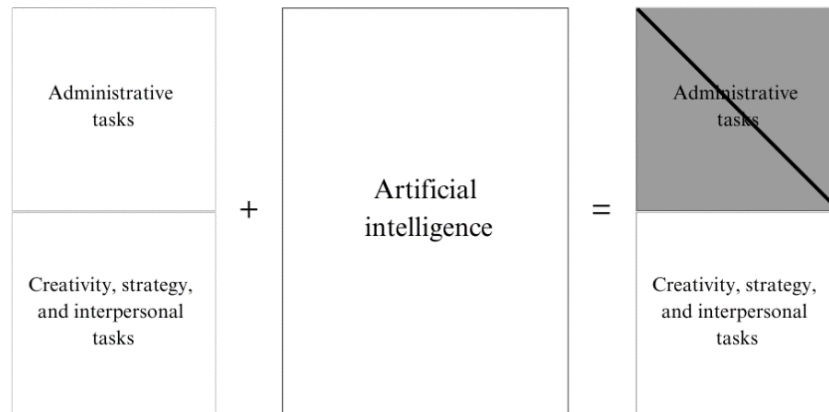


Figure 7 – Visual representation of the impact AI has on leadership.

It seems like the participants are more skeptical for AI to take over leadership tasks of interpersonal, creative, and strategic nature. They want to keep these aspects of the role themselves. On how AI impacts their understanding of leadership the participants had similar thoughts. Participant P1, P3 and P4 share their view on this matter.

P1: “[...] however, I don’t think AI could take over the more cognitive or psychological, emotional... coaching if you like. I would rather have humans do this but could see AI as a tool for helping with this. I don’t see AI replacing me in coaching my people.”

P3: “I think that this first round of adaptation (of AI) will do our routine tasks, rather than for example, decision support and important strategic decisions. [...] a big part of leadership is understanding people and relationships. I believe this part of my job will still be important in the future and could not be as easily replaced.”

P4: *“A hope for the future is to have better analyses and information, so I think you could spend more of your time on relational and business-oriented aspects than administrative tasks. I think AI could help you spend time on the smart and important things. [...] I think a lot of areas will be impacted in the future and so I think this development must happen across areas of competence to really understand the context.”*

The participants believe that AI lets them spend time on more “human” tasks, which resonates with the literature. Using AI in organizations will free up more time to use human intelligence, including interpersonal and strategic tasks (Kolbjørnsrud 2017; Wang, 2021). At the same time, they are skeptical to have AI attempt to take over these tasks. Automating routine tasks and augmenting in more complex tasks is both what they want and believe is possible.

The participants do not think that AI is able to take over the interpersonal aspect of their job, not even in the future. This resonates with the literature, that the current AI technology cannot surpass these human abilities, but maybe in the future (Parry et al., 2016; Titareva, 2021). The literature is mixed when it comes to this issue. Some researchers believe that AI can surpass human abilities in these kinds of tasks in the future (Kolbjørnsrud, 2017; Kolbjørnsrud & Sannes, 2022), but most scholars do not believe this (Jarrahi, 2018; Davenport & Foutty, 2020; Petrat, 2021).

4.2.4 The Role of Leadership in Implementing AI

The role of leadership in implementing AI is motivating and inspiring the organization to see possibilities, and to lead the change process that follows. Participants’ P4 and P5 describe this in the following.

P4: *“I spend most of my time as a leader by thinking about how we can use AI as a part of our daily work and improve the processes we work on. [...] it’s also a lot about assigning cases to our team that works specifically with AI, and then to convince the rest of our organization on what to work on.”*

P5: *“A lot of my current job as the leader of AI in our business is helping other leaders see possibilities. I spend a lot of time accelerating AI projects and [...] focusing on change leadership to see opportunities that we can exploit.”*

The participants try to see possibilities and opportunities for their organization by utilizing AI. Davenport and Mittal (2023) argue that leaders need the ability to see potential in developing AI, but building a culture for change is one of the greatest challenges fulfill this potential. The participants think a lot about what AI can do for their organization, and to succeed they need to have their whole organization with them. This is in keeping with the literature on change leadership (Kotter, 2011; Wijayati, 2022).

Exploiting possibilities with AI through change leadership is important to succeed (Onyeneke & Abe, 2021). Resistance to change can be mitigated by leaders, and having a change mindset has been shown to positively moderate work performance and engagement (Frick et al., 2021; Wijayati et al., 2022). Frick et al. (2021) noted that AI holds a more terrifying outlook on the future compared to previous technologies, and that leaders need to understand that resistance to change will be particularly challenging for AI. The participants understand that implementing AI and using AI-technology in their work will create change throughout the organization.

4.2.5 Leadership Approaches for Implementing AI

There are approaches to leadership that are more important than others under the view of AI and leadership (see Kolbjørnsrud 2017; Huang et al., 2019). The participants think that qualities such as interpersonal skills, openness, being able to motivate people, leading teams, understanding change leadership, and being creative are part of the role leaders working with AI should have. This is exemplified more in the excerpts below.

P3: *“A big part of leadership is being there for others, having interpersonal skills, and giving advice in challenging situations. [...] I think it’s difficult for AI technology to be a bearer of culture, to create social safety in teams, and to motivate individuals. Leadership is about understanding the human mind and being able to relate to this artificial construction we call a company. The feeling aspect of leadership will be harder to replace than the task-oriented stuff.”*

P5: *“I think that the most important leadership task is leading and motivating teams, and you should definitely not remove the interpersonal aspect of this.”*

AI is not able to replicate empathy and emotional intelligence and cannot adjust to different context than the one that it is trained on (Willcocks, 2020; Petrat, 2021). Some employees and customers value the human aspect behind decisions. Using AI may be less preferable in some cases even though it technically could replace a human task (DeCramer, 2019). The empirical data suggests what Petrat (2021) showed: that most managers think that AI should definitely not take over interpersonal tasks, and even if AI takes over interpersonal leadership tasks, employees are skeptical when leadership loses the human aspect.

Interpersonal skills, emotional, and empathetic skills are highlighted in the literature as being needed in the human-AI workplace. When machines take over a lot of standardized tasks, interpersonal skills become even more important (Kolbjørnsrud, 2017; Huang et al., 2019). The participants describe these skills to be important in relation to AI. These skills resonate with the authentic-transformational leadership approach established in the literature (Joo & Nimon, 2014; Geddes, 2017; Parry et al., 2016; Hao et al., 2020). Interpersonal skills and change leadership is an approach suitable for implementing AI in organizations.

4.3 The Organizational Capabilities and Leadership Competencies Needed for Successful Implementation of AI

This section addresses the different AI capabilities organizations have, and needs to have in the future. First, this section discusses the organizational capabilities, and second the leadership competencies needed for successful implementation of AI. This aims to answer the research question of what organizational capabilities and leadership competencies are needed for successful implementation of AI in organizations.

The organizational capabilities and leadership competencies make up the total AI capabilities of the organization (Mikalef et al., 2019a). Implementing AI technology in organizations also becomes a part of the total capabilities of the organization (see Bharadwaj, 2000; Mikalef et al., 2019a).

The participants were asked what organizational and leadership capabilities would ensure successful implementation, and how AI impacted their organization on a broader level. The section starts with a summary of organizational capabilities and leadership competencies, presented in Table 7. The leadership competencies, or skills, of change leadership and interpersonal skills were identified in the previous subchapter. It is included here to compare the findings with the skills identified in the literature. As presented, there is an overlap in organizational capabilities and leadership skills/competencies. The empirical findings showcase what was mentioned by the participants under the two different sections.

Table 7 – Comparison of organizational capabilities and leadership competencies in the literature and empirical findings

Literature	Empirical findings
Organizational capabilities	
<ul style="list-style-type: none"> - Culture for change (Vial 2019; Frick et al., 2019) - Technological understanding (Langer et al., 2021; Wijayati et al., 2022) - People with the right skills (Wilson et al., 2019; Miller, 2019). - Data (Varian, 2018; Mikalef et al., 2019a). - IT infrastructure (Mikalef et al., 2019a; Haefner et al., 2021) 	<ul style="list-style-type: none"> - Enough and quality data - Knowledge of AI technology - Ability to adapt - AI trainers - In-house development - Integrating AI with the rest of the business
Leadership skills/competencies	
<ul style="list-style-type: none"> - Technological knowledge (De cremer, 2019; Langer et al., 2021; Davenport & Mittal 2023). - Understand how AI should be integrated to create value (Brosig et al., 2021; Frick et al., 2021; Haefner et al., 2023). - Not overestimating what AI can do (Davenport & Foutty, 2020; De Cremer, 2020). - Integrating AI with the rest of the business (Mikalef et al., 2019a; 	<ul style="list-style-type: none"> - General understanding of technology - Understand how AI should be integrated to create value. - Not overestimating what AI can do - Change leadership - Interpersonal skills - Hiring decisions - Understanding ethical and trustworthy AI

<p>Petersson et al., 2022; Einola & Khoreva, 2023).</p> <ul style="list-style-type: none"> - Change leadership (Effendi & Pribadi, 2021; Wijayati et al., 2022). - Focus on data (Balaraman et al., 2018; Varian, 2019) - Understanding that change is made by different stakeholders (Wilson et al., 2017; Miller, 2019; Davenport & Mittal, 2023). - Interpersonal skills (Kolbjørnsrud, 2017; Sousa & Rocha, 2019; Huang et al., 2019; Petrat, 2021) - Understanding ethical and trustworthy AI (Arrieta et al., 2020; Langer et al., 2021; Anagnostou et al., 2022). 	
---	--

4.3.1 Organizational Capabilities Needed for Successful Implementation of AI

The capabilities that were repeatedly mentioned during the interviews were: technological understanding and development, the need for more IT-employees, and having more in-house development of AI. Knowledge of how to use AI technology and becoming more “data driven” represents an important area for development, and this applies to the whole organization.

P2: “We need a new set of skills within our organization to succeed. Our employees need technological understanding, and we need someone who know how to train the AI-system. We are implementing an external solution, so we need employees that can import our data and train the system on it.”

Wilson et al. (2017) argued that one human asset in AI capabilities were people that can train AI systems. P2 highlighted this as one of the skills they would need for successful implementation of their AI system. The importance of understanding technology in an organization, when thinking about implementing AI, is well shown in the literature (Mikalef et al., 2019B; Haefner et al, 2021; Davenport & Mittal, 2023). As noted by the participants,

understanding AI technology is important across the organization. The participants P3 and P4 show that knowledge of AI technology and how to use it will be important for their organization.

P3: *“It will be important to increase our competency in using (AI) tools to increase efficiency. The businesses that are able to do this will become more competitive, will need less people, and will have the edge in a market where winners and losers will be greatly defined by how quickly they can adapt and implement new technology. [...] at the same time, I think it’s important that we see the limitations of the technology. We need to know how to use it in a responsible manner and develop competence in this area as well.”*

P4: *“Our employees need to understand the technology in order to help customers find the data they are looking for. It will be a new way of working as we’re developing better solutions. We need people that understand AI, but also people that understand how AI can be applied to our business.”*

Participant P5 mention the need for in-house developers and creating own AI solutions. This can be linked to the existing literature by arguing that AI technology must be implemented with existing IT systems and processes to provide the most value (Brosig et al., 2020; Haefner et al., 2021).

P5: *“We need to a great degree in-house developers and data engineers. We have a lot of data, so much that right now we can’t fully exploit it. We need more employees in our IT department that not only understand the technology, but how we can put it in a context to extract the most value.”*

Implementing AI successfully is an organizational effort. The total technological capabilities of the firm make for effective implementation, as resonates with Petersson et al. (2022). Applying technology to business operations happens in a context where the total capabilities foster this process.

The secondary data source provides valuable insight into their organizational capabilities, and why they have succeeded with AI. S1 stresses the importance of owning the whole value

chain to know where to implement AI. However, they are also aware that they are a smaller company, and that larger organizations may have difficulties in doing this.

S1: *“We have a data team, consisting of data scientists that build the actual AI-solutions. And we have data analysts, machine learning engineers, data engineers and analytics engineers. We don’t have these people placed in a separate department [...] but we have placed them strategically in our company so that they can be close to the production and work together with the rest of our business. You need AI to be a part of what you develop.”*

Developing and training AI, as well as integrating it with the rest of the infrastructure resonates with the literature (Wilson et al., 2017; Mikalef et al., 2019a). Understanding AI and how to implement it requires people with IT knowledge and people that can apply it to the business context. Increasing the AI capability of the organization strengthens its competitive advantage, as in keeping with Palmatier et al. (2007). Organizations must be able to adapt to AI technology.

Human skills related to AI will need to evolve alongside the technology. Organizations need to train their employees and adapt AI capabilities to collaborate successfully with AI systems (Tsai et al., 2022). Adapting and working alongside each other, is where true intelligence is found according to the collective intelligence approach. Evolving AI capabilities and successful implementation becomes an iterative process (Jarrahi, 2018; Peeters et al., 2020).

4.3.2 Leadership Competencies Needed for Successful Implementation of AI

This section discusses the leadership competencies needed for successful implementation of AI in organizations.

The participants were asked what skills leaders should acquire to become more effective leaders of AI in the future. The literature on AI and leadership advice leaders to develop a good understanding of AI technology (see Davenport & Mittal, 2023). As the excerpts below show, leaders themselves don’t necessarily see this as a must in working with AI. Knowing how to utilize AI for business value is the focus.

P1: *“The main skill leaders need to develop is an understanding of the technology, particularly what AI does to the business model. There’s a gap of knowledge that future leaders need to fill [...] and we need to understand who to hire, how to nurture and develop our people that will increasingly be software hungry. [...] Certainly, it would be good if all leaders had some basic understanding of software, but I think we never should underestimate business knowledge and the main knowledge leaders have. I think however, leaders should be bold and dare to take risks with technology.”*

P1 mentions several competencies or skills leaders need to develop. Understanding technology, integrating it with the business model, and hiring the right people resonate with the literature (Frick et al., 2021; Langer et al., 2021; Davenport & Mittal, 2023). The development of the right people in relation to AI is not explicitly stressed in the current literature, just that AI capabilities is an organizational effort (Mikalef et al., 2019a).

P3: *“So, when talking about what role AI will have in leadership, I think you should rather have a process to keep yourself updated frequently (on AI) than developing a deep knowledge as a leader. I think you should stay agile and update yourself frequently, but not that deeply which would require a greater time investment. [...] the leadership role doesn’t require you to have AI understanding as its main focus. It’s more important that leaders understand what opportunities will emerge from this technology.”*

P5: *“... leaders need to understand that we have a problem and tech can solve it. They don’t need to understand coding, just that there are possibilities here. Leaders need to be willing to test and to have a change mindset. This will be the most important skills of leaders regardless. Change or die.”*

P2 and P4 somewhat share the same values but place more emphasis on understanding the technology. They agree that leaders should focus on other skills, but still should have a certain level of technological understanding.

P2: *“Technological understanding could be very useful for leaders as well, but the most important thing is to have a team around you that understands it. As a leader, you need to understand which of your data AI can handle to optimize your workflows.”*

P4: *“You must understand artificial intelligence enough to see how you can use it. Understanding the technology enables you to see where you can implement it for the most efficient use. [...] it’s important that as a leader you know more about it than general knowledge.”*

On an organizational level there needs to be a good understanding of AI technology. Leaders themselves don’t need to be experts, but they need employees that are so. The participants describe that technological understanding of leaders should be good enough but disagree to what level of understanding is needed. This is somewhat contrary to the literature, which varies, but suggests a strong understanding of AI by leaders. Some researchers argue for general knowledge about AI (Peifer et al., 2020), while some argue for a thorough understanding (Davenport & Foutty, 2020; Haefner et al., 2021; Davenport & Mittal, 2023).

P4 suggests that more than general knowledge is needed, but the body of empirical evidence in this study shows that general knowledge of AI is good enough. De Cremer (2020) formulated it as follows: Leaders need enough tech understanding to utilize their leadership capabilities. They should focus on becoming a bit more tech savvy so they can pursue their business strategy, in an environment where AI is part of the business process. This could mean that leaders should focus on the distinct tasks that makes them valuable as leaders, and not stress the need for deep technological understanding. An important competency of leaders is knowing how to utilize AI instead of being experts of the technology itself.

This can be seen in relation to the skill of leaders in not overestimating what AI technology can do, as identified in the literature (Davenport & Foutty, 2020; De Cremer, 2020). The complexity of AI might make it seem like a miracle technology, but is not the reality of the technology today. This view was shared by a couple of the participants and is exemplified in the excerpt from participant P4.

P4: *“It’s easy to get fooled by artificial intelligence. If you only scratch the surface, you imagine it can be used for everything, and I notice that when I discuss it with employees, they think you can sprinkle a bit of AI on everything and it will solve our problems. The fact is that*

it doesn't work like this. You must understand how it works in order to understand what you can use it for."

4.3.3 Understanding Ethical and Trustworthy AI

Another way that implementation of AI both impact the role of leaders, and is considered a competency of leaders, is the ethical and responsible use of AI. Leaders of organizations should be aware that these limitations exist and ensure that the technology is used responsibly (see Langer et al., 2021). The leadership role involves an awareness of these aspects to implementing AI. Biases in the data and focus on XAI is mentioned by P3 and P4 in the excerpts below.

P3: *"In relation to biases that exist in society and our collective knowledge, there is a danger that we either enhance or bring our existing prejudices with us in the data."*

P4: *"If documentation is created by AI, we want to be able to test the model. We work with XAI and explainable models to be able to explain to our users why a decision is being made."*

Participant P5 is describing the black-box nature of AI models, pinpointing the utility of the AI but the caution that should follow.

P5: *"... that our models and things we work on is a black box, that we don't know why it does what it does. We can get an answer (from the AI) and think that this is good, but it's a problem that we can't understand the models because they are too complex."*

Issues concerning biased data resonates with the current literature as one of the main ethical concerns relating to AI (Leslie, 2019; Davenport & Foutty, 2020). There is an interest in understanding black box-models from the participants perspective. Arrieta et al. (2020) looked at businesses' internal AI principles and guidelines and concluded that fair and responsible use of AI is wanted, as well as keeping with the European Commission's guidelines regarding ethical use of AI. According to the literature these considerations are especially important for leaders (Wang, 2021; Peifer et al., 2022). The participants are aware of ethical considerations, but this does not seem to hinder development of AI in the

organization, contrary to what Frick et al. (2021) and Anagnostou et al. (2022) argued: that ethical challenges can hinder AI development in business.

Because it can be difficult to gain insight into the AI's operations, trust in the technology becomes an important topic. If you do not know why the AI is suggesting these outputs, it may be harder to take it into consideration when making decisions. A solution for dealing with trust is having human control of the decisions. Participant P1 and P3 describe their trust in relation to AI, and P5 describes the importance of highlighting this issue across the organization.

P1: *“You can never fully trust software, there’s always the probability of failure [...] so that’s an understanding that every leader needs to have. What is the threshold of trust I can have? So, for some applications you always need to have a human in-the-loop. [...] for fully automated operations that pose a danger to society, I don’t think this ever could be a possibility.”*

P3: *“(I don’t trust the output from AI) at this time being. It depends what kind of recommendations it offers, and it may be easier to trust for more objective tasks. For more value-based decisions, it’s not clear that AI is at a stage where it can be made to take decisions on its own.”*

P5: *“In our job, it’s crucial that you can trust the output a system gives. We use AI as a supplement, and you will always get to know if our systems are based on AI or not, because it’s never 100% certain. Do you want to use AI generated information? Even if it’s not 100% it’s very helpful, but we have to give notice about whether this is human or machine.”*

Kolbjørnsrud (2017) showed that Nordic leaders trust AI-generated output less than other countries. The explanation is that Nordic countries are less developed when it comes to AI, and this is shown in the responses and other sources (Lystad, 2022). To reconcile for the lack of trust, a human is kept “in-the-loop” as discussed above. Following Glikson and Wooley (2020), a lack of trust impacts leaders by limiting the use of AI, and of implementation, which is shown for some of the participants. Lack of trust may keep leaders from implementing AI.

However, increasing implementation also could foster extended trust, by adapting and readapting to the technology (Jarrahi, 2018).

5. Conclusion

This chapter will conclude the research and answer the central thesis question examined in this study: *How do leaders implement and work with AI in organizations?*

The chapter will first summarize the three research questions and answer them from both an academic and empirical viewpoint. The chapter will provide theoretical and practical implications, followed by limitations of the study and recommendations for future research.

5.1 Summary of Research Questions

The purpose of this thesis was to answer three main questions derived from the literature and the empirical data, in order to answer the overarching question of how organizations implement AI, and the role of leaders and its impact on leadership.

1. *How is AI implemented in organizations and why?*

AI is implemented to various degrees and used for different tasks, but with the main intention of optimizing business processes or a strong belief that AI will do so in the future. Different conceptualizations of AI can impact to what degree AI is implemented in the organization. AI replaces routine and standardized tasks, which in turn enables leaders and employees to focus on more complex and meaningful tasks. There is a hope amongst the participants that the administrative part of their daily work will be further automated. In practice, AI is found to be an augmenting technology, meaning that AI and humans act in collaboration to perform tasks.

Integrating AI with the rest of the business is challenging, and having enough quality data seems to be the biggest hinder for successful implementation. Organizations that work with AI on a project basis, as something separate from the business could have greater challenges with seeing results. Of course, testing is necessary, but it should be applied to the business context one is trying to optimize. It is also important to consider that not all AI technology provides the same value for organizations. AI technology can be integrated into other systems but are not revolutionary in the way they perform. The AI that is mostly integrated into the business processes of organizations provide the most value.

2. *What is the role of leaders in implementing AI, and how does AI impact leadership?*

Motivating employees and getting people across the organization to see the value AI can bring is one of the main roles for leaders. Their role as change leaders and agents of change is

one of the main aspects of facilitating implementation of AI. Interestingly, even if AI could take over more complex and meaningful tasks in the future, leaders wish to keep this aspect of the role to themselves, particularly the interpersonal and soft skills. The role of leaders in implementing AI is to motivate employees, see possibilities to utilize technology, and to lead change.

Implementing AI in organizations arguably frees up more time for leaders to spend on tasks that are typically human, like creativity, thinking strategically, and taking care of their employees. Leaders should hone their interpersonal skills and have an understanding of change leadership. The authentic-transformational approach established in the literature covers most of these aspects and can be used as a framework to understand the leadership role and leadership style in relation to AI.

Leaders see many possibilities with the implementation of AI but are also aware of its limitations. Leaders need to be aware of the ethical challenges posed by AI and the impact the technology can have on organizations and society as a whole. Trusting output from an AI system is particularly challenging, but the benefits of automating processes outweigh this concern. Ethical concerns do not seem to hinder implementation of AI, and by keeping a human in-the-loop, leaders feel that AI can't do much harm to their business or society.

3. What organizational capabilities and leadership competencies are needed for successful implementation of AI?

The organizational capabilities and leadership competencies can be summarized as the total AI capabilities of the organization. Leaders only need a general understanding of AI technology. They don't need to be experts themselves if they have a team that understands it. Frequent updates on AI technology are better than deep understanding, as the knowledge should be concerned with how AI is useful in their business. Understanding how AI technology can be utilized and create value for the organization is the key competency of leaders implementing AI. At the same time, it is important that leaders do not overestimate what AI can do, and have some knowledge of ethical and trustworthy AI.

Data is the key capability for implementing AI. If the organization has enough data and quality data, successful training of the AI system is relatively easy. The human capital of the organization is another important capability. Technological understanding, data engineers and

trainers of AI are needed in organizations that implement AI. There is a need for the whole organization to adapt to AI technology, as it will significantly impact the way it operates in the future.

By answering the three research questions, this study has investigated the implementation of AI in organizations, the role of leaders, and its impact. It has answered how leaders implement and work with AI, and what leadership competencies, skills, and leadership approach they consider to be important for its success. Organizational capabilities that are needed to implement AI successfully have been identified and discussed, and leaders are identified as agents of change and facilitators of success.

This study confirms in large part the research model established for this thesis. Regarding AI capabilities of the organization, these were identified as technological understanding, quality data, people with the right skills, the ability to adapt and change, and the development of in-house AI to create the most value. The data supports the notion of IT-infrastructure as an important capability, implied in the integration of AI with the rest of the business and the mention of in-house development.

Leaders act as agents of change, by motivating and inspiring their organizations to see the possibilities of implementing AI. Whether or not the leadership role is the dominating factor for successful implementation is not clear. However, leaders oversee the implementation process, and their main task is to harness organizational capabilities for successful implementation.

5.2 Theoretical Implications

This study contributes to the literature by giving an overview of how AI actually is implemented in organizations of different industries, and shows that AI is implemented to various degrees and used for different tasks.

Research on leadership in relation to AI was found to be limited in the literature, as has the role of leadership in the implementation of AI. This thesis contributes to the literature by looking at how leaders themselves understand their role in implementing AI. Different

definitions of AI were identified and impacts the understanding and implementation of the technology. Additionally, it looks at how implementing AI impacts the role of leaders.

This thesis contributes to the literature by examining what organizational capabilities and leadership competencies are needed for successful implementation of AI. The study contributes to understand what these capabilities are in the eyes of leaders and managers. AI capabilities, including the competencies of leaders, facilitates successful implementation of AI.

5.3 Practical Implications

This study has identified a number of key areas applicable to organizations implementing AI. This section presents several key findings of the study and suggest practical implications and recommendations for leaders and managers.

5.2.1 General Technological Understanding and Knowledge of Implementation

The literature stresses the importance of technological knowledge for leaders and managers. However, it is more important to keep a general level of technological knowledge and rather understand how AI technology can be utilized. Knowing how AI can be implemented to offer business value and help reach the strategic goals of the organization is the level of AI understanding that is needed.

5.2.2 Focus on Data

The strength and limitation of AI is data. Ensuring that the organization has enough data and the knowledge of how to use it is key for successful implementation. Leaders need to understand how their organization can utilize data.

5.2.3 Focus on Interpersonal Skills When AI Enters the Workplace

When AI replace routine and standardized tasks, this enables leaders to spend more of their time on interpersonal skills. Additionally, when AI replaces tasks, a change follows in the organization. Being there for the employees that have to work alongside AI is increasingly important, since the task of leaders is to support employees in change processes. Both leaders and employees share the opinion that a human should keep up interpersonal tasks in the workplace.

5.2.4 Understand Change and Change Leadership

Both the literature and the empirical findings suggest that understanding change is important when implementing AI in organizations. Change leadership is suggested as a main driver of successful implementation, because motivating and inspiring employees is important for their acceptance of AI.

5.2.5 Hiring Decisions and Development of Knowledge

Organizations need people with technological knowledge, skills and abilities; they need data engineers and people to train AI. Leaders need to know who and when to hire, and what skills to focus on if they wish to succeed with AI. Building an organization that is ready to implement AI and ultimately increase productivity requires the right mix of human capital.

5.4 Limitations of This Study

There are a few limitations of this study, the first one being the small sample size. Only five respondents made up the primary data, supplemented with one secondary data source. It is therefore difficult to draw definitive conclusions and ensure validity, as it can only offer indications of some of the findings.

The second limitation is concerning the interview guide. As some of the participants did not work with AI in their own work, they were asked to deliver their thoughts on future use. Additionally, organizations implemented AI to various degrees which has made it difficult to assess the actual usefulness of AI to their business. In sum, these limitations contributed to a considerable amount of the empirical data being rather normative in nature, but which originated from the participants own point of view.

5.5 Future Research

Throughout this thesis, it was established that research on AI from an organizational and leadership perspective is limited. The need for further research is clear from both the literature and the empirical findings of this study. Further research is needed on the actual impact AI has on the leadership role, and to what degree the level of implementation matters in this regard.

Future research could also test specific leadership styles' impact on implementation of AI in organizations. The AI capabilities of the organization should be examined further to support the claims that have been made in this thesis. And finally, research could look into the concept of AI maturity in strengthening the AI capabilities of the organization.

References

Abildgaard, J. S., Nielsen, K., Wählin-Jacobsen, C. D., Maltesen, T., Christensen, K. B. & Holtermann, A. (2019). 'Same, but different': A mixed-methods realist evaluation of a cluster-randomized controlled participatory organizational intervention. *Human Relations*, 73(10). <https://doi.org/10.1177/00187267198668>

Acton, B. P., Foti, R. J., Lord, R. G. & Gladfelter, J. A. (2019). Putting Emergence Back in Leadership Emergence: A Dynamic, Multilevel, Process-Oriented Framework. *The Leadership Quarterly*, 30(1). 145-164. <https://doi.org/10.1016/j.leaqua.2018.07.002>

Agee, J. (2009). Developing qualitative research questions: a reflective process. *International Journal of Qualitative Studies in Education*, 22(4). 431-447. <https://doi.org/10.1080/09518390902736512>

Agrawal, A., Gans, J. S. & Goldfarb, A. (2019). Exploring the impact of artificial intelligence: Prediction versus judgement. *Information Economics and Policy*, 47. 1-6. <https://doi.org/10.1016/j.infoecopol.2019.05.001>.

Akyirem, S., Ekpor, E., Aidoo-Frimpong, G. A., Salifu, Y. & Nelson, L.E. (2023). Online interviews for qualitative health research in Africa: a scoping review, *International Health*, 2023. 1-10. <https://doi.org/10.1093/inthealth/ihad010>

Anagnostou, M., Karvounidou, O., Katritzidaki, C. *et al.* Characteristics and challenges in the industries towards responsible AI: a systematic literature review. *Ethics and Information Technology*, 24(37). <https://doi.org/10.1007/s10676-022-09634-1>

Antaki, C., Billig, M. & Potter, J. (2002). Discourse Analysis Means Doing Analysis: A Critique Of Six Analytic Shortcomings. *Athenea Digital: Revisita de Pensamiento e Investigacion Social*, 1(3). 1-39, <https://doi.org/10.5565/rev/athenea.64>

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R. & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58. 82-115. <https://doi.org/10.1016/j.inffus.2019.12.012>.

Avolio, B. J. (2007). Promoting More Integrative Strategies for Leadership Theory-Building. *American Psychological Association*, 62(1). 25-33. <https://doi.org/10.1037/0003-066X.62.1.25>

Balaraman, V., Brown, S., Duggirala, M., Moore, S., Nie, J. Y. (2018) Complexity sciences and artificial intelligence for improving lives through convergent innovation. *Academy of Management Proceedings*. 17958. Academy of Management Briarcliff Manor, NY

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1). 99-120.

Barney, N. (2023, March). *Leadership*. Tech target.
<https://www.techtarget.com/searchcio/definition/leadership>

Bell, E., Bryman, A. & Harley, B. (2022). *Business Research Methods* (6th ed.). Oxford University Press

Bharadwaj, A. S. (2000). A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. *MIS Quarterly*, 24(1), 169–196. <https://doi.org/10.2307/3250983>

Borgmann, L., Rowold, J. & Bormann, K. C. (2016). Integrating leadership research: A Meta-Analytical test of Yukl's Meta-Categories of Leadership. *Personnel Review*, 45(6). 1340-1366. <https://doi.org/10.1108/PR-07-2014-0145>

Bowman C. & Ambrosini, V. (2003). How the Resource-based and the Dynamic Capability Views of the Firm Inform Corporate-level Strategy. *British Journal of Management*, 14. 289-303. <https://doi.org/10.1111/j.1467-8551.2003.00380.x>

Brosig, A., Westner, M. & Strahringer, S. (2020). Revisiting the Concept of IT Capabilities in the Era of Digitalization. *2020 IEEE 22nd Conference on Business Informatics (CBI)*. Antwerp, Belgium. 84-93. <https://doi.org/10.1109/CBI49978.2020.00017>.

Braun, V. & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology*, 3(2). 77-101. <https://doi.org/10.1191/1478088706qp063oa>

Buckingham, M. (2015, February 9). *Most HR Data Is Bad Data*. Harvard Business Review. <https://hbr.org/2015/02/most-hr-data-is-bad-data>

Burns, J.M. (1978), *Leadership*, Harper and Row, New York, NY.

Carter, N., Bryant-Lukosius, D., DiCenso, A., Blythe, J. & Neville, A. J. (2014). The Use of Triangulation in Qualitative Research. *Oncology Nursing Forum*, 41(5). 545-547. <https://doi.org/10.1188/14.ONF.545-547>

Charlwood, A. & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence? *Human Resource Management Journal*, 32(4). 729-742. <https://doi.org/10.1111/1748-8583.12433>

Chen, W., Liu, C., Xing, F., Peng, G. and Yang, X. (2022). Establishment of a maturity model to assess the development of industrial AI in smart manufacturing. *Journal of Enterprise Information Management*, 35(3). 701-728. <https://doi.org/10.1108/JEIM-10-2020-0397>

Conlon, C., AntosikParsons, K., Flynn, S., Caffrey, L., Byrne, J. & Whiting, S. (2023). Lessons from Pivoting to Online Interviewing: Ethical and Technical Considerations for Qualitative Researchers following the COVID-19 Pandemic. *SSRN*. <http://dx.doi.org/10.2139/ssrn.4345037>

Cowgill, B. (2020). Bias and Productivity in Humans and Algorithms: Theory and Evidence from Resume Screening. *Columbia University*. https://conference.iza.org/conference_files/MacroEcon_2017/cowgill_b8981.pdf

Cunliffe, A. L. & Eriksen, M. (2011). Relational Leadership. *Human Relations*, 64(11). 1425-1449. <https://doi.org/10.1177/0018726711418388>

Davenport, T. H. & Foutty, J. (2020). AI-Driven Leadership. In MIT Sloan Management Review. *How AI is Transforming the Organization*. 3-8. MIT Press.

- Davenport, T. H. & Mittal, N. (2023). Stop Tinerig with AI. *Harvard Business Review*, *January-February*. 116-127.
- De Bruijn, H., Warnier, M. & Janssen, M. (2022). The perils and Pitfalls of Explainable AI: Strategies for Explaining Algorithmic Decision-Making. *Government Information Quarterly*, *39*(2). 101666. <https://doi.org/10.1016/j.giq.2021.101666>
- De Cremer, D. (2019). Leading Artificial Intelligence at Work: A Matter of Facilitating Human-Algorithm Cocreation. *Journal of Leadership Studies*, *13*(1). 81-83.
<https://doi.org/10.1002/jls.21637>
- Dhamija, P., Chiarini, A. & Shapla, S. (2021). Technology and Leadership Styles: A Review of Trends Between 2003 and 2021. *The TQM Journal*, *35*(1). 210-233.
<https://doi.org/10.1177/0018726711418388>
- Effendi, G. N. & Pribadi, U. (2021). The Effect of Leadership Style on the Implementation of Artificial Intelligence in Government Services. *IOP Conf. series: Earth and Environmental Science*, *717*. 012018. <https://doi.org/10.1088/1755-1315/717/1/012018>
- Einola, K. & Khoreva, V. (2023). Best friend or broken tool? Exploring the co-existence of humans and artificial intelligence in the workplace ecosystem. *Human Resource Management*, *62*(1). 117-135. <https://doi.org/10.1002/hrm.22147>
- Ellefsen, A. P. T., Oleśków-Szłapka, J. Pawlowski, G. & Tobola, A. (2019). STRIVING FOR EXCELLENCE IN AI IMPLEMENTATION: AI MATURITY MODEL FRAMEWORK AND PRELIMINARY RESEARCH RESULTS. *Scientific Journal of Logistics*, *15*(3). 363-376. <http://doi.org/10.17270/J.LOG.2019.354>
- Frey, C. B. & Osborne, M. A. (2013). The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting & Social Change*, *114*. 254-280.
<https://doi.org/10.1016/j.techfore.2016.08.019>

Frick, N. R. J., Mirbabaie, M., Stieglitz, S. & Salomon, J. (2021). Maneuvering through the stormy seas of digital transformation: the impact of empowering leadership on the AI readiness of enterprises, *Journal of Decision Systems*, (30)2-3, 235-258, <https://doi.org/10.1080/12460125.2020.1870065>

Geddes, M. (2017, September 11). *Artificial Intelligence and Authentic Leadership: The new “Chicken or Egg” Question?* LinkedIn. <https://www.linkedin.com/pulse/artificial-intelligence-authentic-leadership-new-chicken-mandy-geddes/>

Gehman, J., Glaser, V. L., Elsenhardt, K. M., Giola, D., Langley, A. & Corley, K. G. (2018). Finding Theory–Method Fit: A Comparison of Three Qualitative Approaches to Theory Building. *Journal of Management Inquiry*, 27(3). 284-300. <https://doi.org/10.1177/105649261770602>

Gioia, D., Corley, K. G. & Hamilton, A. (2013). Seeking Qualitative Rigor in Inductive Research. *Organizational Research Methods*, 16(1). 15-31. <https://doi.org/10.1177/1094428112452151>

Grant, R. M. (1991). The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation. *California Management Review*, 33(3). 114-135. <https://doi.org/10.2307/41166664>

Habli, I., Lawton, T. & Porter, Z. (2020). Artificial Intelligence in Health Care: Accountability and Safety. *Bull World Health Organ*, 98. 251-256. <http://dx.doi.org/10.2471/BLT.19.237487>

Haefner, N., Wincent, J., Parida, V. & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting & Social Change*, 162. 120392. <https://doi.org/10.1016/j.techfore.2020.120392>

Hao, M., Lv, W. & Du, B. (2020). The Influence Mechanism of Authentic Leadership in Artificial Intelligence Team on Employees' Performance. *Journal of Physics: Conference Series*, 1438. 012022. <https://10.1088/1742-6596/1438/1/012022>

Herold, D. M., Fedor, D. B. & Caldwell, S. (2008). The Effects of Transformational and Change Leadership on Employees' Commitment to a Change: A Multilevel Study. *Journal of Applied Psychology*, 93(2). 346-357. <https://doi.org/10.1037/0021-9010.93.2.346>

Higgs, M. & Rowland, D. (2011). What Does It Take to Implement Change Successfully? A Study of the Behaviors of Successful Change Leaders. *The Journal of Applied Behavioral Science*, 47(3). 309-335. <https://doi.org/10.1177/00218863114045>

Hoch, J. E., Bommer, W. H., Dulebohn, J. H. & Wu, D. (2018). Do Ethical, Authentic, and Servant Leadership Explain Variance Above and Beyond Transformational Leadership? A Meta-Analysis. *Journal of Management*, 44(2). 501-529. <https://doi.org/10.1177/0149206316665461>

Huang, M., Rust, R. & Maksimovic, V. (2019). The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI). *California Management Review*, 64(4). 43-65. <https://doi.org/10.1177/0008125619863436>

Johannesen, A., Tufte, P. A. & Christoffersen, L. (2017). *Introduksjon til samfunnsvitenskapelig metode* (5th ed.). Abstrakt forlag

Joo, B. & Nimon, K. (2014). Two of a kind? A Canonical Correlational Study of Transformational Leadership and Authentic Leadership. *European Journal of Training and Development*, 36(6). 570-587. <https://doi.org/10.1108/EJTD-12-2013-0129>

Kling, N., Runte, C., Kabiraj, S. & Schumann, C-A. Harnessing Sustainable Development in Image Recognition Through No-Code AI Applications: A Comparative Analysis. In: Santosh, K., Hegadi, R., Pal, U. (eds) Recent Trends in Image Processing and Pattern Recognition. RTIP2R 2021. Communications in Computer and Information Science, vol 1576. Springer, Cham. https://doi.org/10.1007/978-3-031-07005-1_14

De Cremer. (2020, November 2). *Artificial Intelligence Will Change How We Think About Leadership*. Knowledge at Wharton. <https://knowledge.wharton.upenn.edu/article/artificial-intelligence-will-change-think-leadership/>

Kiger, M. E. & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical Teacher*, 42(8). 846-854.
<https://doi.org/10.1080/0142159X.2020.1755030>

Kolbjørnsrud, V. (2017). Kunstig Intelligens og Lederens Nye Jobb. *Magma*, 20(06), 33-42.

Kolbjørnsrud, V., Amico, R. & Thomas, R. J. (2017). Partnering With AI: How Organizations Can Win Over Skeptical Managers. *Strategy & Leadership*, 45(1). 37-43.
<https://doi.org/10.1108/SL-12-2016-0085>

Kolbjørnsrud, V., Sannes, R. (2022). Problemløsning med kunstig intelligens: Bruk av spacemaker i tidligfase eiendomsutvikling. *Praktisk økonomi & finans*, 38(1). 47-64.
<https://doi.org/10.18261/pof.38.1.4>

Kotter, J. (2011, July 12). *Change Management vs. Change Leadership – What’s the Difference?* Forbes. <https://www.forbes.com/sites/johnkotter/2011/07/12/change-management-vs-change-leadership-whats-the-difference/?sh=602d37174cc6>

Krishnakumar, I., Hou, F., Wang, H., Wang, Y., Oh, K., Ganguli, S. & Pandey, V. (2021). Trinity: A No-Code AI Platform for Complex Spatial Datasets. *arXiv*. 2106. 11756.
<https://doi.org/10.48550/arXiv.2106.11756>

Langer, M., Oster, D., Speith, T., Hermanns, H., Kästner, L., Schmidt, E., Sesing, A. & Baum, K. (2021). What do we want from Explainable Artificial Intelligence (XAI)? – A stakeholder perspective on XAI and a conceptual model guiding interdisciplinary XAI research, *Artificial Intelligence*, 296. 103473. <https://doi.org/10.1016/j.artint.2021.103473>.

Leadership Framework. *The Leadership Quarterly*, 33(1). 101594-101611.
<https://doi.org/10.1016/j.leaqua.2021.101594>

LeCompte, M. D. & Goetz, J. P. (1982). Problems of Reliability and Validity in Ethnographic Research. *Review of Educational Research*, 52(1). 31-60. <https://doi.org/10.2307/1170272>

Leslie, D. (2019). Understanding Artificial Intelligence Ethics and Safety: A Guide for the Responsible Design and Implementation of AI systems in the Public Sector. *The Alan Turing Institute*. <https://doi.org/10.5281/zenodo.3240529>

Lincoln, Y. S. & Guba, E. (1985). *Naturalistic Inquiry*. Sage.

Lystad, E. (2022, November 9). *Nora-sjef: - Norske bedrifter mangler kompetanse på kunstig intelligens*. Computerworld. <https://www.cw.no/kunstig-intelligens-noraa/nora-sjef-norske-bedrifter-mangler-kompetanse-pa-kunstig-intelligens/2112918>

MANTERE, S., & KETOKIVI, M. (2013). REASONING IN ORGANIZATION SCIENCE. *The Academy of Management Review*, 38(1), 70–89. <https://doi.org/10.5465/amr.2011.0188>

Marx, G. T. (1997). Of Methods and Manners for Aspiring Sociologists: 37 Moral Imperatives. *The American Sociologist*, 28(1). 102–125. <http://www.jstor.org/stable/27698816>

McDermid, J. A., Jia, Y., Porter, Z. & Habli, I. (2021). Artificial Intelligence Explainability: The Technical and Ethical Dimensions. *Phil. Trans. R. Soc.*, 379. <https://doi.org/10.1098/rsta.2020.0363>

McNally, R. C. & Schmidt, J. B. (2011). From the Special Issue Editors: An Introduction to the Special Issue on Decision Making in New Product Development and Innovation. *Journal of Product Innovation Management*, 28(5). 619-622. <https://doi.org/10.1111/j.1540-5885.2011.00843.x>

Merriam, S. B. (1995). What Can You Tell From An N of 1?: Issues of Validity and Reliability in Qualitative Research. *PAACE Journal of Lifelong Learning*, 4. 51-60. <https://ethnographyworkshop.files.wordpress.com/2014/11/merriam-1995-what-can-you-tell-from-an-n-of-1-issues-of-validity-and-reliability-in-qualitative-research-paace-journal-of-lifelong-le.pdf>

Mikalef, P., Fjørtoft, S. O. & Torvatn, H. Y. (2019a). Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value. In: Abramowicz, W., Corchuelo, R. (eds.) *Business Information Systems Workshops. BIS 2019. Lecture Notes in Business Information Processing*, vol 373. Springer, Cham. https://doi.org/10.1007/978-3-030-36691-9_34

Mikalef, P., Boura M., Lekakos, G. & Krogstie, J. (2019b). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *British Journal of Management*, 30(2). 272-298. <https://doi.org/10.1111/1467-8551.12343>

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267. 1-38. <https://doi.org/10.1016/j.artint.2018.07.007>

Mittelstadt, B., Russel, C. & Wachter, S. (2019). Explaining Explanations in AI. In *Proceedings of the Conference on Fairness, Accountability, and Transparency (FAT* '19). Association for Computing Machinery, New York, NY, USA*, 279–288. <https://doi.org/10.1145/3287560.3287574>

Narayanan, A. (2019). *How to recognize AI snake oil* [PowerPoint slides]. Princeton University. <https://www.cs.princeton.edu/~arvindn/talks/MIT-STS-AI-snakeoil.pdf>

Nilsen, P. & Bernhardsson, S. (2019). Context matters in implementation science: a scoping review of determinant frameworks that describe contextual determinants for implementation outcomes. *BMC Health Serv Res*, 19(189). <https://doi.org/10.1186/s12913-019-4015-3>

Nowell, L. S., Norris, J. M., White, D. E. & Moules, N. J. (2017). Thematic Analysis: Striving to Meet the Trustworthiness Criteria. *International Journal of Qualitative Methods*, 16. 1-13. <https://doi.org/10.1177/1609406917733847>

Onyeneke, G. B. & Abe, T. (2021). The Effect of Change Leadership on Employee Attitudinal Support for Planned Organizational Change. *Journal of Organizational Change Management*, 34(2). 403-415. <https://doi.org/10.1108/JOCM-08-2020-0244>

OpenAI (2022, November 30). *Introducing ChatGPT*. <https://openai.com/blog/chatgpt>

Palmatier, R. W., Dant, R. P., & Grewal, D. (2007). A Comparative Longitudinal Analysis of Theoretical Perspectives of Interorganizational Relationship Performance. *Journal of Marketing*, 71(4), 172–194. <http://www.jstor.org/stable/30164004>

Palys, T. (2008). Purposive sampling. In L. M. Given (Ed.). *The Sage Encyclopedia of Qualitative Research Methods*. (Vol.2). Sage: Los Angeles, 697-8.

Parry, K., Cohen, M. & Bhattacharya, S. (2016). Rise of the Machines: A Critical Consideration of Automated Leadership Decision Making in Organizations. *Group & Organization Management*, 41(5). 571-594. <https://doi.org/10.1177/1059601116643442>

Pavlou, P. A., & El Sawy, O. A. (2006). From IT Leveraging Competence to Competitive Advantage in Turbulent Environments: The Case of New Product Development. *Information Systems Research*, 17(3), 198–227. <http://www.jstor.org/stable/23015886>

Peeters, M. M. M., van Diggelen, J., van den Bosch, K., Bronkhorst, A., Neerincx, M. A., Schraagen, J. M. & Raaijmakers, S. (2021). Hybrid Collective Intelligence in a Human-AI Society. *AI & SOCIETY*, 36, 217-238. <https://doi.org/10.1007/s00146-020-01005-y>

Peifer, Y., Jeske, T. & Hille, S. (2022). Artificial Intelligence and its Impact on Leaders and Leadership. *Procedia Computer Science*, 200. 1024-1030. <https://doi.org/10.1016/j.procs.2022.01.301>

Pennachin, C. & Goertzel, B. (2007). Contemporary approaches to artificial general intelligence. In Pennachin, C. & Goertzel, B. (eds.) *Artificial General Intelligence*. 1. Springer.

Pessach, D., Singer, G., Avrahami, D., Ben-Gal, H. C., Shmueli, E. & Ben-Gal, I. (2020). Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming, *Decision Support Systems*, 134. 113290.
<https://doi.org/10.1016/j.dss.2020.113290>.

Pettersson, L., Larsson, I., Nygren, J.M., Nilsen, P., Neher, M., Reed, J. E., Tyskbo, D. & Svedberg, P. (2022). Challenges to implementing artificial intelligence in healthcare: a qualitative interview study with healthcare leaders in Sweden. *BMC Health Serv Res*, 22(850).
<https://doi.org/10.1186/s12913-022-08215-8>

Petrat, D. (2021). Attitude Towards Artificial Intelligence in a Leadership Role. In Black, N.L., Neumann, W.P., Noy, I. (eds.), *Proceedings of the 21st Congress of the International Ergonomics Association (IEA 2021)*. IEA 2021. *Lecture Notes in Networks and Systems*, vol 223. Springer, Cham. https://doi.org/10.1007/978-3-030-74614-8_100

PwC. (2020, November 4). AI - fra ide til produksjon. [Audiopodcast]. In *PwC-podden*. PwC.
<https://www.pwc.no/no/podcast/pwc-podden/ai-fra-ide-til-produksjon.html>

Rahwan, I. (2018). Society-in-the-loop: Programming the Algorithmic Social Contract. *Ethics and Information technology*, 20. 5-14. <https://doi.org/10.1007/s10676-017-9430-8>

Raisch, S. & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation-Augmentation Paradox. *Academy of Management Review*, 46(1). 192-210.
<https://doi.org/10.5465/amr.2018.0072>

Rose, J. & Johnson, C. W. (2020). Contextualizing reliability and validity in qualitative research: toward more rigorous and trustworthy qualitative social science in leisure research. *Journal of Leisure Research*, 51(4). 432-451.
<https://doi.org/10.1080/00222216.2020.1722042>

Saunders, M., Lewis, P. & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). Pearson Education Limited

Schoville, R. R. & Titler, M. G. (2015). Guiding Healthcare Technology Implementation. *CIN: Computers, Informatics, Nursing*, 33(3). 99-107.
<https://doi.org/10.1097/CIN.0000000000000130>

Sinkovics, R. R., Penz, E. & Ghauri, P. N. (2008). Enhancing the Trustworthiness of Qualitative Research in International Business. *Managerial International Review*, 48(6). 689-714. <https://doi.org/10.1007/s11575-008-0103-z>

Snell, S., & Morris, S. (2021). Time for realignment: The HR ecosystem. *Academy of Management Perspectives*, 35(2), 219–236. <https://doi.org/10.5465/amp.2018.0069>

Sood, A. & Tellis, G. J. (2005). Technological Evolution and Radical Innovation. *Journal of Marketing*, 69(3). 152-168. <https://doi.org/10.1509/jmkg.69.3.152.66361>

Tambe, P., Cappelli, P. & Yakubovich, V. (2019). Artificial Intelligence In Human Resources Management: Challenges and a Path Forward. *California Management Review*, 64(4). 15-42. <https://doi.org/10.1177/0008125619867910>

Timmermans, S. & Tavory, I. (2012). Theory construction in qualitative research: From grounded theory to abductive analysis. *Sociological Theory*, 30(3), 167-186.
<https://doi.org/10.1177/0735275112457914>

Titareva, T. (2021). Leadership in an Artificial Intelligence Era. *Paper for Leading Change Conference 2021*. School of Strategic Leadership Studies, James Madison University.

Tiwari, S. (2020). Artificial Intelligence and Its Role in Human Resource Management. *International Journal of Mechanical and Production Engineering Research and Development*, 10(3). 11607-11614. <https://doi.org/10.24247/ijmperdjun20201109>

Tjora, A. (2017). *Kvalitative forskningsmetoder i praksis* (3rd ed.). Gyldendal akademisk.

Tsai, C., Marshall, J. D., Choudhury, A., Serban, A., Hou, Y. T., Jung, M. F., Dionne, S. D. & Yammarino, F. J. (2022). Human-robot Collaboration: A Multilevel and Integrated

Varian, H. (2019). Artificial Intelligence, Economics, and Industrial Organization. In Agrawal, A., Gans, J. & Goldfarb, A. (Eds.), *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press. (399-419). <http://www.nber.org/chapters/c14017>

Walumbwa, F. O., Avolio, B. J., Gardner, W. L., Wensing, T. S. & Peterson, S. J. (2008). Authentic Leadership: Development and Validation of a Theory-Based Measure. *Journal of Management*, 34(1). 89-126. <https://doi.org/10.1177/0149206307308913>

Wamba, S. F., Dubey, R., Gunasekaran, A. & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, 222. 107498. <https://doi.org/10.1016/j.ijpe.2019.09.019>.

Wang, Y. (2021). Artificial intelligence in educational leadership: a symbiotic role of human-artificial intelligence decision-making. *Journal of Education Administration*, 59(3). 256-270. <https://doi.org/10.1108/JEA-10-2020-0216>

Waters, R. (2023, January 26). Generative AI: the new era of machine learning. *Financial Times*. 15.

Wijayati, D. T., Rahman, Z., Fahrullah, A., Rahman, M. F. W., Arifah, I. D. C & Kautsar, A. (2022). A Study of Artificial Intelligence on Employee Performance and Work Engagement: The Moderating Role of Change Leadership. *International Journal of Manpower*, 43(2), 486-512. <https://doi.org/10.1108/IJM-07-2021-0423>

Willcocks, L. (2020). Robo-Apocalypse cancelled? Reframing the automation and future of work debate. *Journal of Information Technology*, 35(4). 286-302. <https://doi.org/10.1177/0268396220925830>

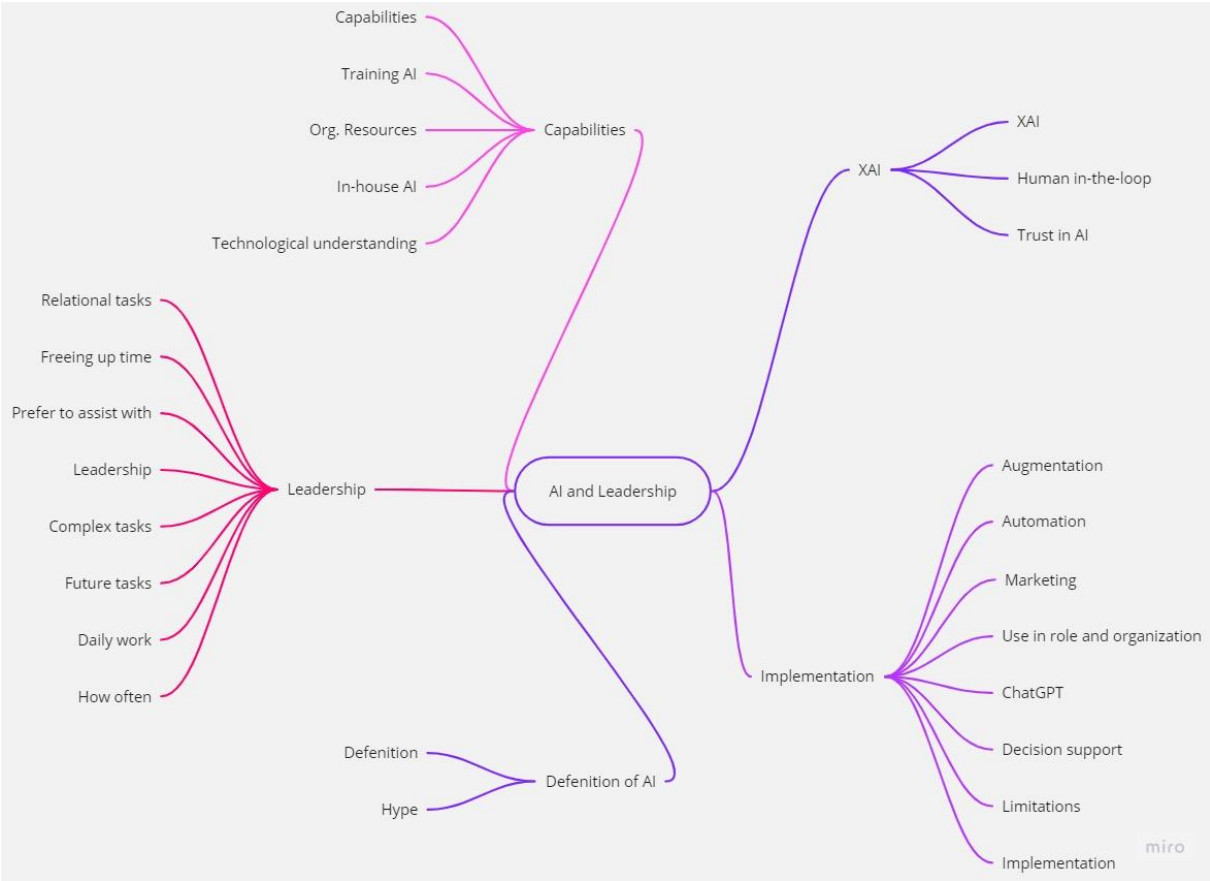
Wilson, J., Daughtery, P. R. & Morini-Bianzion, N. (2017). The Jobs That Artificial Intelligence Will Create. *MIT Sloan Management Review*, 58(4). 14-18.
<http://mitsmr.com/2odREFJ>

Yukl, G. (2002). A Hierarchical Taxonomy of Leadership Behavior: Integrating a Half Century of Behavior Research. *Journal of Leadership & Organizational Studies*, 9(1). 15-32.
<https://doi.org/10.1177/107179190200900102>

Zanzotto, F. M. (2019). Viewpoint: Human-In-The-Loop Artificial Intelligence. *Journal of Artificial Intelligence Research*, 64. 243-252. <https://doi.org/10.1613/jair.1.11345>

Appendix

Appendix A: Mind-map of themes and sub-themes from the thematic analysis



Appendix B: Approval from NSD

Vurdering av behandling av personopplysninger

Referansenummer

727421

Vurderingstype

Automatisk

Dato

04.02.2023

Prosjekttittel

Kunstig intelligens og ledelse

Behandlingsansvarlig institusjon

Norges teknisk-naturvitenskapelige universitet / Fakultet for økonomi (ØK) / NTNU
Handelshøyskolen

Prosjektansvarlig

Daniel Casoinic

Student

Vegard Ressem

Prosjektperiode

02.02.2023 - 25.05.2023

Kategorier personopplysninger

- Almennelige

Lovlig grunnlag

- Samtykke (Personvernforordningen art. 6 nr. 1 bokstav a)

Behandlingen av personopplysningene er lovlig så fremt den gjennomføres som oppgitt i meldeskjemaet. Det lovlige grunnlaget gjelder til 25.05.2023.

Appendix C: Information and form of consent

Invite to participate in research project

Hello, my name is Vegard Ressem. You are invited to participate in a research project that aims to explore the relationship between AI and leadership. You are a leader or middle-manager in a company that has implemented AI systems or aim to do so in the future.

Introduction to the project

As a part of my master's degree at NTNU Business School, my thesis aims to investigate the links between Artificial Intelligence (AI) and leadership, both as practice and process. AI technology is increasingly becoming common in the workplace today and has enhanced and automated certain tasks. AI is predicted to have an even greater impact on business and the way leaders operate in this new landscape in the future, but at this time further empirical research is necessary to better understand this subject.

The parties involved in this research project is NTNU Business School, my supervisor Daniel Casoinic, and myself.

The interview duration

The interview will take about 45 minutes. I will ask you about different workplace tasks and your view on AI and the role it plays within your organization. The interview will be recorded and transcribed for further use. The participation is voluntary, and your answers will remain completely anonymous. If after the interview you wish to withdraw, that is also your right without giving any reason as to why.

Personal data

Your participation in this interview will remain confidential and anonymous, and your data will be handled in accordance with GDPR. The recordings of the interview will be deleted after use. Myself together with my thesis supervisor will be the only ones with access to the

original data. Personal data will only be gathered with your consent, and not shared with any third party. Thank you for your valuable time and participation.

Contact

If you have any questions regarding this research project, or wish to modify/delete your data please contact:

Researcher Vegard Ressem – Mail: vegarre@ntnu.no

Supervisor Daniel Casoinic – Mail: daniel.casoinic@ntnu.no

Informed consent form

Form of consent for participation in research project.

By signing this document, I have read and understood how my participation, and how my data, will be used for this project. I hereby consent to:

- That my participation in this research project is voluntary. I can withdraw my participation at any time without any consequence.
- I can withhold answering questions that I feel uncomfortable with. I will answer to the best of my abilities, but it's my decision to share what I want.
- The interview will be recorded and transcribed. The data is confidential and will be anonymized upon publishing the project. The recording will be deleted after use.
- The project researcher and supervisor are the only ones with access to the data.
- You have the right to gain access to your data used in this project.

Date:

Signature:

Appendix D: Interview guide English

<p>Section 1: AI general questions</p>	
<ol style="list-style-type: none"> 1. When you think of “Artificial intelligence”, what are the first things that come to mind? There are no right or wrong answers. 2. Based on your experience, what is your personal definition of AI? 3. How is AI implemented in your organization, and more specifically in your role? 4. How frequently do you rely on AI in your specific role, and how much is it relied on at an organizational level? 	
<p>Section 2: AI and Leadership</p>	
<ol style="list-style-type: none"> 5. Does the AI system affect your daily work, and how? 6. Do you think AI is having an impact on your leadership roles and your understanding of leadership? 7. Which leadership roles or tasks are particularly facilitated by AI in your case? 8. Are there any leadership tasks that you are able to spend more time on because of AI? 	

<p>9. How do you feel about using more AI in your work, and what tasks would you prefer it to assist with or take over? <i>Why? E.g.: people management, recruitment, hiring decisions, performance evaluation, investment decisions?</i></p> <p>10. Do you think that one day AI could completely take over management and leadership tasks? <i>Why? Why not?</i></p> <p>11. Would you trust the advice from AI systems in making business decisions? <i>Why? Why not?</i></p> <p>12. What skill sets should a leader improve or acquire, with respect to AI, to become a more effective and efficient leader in the future? <i>Why?</i></p>	
<p>Section 3: AI in your organization</p>	
<p>13. How does AI change your organization as a whole?</p> <p>14. To what degree are your employees satisfied with the implementation of AI features in the workplace? <i>Why?</i></p> <p>15. As a leader (manager), how do you think employees would feel if they had an AI <i>algorithm</i> as a leader? <i>How would you feel about having an AI as your leader?</i></p>	

<p>16. What capabilities would your business need to develop further to fully get the benefits of AI?</p> <p>17. What type of resources (tangible, intangible, human) do you think are essential for the successful and effective integration of AI into your organization's business processes? <i>Why?</i></p> <p>18. Which areas of your organization do you think would benefit from a more intensive implementation of AI over the next 5 years? <i>E.g.: Automation, decision-support, marketing, innovation, management?</i></p>	
<p>Section 4: Closing remarks</p>	
<p>19. Do you have any other comments or ideas on the link between AI and leadership, or the use of AI in organizations in general that you would like to add?</p>	

Appendix E: Interview guide Norwegian

Seksjon 1: AI generelle spørsmål	
<ol style="list-style-type: none">1. Når du tenker på «Kunstig intelligens», hva er det første du tenker på? Her er det ikke noe rett eller feil svar2. Basert på erfaring, hva er din personlige definisjon av AI?3. Hvorfor har dere valgt å utvikle eller implementere AI løsninger i din organisasjon?4. Hvordan er/blir AI implementert i din organisasjon, og mer spesifikt i din rolle?5. Hvor ofte er du avhengig av AI i din rolle, og hvor mye er man avhengig av AI på organisasjonsnivå?	
Seksjon 2: AI og ledelse	
<ol style="list-style-type: none">6. Påvirker AI systemet / vil det påvirke ditt daglige arbeid, og hvis ja, på hvilken måte?7. Hvilken påvirkning tror du AI har på din lederrolle og din forståelse av ledelse?8. Hvilke fordeler eller ulemper med AI ser du for deg i din lederrolle?	

<p>9. Tror du at bruk av AI vil frigjøre mer tid til å fokusere på relasjonelle, interpersonale og kreative lederoppgaver?</p> <p>10. Hva føler du om å ta i bruk mer AI i ditt arbeid, og hvilke oppgaver ville du foretrukket at ble assistert eller tatt over? <i>Hvorfor? Lede mennesker, rekruttering, ansettelse, prestasjonsvurderinger og investeringsbeslutninger?</i></p> <p>11. Tror du at AI fullstendig kunne tatt over ledelse og lederrollen en dag? <i>Hvorfor? Hvorfor ikke?</i></p> <p>12. Ville du ha stolt på råd fra et AI-system for å ta forretningsbeslutninger? <i>Hvorfor? Hvorfor ikke?</i></p> <p>13. Hvilke egenskaper tror du en leder burde utvikle eller anskaffe, med hensyn til AI, for å bli en bedre og mer effektiv leder i fremtiden? <i>Hvorfor?</i></p>	
<p>Seksjon 3: AI i din organisasjon</p>	
<p>14. Hvordan tror du AI vil påvirke din organisasjon på overordnet nivå?</p> <p>15. Hvilke ferdigheter burde din organisasjon utvikle videre for å fullt ut kunne utnytte fordelene med AI?</p> <p>16. Hvilke ressurser (materielle, immaterielle, menneskelige) tror du er</p>	

<p>nødvendige for ytterligere integrering av AI inn i din organisasjon? Hvorfor?</p> <p>17. Hvilke områder i din organisasjon tror du ville hatt fordel av en intensiv implementering av AI over de neste 5 årene? F.eks. automasjon, beslutningsstøtte, markedsføringstiltak, innovasjon, HR og ledelse?</p>	
<p>Seksjon 4: Avsluttende kommentarer</p>	
<p>18. Har du noen ytterligere tanker om forholdet mellom AI og ledelse, eller bruken av AI i organisasjoner generelt som du vil tilføye?</p>	



 **NTNU**

Norwegian University of
Science and Technology