The Impact of AI Adoption Challenges on Organisational Readiness

An Interview Based Study in the Norwegian Public Sector

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Abstract

Although Norway is described as highly digitised, they are, similar to other governments, still in a nascent phase of AI adoption. Given AI's high computational ability, availability of relevant data, and algorithms, Norway is being challenged to unprecedented levels. Since 1/3 of Norway's workforce is employed in the public sector, eliciting the public sector's strong position in society, challenges perceived by this sector may allude to the government as a whole. This thesis aims therefore to explore the challenges of AI adoption and their associated impacts on the Norwegian public sector's readiness. In this context, AI adoption refers to the generation, development, and implementation of AI.

To investigate the impact of AI adoption challenges, an interview based study was conducted. We conducted 13 interviews with informants from eight public organisations in Norway and the obtained data was analysed using thematic analysis. The results identified five challenges: policy and legal, managerial, social, technological, and data. These results were discussed in relation to the theoretical framework of organisational readiness as well as prior research in the field of IS to explore the challenges' impact on the sector's organisational readiness.

The results suggest that three of the five identified challenges, namely managerial, social, and technological, impact organisational readiness through factors such as resources, culture, strategy, innovation valance, cognitive, and IT. However, two challenges, i.e., policy and legal and data, had no direct impact on the original framework, despite these challenges being key aspects of AI adoption in the public sector. This resulted in this study's reconceptualised organisational readiness framework to include two context-specific factors, namely data and government interventions, and exclude the partnership factor.

Keywords: *Artificial Intelligence, AI Adoption, Organisational Readiness, Public Sector*

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Ahlam Aatif & Mai Julie Nguyen
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List of Acronyms

AI	Artificial Intelligence.
GDPR	General Data Protection Regulation.
HR	Human Resources.
HRO	High Reliability Organization.
IS	Information Systems.
IT	Information Technology.
ML	Machine Learning.
PS	Public Sector.
RQ	Research Question.

Chapter 1

Introduction

"Artificial intelligence - AI - represents great opportunities for us as individuals, for business and for the public sector. Used at its best, the technology can contribute to achieving the sustainability goals - not only here in Norway, but also throughout the world ."

Nikolai Astrup,
Norwegian Minister of Digitisation

1.1 Motivation

Originating in 1956 during the Dartmouth Summer Research Project [1], Artificial Intelligence (AI) has not only become unavoidable, but its study has become a necessity. Many scholars reckon AI to be a "*power force multiplier and enabler for several high-tech domains*"[2] as it can potentially blur the boundaries between digital, physical, as well as the biological spheres [3]. Given the technology's attributes of high computational ability, availability of relevant data, and algorithms [4] which can alter the way organisations and society ought to operate, many governments have accentuated the significance and necessity of AI.

The Norwegian government announced its first national strategy for AI where they bring to the fore the significance of AI [5]. According to this strategy, AI can contribute to more efficient and user-oriented services in the public sector due to Norway's advantageous position of possessing high quantity and quality data [5]. In addition to Norway's highly digitised state with vast amounts of high quality data [5, 6], there is a high level of trust among the population, both towards the private and public sector. Because of the different setting in which Norway operates in, AI will not only enable better problem solving, but it will too facilitate problem solving in novel ways. Since almost 1/3 of Norway's workforce is employed in the Public Sector (PS), meaning that the sector uses a large amount of society's total resources, the overall value creation in Norwegian society is significantly reduced if resources are not used efficiently: *"When the public sector has such a strong position in society, it becomes crucial how the state and the municipality behave in meetings with the business community. The public sector must prioritise correctly, use resources efficiently and be of high-quality case processing and service deliveries."* [7]. However, a published strategy is only a first step. As stated by both the national strategy and prior research, Norway, alongside other governments, are still in the nascent phase of AI adoption [5, 6].

Norway is still in the nascent phase, with only a few AI applications in production [6]. A survey on the status, challenges, and needs of the Norwegian public sector [8] shows that many organisations are still in a planning or pilot phase where they attempt to figure out AI's usage in their business. The survey further illustrates that over half of the participated organisations face challenges associated with AI adoption. Any effort to address these challenges are confounded by the subtle ways AI interacts with society, due to its novel and pervasive nature [9]. Since some AI applications are relatively new, we are compelled to wait and observe the consequences of the technology as it unfolds. Understanding the potential consequences posed by AI and its associated challenges are therefore not always obvious. Thus, the public sector is urged to proactively cope with AI by understanding what is apparent to them - by understanding the inevitable accompanied challenges of adopting the technology.

Based on this, this thesis will explore potential challenges of AI adoption as they are perceived by the public sector. To handle challenges, researchers are urging sectors to follow the path of transformation and self-evaluate continuously [3]. For the public sector to overcome challenges, organisations need to therefore actively work on expanding their thinking to include ideas which has previously never been considered. Companies need therefore to assess their state to effectively adopt novel technologies - to assess their readiness. Following this premise, we will attempt to investigate the relationship between this study's identified challenges in relation to readiness - more specifically through Lokuge et al. (2019)'s theory of Organisational Readiness for Digital Innovation [10]. Understanding the public sector's readiness indicates the necessary state to engage in AI adoption, with various factors impacting their organisational readiness for adoption [10].

1.2 Research Aims and Research Questions

As briefly delineated, an ongoing problem remains in the PS where, despite them being in an advantageous position, they are still in a nascent phase of AI adoption. Following AI's broad effects and fast pace of change, assessing the public sector's state to adopt novel technologies is required since AI adoption demands an in-depth comprehension of AI readiness [10]. This research therefore aims to contribute to the understanding of this problem by exploring AI adoption and challenges in the PS from a viewpoint of organisational readiness. To achieve this aim, our study involves two main tasks: firstly, to examine the challenges of AI adoption, and secondly, to understand the challenges' implications on the organisational readiness of the public sector. By utilising the lens of organisational readiness for Information Technology (IT) innovation [10], this thesis aims to explore the challenges related to AI in the PS by addressing the following Research Question (RQ):

What are the challenges that impact the organisational readiness for AI adoption of the Norwegian public sector?

To answer the RQ, this thesis is steered into themes such as organisational readiness, AI adoption and its challenges, as well as the relationship between them. We have conducted an interview based study on the challenges of AI adoption where we have interviewed informants from eight public organisations. To establish a shared understanding of the term "adoption" between the researchers, interviewees, and readers, we employ Damanpour definition of "*conceived to encompass the generation, development, and implementation of new ideas or behaviors.*" [11]. Through this thesis, we contribute to research by providing empirical groundwork for further theorising on AI adoption and readiness. Further, we provide insight on AI adoption challenges which may be of interest to public organisations.

1.3 Thesis Outline

The outline of this thesis follows the logical order from defining a research problem and its corresponding research setting, to analysing empirical evidence and connecting it to the theoretical framework and previous literature. Following the introduction where we describe our motivation for this research and introduce the research problem, the remainder of this thesis is structured as follows:

Chapter 2 presents our research context where we describe the current state of AI in the Norwegian public sector. The research context is presented to understand AI and its usage in the Norwegian context.

Chapter 3 contains previous research in the field of Information Systems (IS). Literature from two research domains are reviewed to understand the current discussions on AI, namely AI adoption and AI management.

Chapter 4 describes the theoretical framework used to address the RQ of this study. The chapter thus discusses the theory of Organizational Readiness for Digital Innovation.

Chapter 5 presents the methodological approach that shaped this thesis, as well as the methods used to obtain and analyse data. Following Saunders et al. (2012)'s suggestions, this chapter highlights research philosophy, approach and choice, and time horizon. Thereafter, data collection and analysis are presented. Lastly, we reflect upon the study's quality and ethical considerations.

Chapter 6 provides an overview of the identified challenges of AI adoption from our data collection and analysis.

Chapter 7 discusses our findings in relation to our theoretical framework and literature review to answer our RQ.

Finally, **Chapter 8** rounds off the thesis with concluding remarks based on the previous chapters. This chapter presents potential avenues for further research and limitations we faced during this research.

Chapter 2

Research Context

This chapter lays the foundation of our study. We will first define the term AI and the different approaches to it in Section 2.1, before we introduce the birth of AI in Section 2.1.1. At last, we will introduce the status of AI in Norway in Section 2.2.

2.1 What is AI

With the differing definitions of the complex technology that is AI, we employ AI HLEG's definition throughout this study. The concept of AI has sparked the curiosity of researchers and scholars, and it has since been popularised by corporations and undertaken by governments. Despite its origin in 1956, AI is a modern and novel field that can be applied to a wide range of domains - from learning and perception to the more specialised such as medical diagnosis, fraud detection, and autonomous vehicles. However, there is an increasing need for us to understand what AI is capable of and what impact it will have on society. Thus, it is vital to be explicit about what is meant by the term AI.

What is AI? Although it appears to be a simple question, defining AI is no easy task, since AI itself is complex technology. The field itself is expansive, and different approaches have resulted in different definitions, such as *human thinking*, *rational thinking*, *human acting*, and *rational acting*, as provided by Russel and Stuart (2010) in *AI: A Modern Approach*[12].

The first approach, *human thinking*, is close to Bellman's (1978) and Haugeland's (1985) definitions, which define AI as *"[The automation of] activities that we associate with human thinking, activities such as decision-making, problem-solving, learning [...]"*[13] and *"the exciting new effort to make computers think [...] machines with minds, in the full and literal sense"*[14]. In this context, AI is concerned with cognitive processes and reasoning, as well as measuring the degree of success in the form of fidelity to human performance [12]. It is therefore necessary to study how we as humans think to ensure that the machine's behaviour corresponds to human behaviour. Thus, combining AI's computer models and experimental approaches from psychology will allow the development of precise and valid theories of the human mind.

The second approach, *rational thinking*, is similar to human thinking in the sense of thought processes and reasoning but differs in the way it measures success. According to a definition provided by Charniak and McDermott (1985), AI is *"the study of mental faculties through the use of computational models"* [15]. Likewise, Winston (1992) defines AI as *"the study of the computations that make it possible to perceive, reason and act"* [16]. Compared to human thinking, which measures success in the form of loyalty to human performance, this approach measures success against *rationality*, i.e., doing the right thing.

While the perspective of human and rational thinking is tightly related to reasoning and cognitive processes, the views of human acting and rational acting are concerned with behaviour. AI in the third aspect, *human acting*, can be explained as a computational artefact that acts like humans or how we expect humans to act[17]. Alan Turing's well-known Turing Test reflects this viewpoint by stating that a machine is considered intelligent if a human interrogator cannot distinguish whether it is a human or a computer. Kurzweil (1990) supports this statement by defining AI as *"the art of creating machines that perform functions that require intelligence when performed by people"* [18] In the same way, Rich and Knight (1991) use the term AI to refer to *"the study of how to make computers do things at which, at the moment, people are better"*[19].

The fourth approach, *rational thinking* focuses on the other hand on a rational agent achieving the most optimal outcome or most optimal expected outcome if there is uncertainty. Poole et al. (1998) and Nilsson (1998) corroborate this understanding of AI, referring to it as *"the study of the design of intelligent agents"*[20], which is *"concerned with intelligent behaviour in artefacts"*[21]. Such artefacts are frequently referred to as *rational agents*, which comprise the following properties[22] [17]:

- **Autonomy**: The ability to operate without direct human assistance
- **Social ability**: The ability to interact with other agents or humans
- **Reactivity**: The ability to perceive the environment and respond to changes that occur in it
- **Pro-activeness**: The ability to exhibit goal-directed behaviour by taking the initiative

Furthermore, this viewpoint emphasises the significance of correct reasoning or inference. Agents are rational if they choose to perform actions that are in their own best interests, given their assumptions about the world. Thus, the ideal AI would be able to inhabit and act upon environments in the same way that humans do with their own, in addition to good decision-making and acting upon them in the same manner.

The High-Level Expert Group on AI (AI HLEG) offered "a crude oversimplification" definition of the term AI that draws upon the previous definitions of AI. It is defined as follows by the High-Level Expert Group on AI within the European Commission's Communication on AI (2019) [23]:

> *Artificial Intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.*
>
> *As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation and reasoning, search, and optimisation), and robotics (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems)."*

To go more in-depth of the definition provided by AI HLEG, the first part of the definition explores what the AI system entails through three main capabilities: 1) perception, 2) reasoning and decision-making, and 3) actuation. As presented earlier, AI systems are said to be rational when it first perceives the environment through some sensors (e.g., microphones, cameras, input devices, or sensors of physical quantities) and thus collects and interprets data. The system then processes the information derived from this data and chooses the optimal action based on the perceived data. Finally, it behaves per some actuators, potentially changing the environment. It is worth noting that, due to constraints like time or computational power, rational AI systems do not always take the most optimal action for their goal and thus achieve only bounded rationality[23].

The second part of the definition encompasses the three categories of approaches and techniques used to build AI systems - namely *reasoning*, *learning*, and *robotics*. Knowledge representation and reasoning, planning, scheduling, search, and optimisation are among the techniques included in the first category, *reasoning*. These techniques enable to reason on sensor data. The second category, *learning*, covers techniques such as machine learning, decision trees, and several other learning approaches. These techniques are effective when AI systems have to solve problems that are hard to define and cannot be comprehensively described by symbolic behavioural rules. The last category, *robotics*, refers to embodied

AI or a physical machine that tackles the world's dynamics, uncertainties, and complexity. Perception, reasoning, learning, action, and interaction capabilities with other systems, are commonly integrated into the control architecture of the robotic system. Autonomous vehicles (self-driving cars), robotic vacuum cleaners, and drones are some prominent examples of robots we usually find in our time period.

To comprehend the term AI, one should consider additional issues and perceptions about AI. First, there exist two types of AI, namely *weak* (known as narrow or artificial narrow intelligence) AI and *strong* (known as general or artificial general intelligence) AI. A weak AI is trained to perform tasks for specific purposes (e.g., pattern recognition and image processing), while a strong AI has intelligence equal to humans and is trained to perform tasks that humans can do. The majority of existing AI solutions are mainly weak AI. Second, some AI systems can be opaque due to their *black-box* characteristics, making it impossible to trace back the reason for certain decisions. This implies a lack of *transparency* where a model cannot be understood on its own [24]. An explainable AI, on the other hand, is "one that produces details or reasons to make its functioning clear or easy to understand" [24]. To mitigate such issues, explainable AI would thus be an effective tool by offering explanations for the taken actions [25]. Third, some machine learning models rely on massive amounts of data in order to perform well, with fairness playing a critical factor, especially in decision-making. In the context of *fairness*, there is a concern with unwanted bias - defined as a systematic error - "that places privileged groups at a systematic advantage and unprivileged groups at a systematic disadvantage" [26]. Bias can thus occur due to the training data, resulting in unbalanced and unfair decisions which may, disproportionately, harm vulnerable groups. Lastly, while present AI systems are goal-directed, they can also have the flexibility to choose which path to pursue in order to reach the given goal.

In summary, defining AI is not simple. The field itself is expansive and AI as a technology is complex. However, in its simplest form, AI belongs to the field of science and engineering, which involves complex problem-solving. AI is proven to be rational when it displays intelligent behaviour by analysing its environment and taking actions to achieve the given goal. Moreover, subfields within AI that are used to build AI systems include three categories: 1) reasoning; 2) learning; and 3) robotics. These disciplines comprise, for example machine learning, robots, and learning rational agents, which aim to learn how to solve tasks that cannot be comprehensively described in a symbolic way, as well as adapting their behaviour over time to better achieve the given goal. We will thus refer to AI in our thesis through AI HLEG's definition. Having defined what is meant by AI, we will elucidate the historical evolution of AI, which will be presented in the following subsection 2.1.1.

2.1.1 The Birth of AI

Success, misguided optimism, and resultants cuts in enthusiasm have all occurred in the history of AI[12]. There have been cycles of adopting new creative approaches and then refining the finest of them. Having the definitions of AI in mind, we will now trace the historical nascent of AI in this part by presenting key events. However, this section will concentrate on past events rather than describing the technological advancements in detail.

Despite the notion of "a machine that thinks" stretching back to Ancient Greece, the mid of 20th century proved to be a time when significant advances in AI came to fruition. The roots of modern AI can possibly be traced back to the 1950s, when the Turing Test was introduced and the term AI was coined.

Alan Turing, who is known for breaking the Enigma code during the Second World War, articulated and published his paper *Computing Machinery and Intelligence* (1950), which has proved to be influential and sparked debates over the years [27]. Turing's paper considers the question "Can machines think?" in which he prompted the discussion on how to build intelligent machines and test their intelligence. Turing subsequently proposed a method for determining whether "machines can think", which became known as the Turing test. The test, called the "Imitation Game" in his paper, was devised as a simple demonstration of machines' ability to reason. The test takes a simple pragmatic approach, assuming that a machine or a computer can think if it is indistinguishable from an intelligent human and thus deemed to have passed the test. In other words, the test results focus on the degree to which the machine's answers are similar to those given by humans, rather than its ability to provide the correct answers.

The Dartmouth Summer Research Project is widely regarded as the official birthplace of AI as a research discipline [1]. In this historic conference dated back to the summer of 1956, McCarthy brought together leading researchers from a variety of fields, including neural nets, automata theory, and the study of intelligence for a discussion on AI, the concept which he coined at the very event [12]. The purpose of the discussion is to "proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" [28]. Furthermore, it was attempted to "find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves".

2.2 AI in Norway

Regardless of how difficult it is to predict the future, the Norwegian government highlights the probability of being affected by various challenges such as age wave, increasing globalisation and climate change [5]. Hence, it is necessary to work smarter and effectively to stay competitive and remain on the same level of welfare [5]. Digitalisation and utilising new technologies will therefore be vital components of the future. The government in Norway intends to take the lead in developing and deploying AI which protects the civilians' rights and liberties. As such, the government has made measures to further improve the welfare state along the technological advances.

According to the government, Norway is in an advantageous position to flourish in AI for a variety of reasons [5]. First, Norway has a unique relationship in terms of trust in business and public sectors. Additionally, the Norwegian society is characterised by high level of trust and respect for core values such as human rights and privacy. Second, the business sector and the population are digitally competent. Third, Norway has a solid infrastructure and high-quality data registers spanning over decades. Fourth, Norway has well-developed e-governance and public organisation that have made significant progress in digitalisation and have the capacity and experience to experiment with new technologies. And lastly, employees, unions, and the government work together in a tripartite structure, which facilitates cooperation when restructuring is required.

In 2018, the Norwegian Board of Technology, hereinafter referred to as Board and NBT, addressed the challenges and opportunities of AI in a report which is available online [29]. The Board is an independent body for technology assessment which was established by the Norwegian government in 1999, in response to a request from the Norwegian Parliament[30]. They are entrusted with providing independent advice on emerging technologies to the Norwegian Parliament and other public authorities. The report composed by the Board believes that a strategy for AI is needed and proposed 14 ideas which, among other things, address the challenge of necessary competencies, the need for data, and responsible development. These proposals include: 1) an immediate research; 2) establish a key institution; 3) define ambitious and concrete goals for Norway; 4) Master's degree reinforced with AI; 5) give everyone the opportunity to learn about AI; 6) open public data; 7) data sharing that serves the community; 8) give citizens real control over their own data; 9) ethical guidelines; 10) right to an explanation; 11) requirement for open algorithms in the PS; 12) auditing algorithms; 13) ethics by design; and finally 14) national dialogue on AI.

Taking the advice from the Board, the Norwegian government launched the national strategy for AI in January 2020, aiming at civilians in both public and private sectors, excluding the defence sector [5]. The strategy serves as a way of addressing what AI entails and the areas in which Norway will need to exploit AI's advantages. As AI is a constantly growing field, the strategy will be adjusted and evaluated in accordance with technological and social developments. Nevertheless, the government has a number of measures that will be enacted in accordance with the strategy. They will first and foremost facilitate "world-class AI infrastructure" by enacting digitalisation-friendly regulations, providing adequate language resources, establishing fast and reliable communication networks, and providing sufficient computing power, as well as making data sharing easier within and across industries and sectors. The government will also invest in AI in domains where Norway has significant advantages, for example, energy, health, and public administration. Ultimately, they have the ambition to exploit the innovative potential of AI to their advantage.

Chapter 3

Literature Review

The objective of this chapter is to provide an understanding of the research field in which this thesis is positioned, namely the research area of IS, by reviewing literature. Our literature review aims thus to describe the current research in relation to our research setting and RQ, which were presented respectively in Chapter 2 and 1. Although AI adoption in the public setting, and consequently the research on it, is still in the nascent phase, we are witnessing a slow emergence of studies assessing the importance of challenges. For the literature review of the PS, we draw attention to two particular topics to understand the current discussions in IS research on adoption and AI, namely AI adoption and AI management. Literature included in these section were found through the library search functions, Oria and Scopus database, as well as Google Scholar using these keywords (TITLE ("Artificial Intelligence") AND TITLE ("Challenges" OR "Barriers" OR "Obstacles" OR "Limitation" OR "Adoption" OR "Innovation" OR "Public Sector" OR "Readiness" OR "Organizational Readiness"). We also utilised the snowball method to find other relevant sources in the bibliography of pertinent articles. Other literature was acquired through recommendations from our supervisors and people within the industry and academia of AI and PS.

3.1 AI Adoption

Derived from the theories of IT adoption, the process of AI adoption describes the decision to completely employ the technology; with Damanpour defining the adoption procedure as "*conceived to encompass the generation, development, and implementation of new ideas or behaviors.*" [11]. In comparison with traditional IT, the broad-purpose nature and high implementation complexity of AI "*differentiates it from other digital technologies that are typically easy-to-use and easy-to-deploy*" [31]. Moreover, AI adoption requires sustained interdisciplinary efforts between IT and those who want to apply AI, and concerted efforts across the different organisational sections and external segments. Jöhnk et al. (2021) emphasised the need for significant changes in strategy, resources, competence, data, and culture [31]. As such, theoretical frameworks which considers technological, organisational, and environmental factors are deemed necessary.

Research on adoption mechanisms has had a long tradition of being at individual and organizational level, which has resulted in the development of various theoretical frameworks in the IS field to explain different technology adoptions [32–34]. However, the limited research on AI in the PS mostly relates to the technology's impacts which, as of now, are speculative in nature. Since the state and implementation of AI in the PS is still nascent, it is difficult to study its implications as they yet have occurred. Studying facets of AI related to challenges as they are currently perceived by the PS may provide an understanding of potential implications. The existing research on the perceived challenges of AI adoption has, firstly, illustrated the technology's potential implications on the workforce - following the increasingly replaced jobs and the threats of unemployment [35, 36]. Second, this field is increasingly highlighting the ethical challenge of balancing data collection and privacy [37]. Lastly, as the PS needs a productive supervision with laws and regulations, regulatory challenges need to be reflected on. As the debate on AI adoption is still unfolding, scholars are attempting to draw further attention to the AI challenges. Within section 3.1.1, we will go more in depth into AI adoption within the PS, before we move on to section 3.1.2 where we highlight challenges related to adoption.

3.1.1 AI Adoption in the Public Sector

The objective of adopting AI in the PS is often to create societal value by streamlining existing processes to better customize public goods for citizens [38, 39]. In a PS context, the aim of AI can also be to deliver new services for users and design policies to solve societal challenges [40]. As this technology does not base decisions on pre-programmed logic, but rather exhibits learning capabilities, it is thus an ideal technology for the PS where the environment is ever-changing and pre-programmed logic cannot reckon for all potential cases [41]. Following the nature of the public's objectives and problems, scholars are accentuating the unique setting of AI adoption in the public sector, and empirical studies are thus slowly emerging.

Studies on AI adoption takes many forms. Literature by Wang et al. (2020) has empirically studied chatbot projects in a Chinese setting to understand the determinants in AI adoption. They established a relationship between readiness factors and pressure which impacts adoption stages where "*pressure can encourage local governments to implement chatbots*" [42]. While Wang et al. focus on determinants, Wirtz and Müller (2019) demonstrate an integrated framework for public management in hopes for better understanding the embedment of AI into administrative processes. Other research on adoption has focused on challenges, such as the literature from Kankanhalli et al. (2019) that conceptually identify AI adoption challenges in the PS [43] and the interview-based study with German municipalities that analyse AI adoption challenges from an employee perspective [44]. Literature exploring perceived challenges of AI adoption will be described in greater detail in the next section.

3.1.2 Challenges of AI Adoption

Scholars are currently attempting to map and test out the perceived challenges of AI. Sun et al. (2019)'s analysis of the stakeholders, which is based on a health care setting, identifies seven dimensions of challenges: social, economic, ethical, political, legal and policy, organizational and managerial, data, and technological challenges. Based on these seven dimensions, we will dive into the perceived challenges of AI adoption by underpinning various literature on AI adoption challenges to these dimensions.

Social Challenges

Sun et al. (2019) identifies three main social challenges which affect AI-adoption in healthcare, where two of them are applicable to the general PS [45]. The first one describes the lack of "innovation spirit" in society. The social driving force of innovation lies, according to the study's participants, in the mindset of the people - mindset that actively pursues change, rather than adapting to it. This is further addressed by Thrall et al. (2018) who emphasise culture's effect on people's reticence to interact with novel technology [46]. Such social challenges are highlighted as a possible challenges to further AI adoption. Secondly, a societal misunderstanding of AI technologies' capabilities exists in the PS. On one side of the spectrum, society has limited knowledge on AI's advantages and values as the technology is still novel. On the other side, the general public has high expectations from the technology, which might result in the practitioners resisting to adopt AI. Following the introduction of AI, organisations as well as the general public began to assign "magic" attributes to the technology. Consequently, people had high expectations for the technology, which often was followed by disappointments from people who commenced the adoption of AI. As such, practitioners facing the actual technology after the hype experienced frustration since they encountered "difficulties on AI Adoption" [45].

Economic Challenges

Economic challenges in Sun et al. (2019)'s study was only mentioned by one stakeholder: hospital doctors and hospital managers [45]. They pointed out that the adoption of AI is a costly investment that is not matched with increased profits. The other stakeholders, namely government policy-makers and IT firm managers, did not mention any economic challenges. Their lack of focus on these challenges illustrates a discrepancy between practitioners and the content of policies. This discrepancy is highlighted by Reza Tizhoosh and Pantanowitz (2018) where they argue that laboratories, which are currently facing financial pressures, may be exacerbated by the added pressures of adopting AI [47]. Adopting AI requires fundamental components for training AI, such as GPUs, which may be financially limited due to these economic challenges.

Ethical Challenges

As revealed through Sun et al.'s analysis of policy documents, the awareness of ethical challenges were discussed in the government policies [45]. These documents frame AI as disruptive with strong implications on ethics which need careful monitoring and ethical considerations that must diverge from traditional technologies. From the study's analysis, two ethical issues were identified: society's lack of trust towards unfamiliar AI-based decision-making and concerns related to data sharing. The combination of these ethical challenges in addition to AI's complexities might foster anxiety in the sector as it disables the feeling of safety. Given this anxiety in the public sector, Duan et al. (2019) urges for ethical guidance and policies to prevent misuse of AI and strengthen trust within the society [48]. Gupta and Kumari (2018) reinforces these points and highlights the ethical issues related to the use of AI and data sharing issues [49]. According to their study, AI systems may exhibit discrimination which highlights the criticality of ethical AI.

Political, Legal, and Policy Challenges

The three stakeholder-groups in Sun et al. (2019)'s study highlighted the relevancy of challenges in areas of politics, legality, and policy. Three issues were identified by the research and appear at three main levels:

1. **Macro-level**: Political concerns in regard to potential national threats deriving from overseas AI firms handling data
2. **Meso-level**: Lack of policy regulations for the market
3. **Micro-level**: Absence of legal regulations of AI usage for decision-making

The first challenge, which appears on a macro-level, relates to foreign firms' collection and storage of data and hence its possible threat to national security as well as an existential threat for the continuance of AI-adoption in the PS. Giving foreign organisations access to personal and sensitive data could make governments more vulnerable. Demonstrated by Sun et al., foreign companies collecting personal data on Chinese patients could expose China to possible biological warfare. With such misuse of data, AI will inevitably die. Sensitive data should therefore not be held by foreign firms as it runs the risk of a "security problem" which may lead to governments closing "the door on AI us" [45].

On a meso-level, issues of AI-regulations, or lack thereof, in the sector was highlighted by the study. With an absence of a shared official definition of what AI entails, uncertainty within the market rises. Uncertainty within the market continues to rise with the lack of shared official standards on how to use AI and how to evaluate its performance. Questions arise on the legitimacy of the technology usage as there are no standards and regulations to follow. With no official standards, comes different regulations.

The last identified issue is of micro-level and highlights the absence of rules on accountability in AI-based decision-making. With AI somewhat replacing decision-making procedures that were traditionally executed by people, we are left with no rules on how to engage AI in the system of legal accountability. The challenge of AI-adoption revolves therefore around the regulations and standards needed to clarify responsibilities. Since AI-systems cannot be responsible for the results they output, the issue of rules on accountability poses as a challenge for the adoption of AI-systems.

Organisational and Managerial Challenges

Challenges of organisational and managerial domain are numerous and are highlighted by Reza Tizhoosh and Pantanowitz (2018) during the implementation of AI [47]. According to their research, successful AI adoption depends on usability, trust, and financial return on investment. Sun et al. (2019) refers to the same points by illustrating the challenges through IT managers and policy-makers perceptions [45]. According to Sun et al. (2019, these challenges occur in three levels:

1. **Strategy level**: Lack of strategies for AI-adoption
2. **Management level**: Resistance to data sharing in the organisation
3. **Human Resources (HR) level**: Lack of competent workers

First of all, strategies that require management to form a plan on resource allocation and goals (i.e., top-down strategies) are deemed necessary for AI-adoption. Through strategies, organisations can better align the usage of AI with their business objective. At the management level, however, the perceived challenges relates to the resistance of data sharing and data ownership. Data equals value, and thus, managers would rather own these values for themselves than share them with other organisations [45]. A tension between organisations wishing to restrict data access and the need for data integration is therefore the foundation of the managerial challenge. Lastly, at HR level, the shortage of a competent workforce with interdisciplinary skills poses as an obstacle for AI-adoption.

Data Challenges Since AI systems requires large datasets, the first data challenge relates to insufficient size of the databases [45, 50]. This issue arises due to the public sector still being in a nascent phase of AI-adoption, and thus has no available and adequate datasets. Databases of small sizes results in AI-models creating oversimplified outputs that are only useful for simple problems. The second issue looks at the levels of data integration, meaning the connection between longitudinal data, such as historical data of an individual, and demographic data like age and gender. AI-systems require not only high quality of data, but a good quality of data integration to get a full picture of what we wish to inspect through the AI-models [45, 47]. The last identified challenge is connected to the absence of standards. In simpler terms, it refers to how and what data is collected in addition to how it is stored. With no consistent data governance, meaning activities regarding decision rights and accountabilities for data-related processes [51], data can be excluded from the databases and varying data structures are implemented - resulting in critical consequences for AI decision-making. Campion et al. (2020), who explored AI adoption in relation to the inter-organisational collaborations, suggests that these three identified data challenges to be the greatest challenges for AI adoption[52].

Technological Challenges

A reoccurring challenge was linked to AI's characteristics. These challenges encompass issues of processing unstructured data and the lack of transparency of algorithms. Algorithms transforming data into decisions, combined with the limited understanding from public stakeholders on how they work is perceived as a major concern [45, 47, 53]. However, this technological concern was only shared with the policy-makers and hospital manages and doctors according to Sun et al. (2019); IT managers find the nature of technologies irrelevant to AI-adoption [45]. IT-managers argue that AI is no different from other traditional technologies, of which their inner mechanisms are comparably unknown to the public.

Challenge	Description	References
Social	Cultural barriers; Unrealistic expectations towards AI technology; Country specific practices and insufficient knowledge on values and advantages of AI technologies.	Thrall et al. (2018) Sun et al. (2019)
Economic	Computational costs and its affordability; High costs which are not matched with increased profits	Reza Tizhoosh and Pantanowitz (2018) Sun et al. (2019)
Ethical	Responsibility and explainability of AI; Moral dilemmas on privacy and data sharing; Lack of trust	Sun et al. (2020) Gupta and Kumari (2017) Duan et al. (2019)
Political, Legal, and Policy	Governance of AI systems; Responsibility and accountability; Privacy and safety issues; Potential security threats from foreign-owned firms collecting data; Absence of rules on accountability and ownership in the use of AI; Lack of official industry standards of AI use and performance evaluation	Sun et al. (2019)
Organisational and Managerial	Understanding of needs of the AI systems; Managerial resistance to data sharing; Lack of AI knowledge and skills; Lack of strategy for AI development; Lack of interdisciplinary collaboration	Sun et al. (2019) Reza Tizhoosh and Pantanowitz (2018)
Data	Quantity and quality of input data; Insufficient size of available data pool; Lack of data integration and continuity; Lack of standards of data collection; Lack of data integration and continuity and lack of standards for data collection	Xu et al. (2019) Risse (2019) Sun et al. (2019) Khanna et al. (2013) Varga-Szemes, Jacobs, and Schoepf (2018)
Technological	Lack of transparency and interpretability; Design of AI systems; AI safety; Specialisation and expertise; Architecture issues and complexities in interpreting unstructured data	Sun et al. (2019) Reza Tizhoosh and Pantanowitz (2018) Cleophas and Cleophas (2010) Kahn (2017)

Table 3.1: AI Adoption challenges identified from literature

3.2 Managing AI

Scholars within the field of IS have a history of studying AI, with a main focus on primitive decision-making systems [54]. Such systems were not able to iteratively learn and improve their methods, and were thus dependent on human agents to adjust them. In contrast, current AI aids managers with decision-making while simultaneously learning and adjusting their actions. Such technology is therefore overlapping in much higher degrees and becoming entangled with organisational applications. With this, AI introduces new ways of management.

AI management differs from traditional IT management. This novel technology, which is characterized by the ever-evolving and ever-emerging computing capabilities, references traits of human intelligence to address complex problems regarding decision-making [55]. The decision-making relates to three interdependent aspects that effects managers when dealing with AI:

- **Autonomy**: Operating without direct human intervention
- **Learning**: Improving through experience and data
- **Inscrutability**: Becoming unintelligible to particular audiences

These facets are reinforcing each other - learning emerges from, and contributes to, autonomy; learning and autonomy leads in inscrutability; the management of autonomy, learning, and inscrutability shapes AI. The objective is thus to manage the technology in a way that increases performance and scope, while continuously increasing the degree of autonomy, learning, and inscrutability.

Management includes the communication, leadership, coordination, and control over the tasks within an organisation, with decision-making being the key activity for managers [55]. At its core, management is essentially about decision-making, both strategic decisions and task-level decisions. At times, these decisions can either be predictable, also commonly referred to as programmable decisions, or complex choices under an uncertain environment, namely non-programmable decisions. AI's continual automation of managers' decisions is predominantly programmable, but we are now witnessing an increase of non-programmable decision-making. Ensuing this change of decision-making processes, Berente et al. specify that the role of managers are subsequently following this change. With AI's novel capabilities, managers must adapt their roles with the technology. Decisions need therefore to incorporate the technology, and managers have to understand the facets of AI [55]. With each facet, there is potential managerial issues which Berente et al. reflect around.

Managing Autonomy

Essentially, AI is an "autonomous agent" which processes data that has not necessarily been directly delegated by people [55]. In a way, AI's autonomy is generative since it is often driven by their ability to control data and choose from their volition, and is thus not derived from the plans of humans. Furthermore, with AI becoming increasingly autonomous, the interplay of the technology and humans take on differentiating configurations. While human agents delegate tasks to autonomous actors in reflexive, anticipatory, and supervisory ways, autonomous actors are also evaluating and controlling humans [55]

The main challenge associated with the relationship between autonomous and human agents revolves around comprehending their respective power. As the distinction between what machines and humans ought to do is becoming increasingly blurred, knowledge workers are forced to adapt their roles in regards to the autonomous actors. Additionally, knowledge workers might decouple their actions from the exchange with AI to preserve their knowledge. This particular interaction between AI and humans has historically been discussed in relation to augmentation. The challenge of augmentation is understood in relation to fairness that various augmentation strategies develop.

Reliance on augmentation could have negative implications on dependency. With people increasingly relying on the technology to augment decisions, they become dependent on the tools, especially when tasks become more complex. Consequently, unique human knowledge diminishes with an increased interaction between humans and AI in decision-making settings, possibly undermining the productivity of the collaboration between autonomous and human actors. Berente et al. describes a consistency with the expected learnt impotence as people become reliant on AI. The implications of lost autonomy and the tension between augmentation and automation remains a key managerial challenge.

Managing Learning

Two main managerial issues related to AI learning were identified by Berente et al. Firstly, AI's learning capabilities has expanded from only proprietary datasets, to feeding off all types of data within and beyond the organisational bounds as a consequence of the widespread availability of data [55]. This can result in the emergence of managerial challenges like privacy, trust, security, governance, and questions on legal and data ownership. With the ability to generate codified knowledge, unanticipated consequences relating to algorithmic fairness, bias, and value-agnostic choices arise. With such potential results, managing AI should be associated with mental models of the AI system in question, and continuously learn about the relationships between input and output in an AI model. Secondly, the technological progress of simple tasks, like recognition or data storage, have enabled AI's learning capability to evolve from elementary approaches (e.g., inductive learning) to large-scale approaches (e.g., reinforcement learning). Common for such new approaches is the elimination of human mediation. As learning becomes more available by AI, in addition to it becoming cheap and ubiquitous, human oversight becomes less needed. Managing AI therefore implies managing learning with regard to correction and adaption of AI and human components.

Managing Inscrutability

With AI increasingly learning and becoming autonomous, it also becomes more inscrutable. The term "inscrutability" carries four interconnected emphases which moves from the technology to the human actor and is, at large, structured as a continuum to draw light to varying aspects of decision-making inscrutability:

- **Opacity**: Lack of visibility in the AI and illustrates the data that can potentially be scrutinized
- **Transparency**: Inclination to disclose owners of the system, and the amount they are willing to disclose, or in some cases: occlude
- **Explainability**: Ability to be understood, which is a characteristic for the algorithm
- **Interpretability**: Particular people's understandability and calls attention to the interpreter, instead of the algorithm

Regardless, inscrutability is viewed as a managerial challenge due to organisational responsibilities varying for distinct AI algorithms and managers' necessity to understand the decisions' implied issues of culpability, accountability, liability, and fiduciary responsibility. Moreover, inscrutability challenges manifests itself for managers when they attempted to evaluate AI performance. They quickly notice that differing knowledge, meaning know-hows and know-whats, is used to train the systems.

These reinforcing aspects and their related challenges can be summarised through Table 3.2
.

Management Aspects	**Description**	**Characteristics**
Autonomy	Acting without any human intervention	Understanding autonomous and human agents' respective powers
Learning	Improving through experiences and data	Large-scale data which may result in challenges of privacy, trust, security, governance, and data ownership
Inscrutability	Becoming unintelligible to particular audiences	Self-evolving algorithms

Table 3.2: Summary of AI management

Chapter 4

Theoretical Framework

This chapter introduces the relevant theory that is used as a theoretical lens to address the RQ of this study. We use specifically the theory of Organizational Readiness for Digital Innovation as a theoretical lens to provide a foundation for discussions regarding the challenges of AI adoption impacting organisational readiness (Section 7). The theory is explained in further depth in the following section.

4.1 Organizational Readiness for Digital Innovation

Lokuge et al. propose in *Organizational readiness for digital innovation: Development and empirical calibration of a construct* (2019) a multidimensional formative construct for assessing organisational readiness for digital innovation. Such a construct would facilitate comprehensive research on the importance of digital innovation, as well as benchmarking to track organisational readiness.

Readiness refers to the "*state* that is attained *prior* to the commencement of a *specific activity in relation to psychological, behavioural, and structural preparedness of the organizations*" [10]. The definition emphasises the significance of timing, state, and the certain activity that is getting ready for. Readiness can be observed at multiple levels, such as individual, organisational and individual levels. Lokuge et al.'s study, however, concentrates on the organisational level, and defines organisational readiness with reference to digital innovation as "an organization's assessment of its state of being prepared for effective production or adoption, assimilation and exploitation of digital technologies for innovation"[10]. It has also considered product and process innovations that are initiated with digital technologies, which is in line with Nylén's study (2015) [56]. Here, innovation refers to "production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and establishment of new management systems", stated by Crossan & Apaydin. Accordingly, Lokuge et al. propose digital innovation as "innovation enabled through or triggered by digital technologies" [10]. It is also worth noting that organisational readiness for digital innovation is not a homologous construct, meaning that it is best conceived as a continuum of readiness rather than seeing it as a binary variable of "ready" or "not ready". Assessing the readiness state as a degree in a continuum will reveal how "ready" the organisations are based on the factors that impact their organisational readiness, implying that readiness can be increased through these factors.

Lokuge et al. derived a construct, also referred to as a framework, which they called *a priori model*, for assessing organisational readiness for digital innovation. They thereof advocated 21 measures categorised under seven subconstructs, including *resource readiness*, *IT readiness*, *cognitive readiness*, *partnership readiness*, *innovation valance*, *cultural readiness*, and *strategic readiness*. The seven subconstructs of the a priori model of organisational readiness for digital innovation are all conceived as a formative composite construct, in the sense that readiness subconstructs are considered to be the cause of the latent construct, i.e., organisational readiness [10]. In this study, the seven subcontstructs of the organisational readiness will also be referred to readiness factors.

The need of flexibility of resources in changing the IT assembly to perceive and respond to dynamic markets is highlighted by *resource readiness*. It places a strong emphasis on the organisation's flexibility in configuring and reconfiguring its resources to meet the needs of digital innovation. The subconstruct is characterised as the flexibility of a shared set of financial, technological, and human resources that serve as the foundation for digital innovation. Three measures are constructed as part of this subconstruct, including 1) flexible financial resources; 2) human resources; and 3) flexible infrastructure resources.

IT Readiness refers to the IT portfolio' ability to facilitate digital innovation. The stability of the enterprise systems is largely focused in this context. It is stated that digital technologies can only be advantageous when the enterprise system is stable, as the stability influences the innovation capacity of digital technologies. Furthermore, it is argued that organisations that employ IT to complement core competencies will have greater strategic flexibility, resulting in innovation and increased performance. Moreover, the importance of accessibility to digital technologies and maintenance of a secure and stable environment, in terms of IT infrastructure readiness, are also emphasised. Based on these highlights, three measures are developed within this subconstruct: 1) stability of the enterprise system; 2) availability of digital technologies, and 3) stability of the IT infrastructures.

The strength of an organisation's knowledge base in facilitating digital innovation is known as *Cognitive Readiness*. Herein, knowledge of business processes and softwares is a crucial component of the subconstruct. It is believed that such attributes are particularly relevant for organisations that must quickly adjust to new and unforeseen challenges. Furthermore, the aspect of technical skills of IT employees, as well as the adaptability of the staff for technical and organizational changes, are essential for initiating digital innovation. To measure cognitive readiness, three measures are established, 1) knowledge; 2) skills; and 3) adaptability of the employees.

Partnership readiness is referred to the affiliation of external stakeholders to an organisation's digital innovation. In this aspect, the importance of initiating and maintaining relationships with vendors, consultants, and customers, and partnerships with customers and vendors, are viewed as crucial facets of digital innovation. Thus, the following measures are developed to measure partnership readiness: 1) IT vendor relationship; 2) relationship readiness with management consultants; and 3) readiness for establishing partnerships with customers or vendors.

The optimism of stakeholders toward digital innovation is measured by *Innovation Valance*. It is believed that positive attitudes of the employees may contribute to open-ended creativity, which is significant for digital innovation. Likewise, motivation is a prominent component that promote open-ended value creation. Furthermore, leaders that motivate staff to be empowered to make better decisions and commit beyond their traditional boundaries, is a notable attribute that fosters digital innovation. As such, these measures are used to measure innovation valance: 1) attitude of the employees; 2) motivation; and 3) empowerment.

The strength of an organisation's core values that promotes digital innovation is defined as *Cultural Readiness*. A salient factor for any innovation is the strong organisational culture that promotes sharing ideas, decentralised decision-making, and low-risk aversion. By that, the following measures are developed to measure cultural readiness: 1) sharing of ideas in a connected workplace; 2) decentralisation of decision-making culture; and 3) risk aversion.

Strategic Readiness is related to a set of managerial activities that an organisation engages in to facilitate digital innovation. The importance of clarity, continuous refinement, and communications of strategic goals are salient attributes here. A lack of attention to the changes and uncertainty of what is expected has proven to be factors in unsuccessful innovation projects. Hence, the subconstruct emphasises the importance of knowledge that communicates a plan of actions that defines the guidelines for compliance in digital innovation is important. As a result, the following measures are included in the a priori model: 1) the clarity of goals; 2) relevance; and 3) strategy communication.

The following figure summarises Loguke et al.'s figure a priori model of organisational readiness for digital innovation.

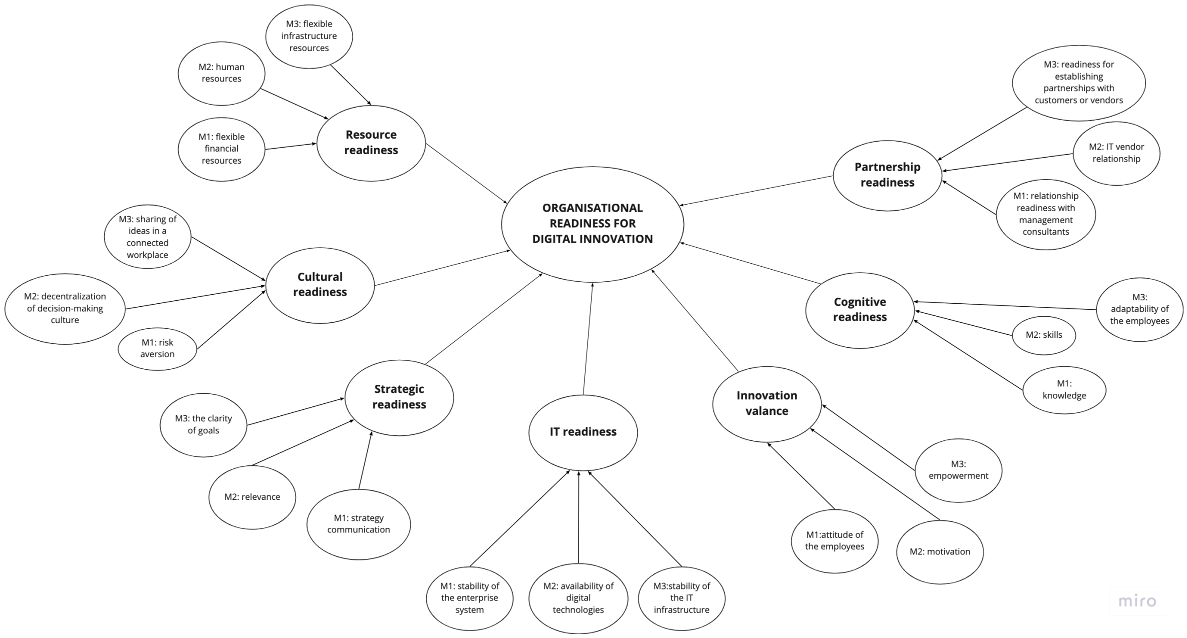


Figure 4.1: Lokuge et al.'s a priori model of organizational readiness for digital innovation

To recall, our study's objective is to identify the challenges that impact the organisational readiness for AI innovation in the Norwegian public sector. Since AI is still in the process of being evaluated and assessed, it is not much in use yet. As mentioned earlier, the notion of readiness for digital innovation has been measured at the organisational level. To talk about organisational readiness is therefore a good fit and pertinent to the aims of our study, as it allows us to investigate the challenges that impact the organisational readiness for digital innovation, particularly AI adoption of the Norwegian PS. Additionally, Lokuge et al.'s definition of digital innovation is of relevance for AI adoption as the key terms in their definition (i.e., production, adoption, assimilation, exploitation, renewal, enlargement, and development) can be considered to be AI's characteristics. Furthermore, unlike other organisations, PS entities are mandated to protect the public goods, making the foundation for implementing AI arguably more complex as the public operates within a context shaped by factors such as bureaucracy, politics, and regulations. To assess the readiness of public organisations, understanding the context in which these organisations operate under, meaning the public sector and its associated factors, is vital. Thus, by exploring the PS as a whole, we may be able to provide an understanding of AI adoption challenges [57]. Since the current a priori model does not take these factors into account, there is a necessity to consider them. As such, we will take a different perspective on the construct of the theory by using it to study the PS. Moreover, while we have limited our scope to identifying the **challenges** that impact organisational readiness, we will **not** focus on the degree to which the challenges have an impact. We would rather discuss the challenges that impact organisational readiness for AI adoption. Overall, since existing research is still at an early stage of understanding the PS' readiness for such an emerging technology, using organisational readiness to explore AI adoption challenges in the Norwegian public sector is particularly apt in the empirical context of our study.

Chapter 5

Methodology

This chapter outlines the research methods and methodologies underpinning this study to answer the research question. To include the practical and philosophical aspects of research, we emphasize both methodology and methods in our study: the latter being techniques to gather evidence while the former describing the choice of strategy, process, and plan which settle the method [58–60]. This chapter thus provides descriptions on the participants, meaning the criteria for inclusion and sampling methods, as well as the choice of research design and the reasoning behind it. Techniques used for data collection and the conducted procedures, in addition to methods of analysis, are illustrated and explained in Section 5.3 and 5.4. Lastly, ethical issues that potentially followed and the research quality of our thesis is discussed. The research question leading to this thesis, and consequently our methodology, could be formulated as follows:

> *What are the challenges that impact the organisational readiness for AI adoption of the Norwegian public sector?*

To answer our research question, we conducted an interview based study where we complied to all stages of Saunder et al. (2019)'s research onion model [61]. Each layer offers important insight on various aspects of research which should be examined in order to develop a sound methodology, and should therefore not be overlooked. The topmost layer comprises the research philosophy and describes a set of beliefs on the assumptions of reality. This shapes the fundamental idea behind the second layer: the research approach. During this step, we attempt to demonstrate the approach we resort to when conducting researcher. In the third and fourth layer, the research strategy and choice is adopted respectively. The former concerns itself on how the researchers plan to collect data, while the latter is determined by the obtained data and methods of analysis; either qualitative, quantitative, or mixed-method. The time horizon is identified in the fifth layer and describes the time frame which the project is intended for completion, while the last stage of the model entails any decisions on procedures and techniques. To achieve a holistic approach to our research methodology, the research model's six layers were included to develop our research design—starting with the research philosophy.

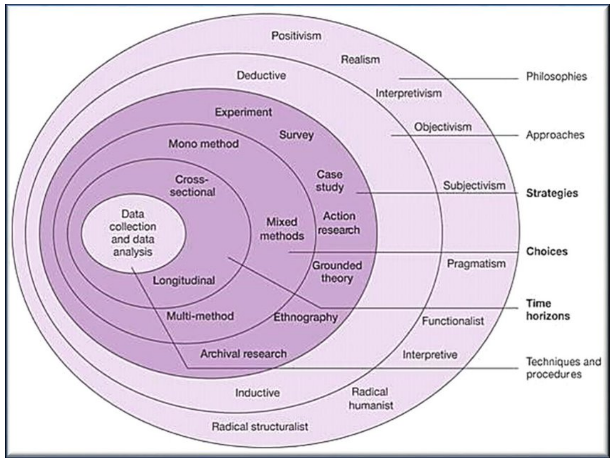


Figure 5.1: Research onion presented by Saunders et al. (2019)

5.1 Research Philosophy

Our research philosophy is rooted in an interpretive nature and reality of knowledge [62]. This fundamental philosophy is subjective and molded by our perceptions and is thus more suited for research which requires interpretation of a flux of practices, experiences, and processes [61, 62]. Research within this field of philosophy assumes that understanding reality takes place through social constructions like language, consciousness, and opinions. This philosophy is applied on a studied social reality which cannot be quantified, but on situations "*as they unfold naturally, more specifically, they tend to be non-manipulative, unobtrusive, and non-controlling*" [63]. A phenomenon can therefore only be explored contextually and subjectively through this type of research. Unlike positivist philosophy, which states that reality is understandable, interpretivism asserts that the nature of reality is "*imperfectly understandable*" [64]. Therefore, interpretivist studies do not aim to provide absolute truths, but rather recognise that further development of theory from prior literature can draw closer to the truth. To study a complex phenomenon, such as organisational readiness, starting with interpretive philosophy is hence preferable due to its observation and investigation of reality going beyond the phenomenon itself [65].

Organisational readiness is a complex venture demanding both human and technological interventions, as we have illustrated in Chapter 4. We must understand the many complex realities that the Norwegian PS faces, and which AI might further complicate. Like other interpretive researchers, we start out with the belief that " *[...] access to reality (given or* *socially constructed) is only through social constructions such as language, consciousness and shared meanings"* [66]. The philosophical base of this paradigm, and consequently our interview-based research, attempts therefore to understand organisational readiness and AI through the perceptions people in the PS assign to it. The philosophical assumptions behind this thesis will therefore be within the paradigm of interpretivism as we believe the value and knowledge surrounding this topic cannot be achieved unless we understand the context and the actors' perceptions of the phenomenon. We attempted to explore their perceptions through qualitative methods, which we interpreted at two levels: the first level involves viewing the phenomenon from a subjective lens of our participants, and the second level which entails understanding the meaning of our informants' experiences. This way, we can provide a richer narrative of the phenomenon which communicates why the participants responds in the manner they do. Interpretive methods in our study, as well as other studies on IS, are *"aimed at producing an understanding of the context of the information system, and the process whereby the information system influences and is influenced by the context"* [67]. Hence, it does not predefine variables. Rather, it focuses on the complexity of human senses as the situations unfolds [68]. As we base our thesis on an interpretive philosophy, we assume that reality is accessed through social constructions, and thus we attempt to understand the context of organisational readiness through introspective reflections, interviews, and other texts which describe routine and meanings in our participants' lives.

5.2 Research Approach and Choice

Studying the phenomenon of organisational readiness and AI as it yet unfolds can take multiple forms, however, there are two main data types one could utilise - namely quantitative and qualitative [69]. As we wish to gain an understanding of how AI impacts the PS's readiness, a qualitative approach was the natural choice for our thesis. Qualitative data is usually used when one wants a deeper understanding of the participants' experiences, and is thus a way of comprehending the research question through their context and point of view [66]. We thus explore our research question by interviewing people working with AI within the PS, employing an interview based study as a qualitative research design. Denzin and Lincoln (2005) further draw qualitative research as a multidimensional method involving an interpretative approach to the topic [70]. The nature of qualitative research hence enables the development of a holistic picture of the studied phenomenon. In this study, this means that the practice of our research is reflexive and produces context situated and theory-entangled knowledge through the interactions between theory and methods, as well as the researcher and the researched. As we embark on this qualitative research, we recognise that realities are both complex and multifaceted.

Following the multifaceted nature of qualitative research, its objective is exploratory rather than explanatory [71]. Exploratory qualitative research allows the researchers to describe the experiences of the informants, which can either support or defy the study's theoretical assumption [59]. In this thesis, we aim to map out the perceived challenges of AI adoption as well as explore the perceptions of organisational readiness across the Norwegian PS in relation to AI; a phenomenon which has yet to be studied in the realm of academia. An exploratory qualitative approach was thus conducted to gain a better understanding on this existing phenomenon. Furthermore, we aim to describe the organisational readiness of the PS without presenting the findings as conclusive results. Rather, we wish to illuminate AI's effects on the Norwegian PS through exploration by using this research to identify perceived challenges of AI-adoption. As a result, the methodological layer of research choice in our thesis implies direct involvement with the target group, as there is limited academic research in this domain.

The methodological layer of research approach concerns itself with the research reasoning of drawing conclusions: a deductive and inductive lens [61]. Deduction begins by identifying a relevant theoretical framework, which is then tested to reason deductively. Inductive reasoning, however, draws conclusions by going from the specific to the general. In this study, we gathered data, which we then used to search for patterns. Once we implemented a broad view to search for common themes, we drew general conclusions which we incorporated into theories. In simpler terms, we adopted a bottom-up approach of making generalised arguments based on our data. Our exploratory process began with relevant data collection within the topic of interest. Once we obtained substantial data, we could identify overarching themes from discerned patterns and thus generalise into relevant theories. This way, the domain was understood through the data and the analysis was controlled by our informants, whom we will describe in greater detail in Section 5.3.1. An inductive approach was thus aligned with our interpretive research philosophy, since the data collection and analysis were part of a continuous process between us and our comprehension of the topic [72].

5.3 Data Collection and Sampling

Our data collection has been constructed through two iterations: in-depth interviews with the target group from various Norwegian public organisations and document analysis. Utilising more than one method to investigate the case enabled us to explore the field from different perspectives, where our focus has been to gain an understanding of what AI challenges impact the organisational readiness of the Norwegian PS. To further describe our research design, we will present and defend the utilised methods of data collection in this chapter.

5.3.1 Informants and Informant Selection

Non-probability sampling was the chosen sample selection method, meaning that our informants were not selected randomly [61]. Through this approach, our informants are restricted to specific types of organisations and individuals who are best positioned to contribute to the desired data [73]. Our target group is therefore organisations and researchers within the field of AI and the PS. As with any method, this approach carries limitations. Non-probability sampling risks reducing the generalisability of the findings. However, since we have sought a strategically chosen sample, generalisability is a more conceptual limitation due to its complexities of generalising back to the population [74]. Nevertheless, following this research's novelty, it is considered the most viable method. As the PS in Norway is still in their nascent phase of AI adoption, there are few organisations that possess the experience of AI adoption which legitimises our usage of the non-probability sampling [73].

Potential bias that might have risen from our sampling approach was somewhat reduced through the diversity in the interviewees, which accounts for one of the requirements of the sampling criteria [61]. Other selection criteria, to ensure reliable data from reliable respondents, are: (i) informants from the industry must have experience in AI-related projects, (ii) informants from both academia and industry should be included and have experience from Norway, (iii) informants from the industry must work in the Norwegian PS, (iv) informants from the industry must include both managers and coordinators of daily operations (i.e., data scientists). Candidates who met these criteria were reached out through e-mail and from referrals from interviewed participants, the researchers themselves, and their supervisors using snowballing sampling. This form of sampling occurs when we rely on our informants to put the researchers in touch with other contacts. We ensured sample diversity by encouraging our respondents to refer us to people other than their closest acquaintances.

The diversity and "richness" of data collection is deemed more important than a predetermined number of interviewees [75]. Nevertheless, the designated number of informants cannot be identified until the qualitative study is conducted. The number of informants is therefore dependent on the extent the domain has been explored, and the research question addressed [76]. When a degree of saturation is reached, which we define as no new information emerging, we can conclude with a satisfactory number of interviews [76]. The sample size was therefore determined by the data gathered. However, we set a predefined goal of 10-15 interviews to ensure a saturation point and that our research topic could be explored adequately. Reaching this predefined goal was met with difficulties. Some of our e-mails to the candidates were left unanswered, while others simply did not have the time to participate in this study. As such, 13 interviews were executed with eight different public organisations to enable multi-disciplinary data.

To gain multi-disciplinary data, the informants invited are from both academia and industry with heterogeneous backgrounds. Detailed depictions of our informants and their positions is illustrated below.

Informant-ID	Week	Activity	Location	Role
MSID-00	8	Casual chat	Digital	Senior Adviser/PhD
MSID-01	9	Casual chat	Digital	Chief Data Officer
MSID-02	9	Casual chat	Digital	Data Scientist
MSID-03	10	Interview	Digital	Senior Adviser
MSID-01	11	Interview	Digital	Chief Data O fficer
MSID-04	11	Interview	Digital	Technical Business Architect
MSID-05	12	Interview	Digital	Data Scientist
MSID-06	12	Interview	Office	Senior Adviser
MSID-07	12	Interview	Office	Senior Adviser
MSID-00	13	Interview	Digital	Senior Adviser/PhD
MSID-08	13	Interview	Digital	Head of Research
MSID-09	13	Interview	Office	Head of Data Analytics
MSID-04	15	Casual Chat	Home	Technical Business Architect

Table 5.1: Informants

5.3.2 Interviews

Various methods can be applied for qualitative research, for example interviews, focus groups or ethnographic studies, however, for our research aim, we concluded with interviews being the most suitable method as they are widely used to access people's perceptions, experiences, feelings, and attitudes towards reality. Such interviewing, as described by Boyce et al., is a qualitative technique involving "*intensive individual interviews with a small number of respondents to explore their perspectives on a particular idea, program, or situation*" [77]. To answer our RQ, our interview based study explores perceived challenges of AI in public organisation. In our research, similar to other qualitative studies, the interviews are open-ended and exploratory to gather detailed data about the topic of AI adoption in the PS. Our goal through the chosen data collection technique is thus to explore our participants' opinions, thoughts, and experiences from a sample size of, in total, 13 interviews. As this thesis has a cross-sectional time horizon, with a short, predefined time frame of 17 weeks, we are unable to interview nor get a hold of a large sample size, making interviews a suitable approach.

However, interviews vary in their degree of structure. Interviews in qualitative research tend to be more flexible to focus on the informants' experiences and thoughts for rich and in-depth data [78]. Consequently, structures that focus on the interviewees, namely unstructured and semi-structured interviews, were used for this thesis.

Unstructured Interviews

This technique was developed in the disciplines of sociology and anthropology to elicit people's own social realities. The definition of unstructured interviews varies, however in this thesis we implement Minichiello et al. (1990) definition of *"interviews in which neither the question nor the answer categories are predetermined [...] Instead, they rely on social interactions between the researcher and the informant"* [79]. The foundation of our unstructured interviews is to uncover unexpected themes to further develop an understanding of the participants' realities from their own perspectives. To make sense of the environment in which our informants operate in, we approach it through the participants' own position and terms, which corresponds to our chosen research paradigm: interpretivism [70]. We therefore went into the interviews with no hypothesis to inquire theory development in lieu of theory testing. With these goals in mind, we can allow the conversation to be mutually formed by us and the interviewees to facilitate the informants' responses and obtain their perceptions of AI adoption in the Norwegian PS. Additionally, to establish a sense of comfort, trust, and informality in our unstructured interviews, we refrained from recording them and only utilised live notetaking.

Semi-Structured Interviews

This method of data collection is the most common in qualitative research in information systems [66]. Semi-structured interviews are selected for our exploratory thesis to let the participants' responses lead the way to our research question and aid in a robust development of knowledge, rather than using a defined script that eliminates spontaneous exploration. Dunn (2000) explains the structures of interviews as a continuum: "*In the middle of this continuum are semi-structured interviews. This form of interviewing has some degree of predetermined order but still ensures flexibility in the way issues are addressed by the informant*" [80]. According to Noor (2008), this method enables the informants to elaborate on their answers to unveil new dimensions which can be added to the research, in addition to allow an understanding of the context [81]. Following the exploratory nature of our thesis, we thought it was best to utilise this method, as it is more suitable and more common in exploratory qualitative research [82].

Although such interviews tend to be exploratory, allowing free flow of questions, the interviews were somewhat structured to ensure consistency in the questions asked throughout multiple interviews [61]. Two semi-structured interview guides were therefore made in advance - one for the organisations and one for researchers within the field of AI and the PS. In one instance, our participant had a significant role in both a public organisation and in the research field. To exploit their unique knowledge, we opted for a somewhat mixed interview guide with relevant questions and sets of associated prompts from both interview guides. However, we did not use every question and prompt from the guides to ensure that we stayed within a predefined time frame of 45-60 minutes. This way, we were able to explore the topic while simultaneously establishing a red thread throughout the interviews.

The interview was carried out with open and probing questions to ensure a red thread throughout our conversation. Open-ended questions encourage the informant to openly elaborate on their thoughts and are used when further answers and evidence about the participants perspectives are needed [83]. Probing questions were used when further exploration of the informants' answers were deemed important [61]. As we had not a clearly defined theoretical framework at the time of our data collection, the chosen interview questions were thus informed and shaped by our working research question of "*What are the challenges of AI adoption in the Norwegian public sector?*" in addition to the overall topic and the contextual setting of AI in the Norwegian PS. These open-ended and probing questions, alongside our rough interview guides, went through multiple iterative revisions concurrent with the interview executions. Since the informants had varying backgrounds, it often occurred that some prompts and questions were omitted, altered, or added iteratively depending on the participant's role. As all required information is covered per session, this way of conducting interviews is acceptable according to Saunders et al. (2012) [61].

Interview Execution

Following the events of Covid-19, and its remnant consequences on people's daily life, we gave our informants the option of a digital or a physical interview. The main consideration for interviews is that the interviewees feel comfortable, either it being online or in physical spaces. The comfort of the interviewees can thus be directly linked to the location in which the interview is conducted, hence establishing a setting where the interviewees are comfortable is paramount to a successful interview; both for the informants' well-being and the quality of the answers. The choice of locality, either it being virtual or physical, should therefore examine the participants' comfort and ability to openly answer our questions, which is why we left the choice in the hands of the informants themselves [84].

Although we acknowledge the environmental limitations related to a digital interview, like the insufficient observations of body language, behaviour, and emotions, we found it important to establish an environment where the participant can openly express their thoughts and feelings from the start [85]. Despite these possible disadvantages, digital interviews allowed for an efficient conduction of many interviews over a relatively short time frame [86]. Nevertheless, some informants had to opt for a digital interview, as they either had a time constraint or lived far away. Virtual interviews thus allowed us to include people with geographical limitations, meaning interviewees who lived further away, cutting travel expenses for the interviewers and the interviewees [87]. This means that people who previously were not able to participate in research due to geographical distance or a time constraint, can now be included. Based on the preferences of our subjects, we used Zoom and Microsoft Teams - two applications which support video communication - which somewhat reduced the limitation of lack of facial expressions.

In some instances, our informants preferred physical interviews. Whilst physical interviews might not be as time efficient, there are many advantages of face-to-face interviews. Through physical interviews, non-verbal cues like mannerism and body language, can add richness to the study and, as Opdenakker (2006) argued, give *"the interviewer a lot of extra information that can be added to the verbal answer of the interviewee"* [88]. Additionally, there are no significant delays between questions and answers, which can facilitate direct reactions from either party. Hence, such synchronous communication enables more spontaneous and raw answers, without extended reflection. These raw answers can serve as insight on the participants' perceptions of AI in the Norwegian PS.

Role of the Interviewer

Interviewers have a unique role in both an unstructured and semi-structured interview. As there are no strictly defined frameworks, the interviewers and their ability to move the conversation plays an integral part of the research as well as being, to a great extent, the defining point of a successful interview [79]. The role we adopted as a learner and a friend interested in the interviewee's thoughts, although constrained by characteristics such as gender, age, and ethnicity, was critical to our efficient interview process [89]. This distinctive role enables and builds an informal rapport between the interviewees and interviewers, which makes it possible to achieve a deeper understanding of the interviewees' thoughts and experiences.

To understand the interviewees', we implemented key actions, such as nodding, agreeing, and smiling, to increase their level of comfort and trust. Only when a trustful environment is established, can the informants share their complete experiences [90]. We also started the interviews with "easy" warm-up questions to ease them into the subject of AI-adoption.

Some examples of such questions were: "*Could you tell us a bit about your background?*" and "*How does a typical workday look like for you?*".

5.3.3 Document Studies

Supplementing our in-depth interviews with additional data sources, such as reviewed government documents, relevant articles, and web pages, was done to gather further information regarding AI in Norwegian PS. The included documents were selected from public organisations and governmental websites to gather information on the policies, strategies, and regulations on AI. Reports and letters to the government are also included to understand the relationship between national and sector levels. To further understand people's perceptions on AI in the PS, we used podcasts and news articles. As illustrated by Bowen, such data can provide indicators of contexts that may impact the studied phenomena [91]. Supplementing document studies to our data collection provides background information in addition to historical insights, which we deem helpful in understanding the historical origins of AI adoption in Norway. These documents can indicate conditions that might affect the organisational readiness of the sector. Moreover, we use the data drawn from our document studies to further contextualise the obtained data during our interviews.

Title	Author	Document Type
NAV - sluttrapport	Datatilsynet	Report
Nasjonal strategi for kunstig intelligens	Kommunal- og distriktsdepartementet	Strategic Plan
Kunstig intelligens – muligheter, utfordringer og en plan for Norge	Teknologirådet	Report
Kunstig intelligens og personvern	Datatilsynet	Report
Meld. St. 22 (2020–2021): Data som ressurs— Datadrevet økonomi og innovasjon	Kommunal- og distriktsdepartementet	Report to the Storting
Forskningsetisk betenkning om kunstig intelligens	De Nasjonale Forskningsetiske Komiteene	Report
Innspill til strategi for kunstig intelligens	NAV	Letter
AICast	Den Norske Dataforening	Podcast
KI-forordningen om europeisk regelverk for kunstig intelligens	Europalov	Proposal to the European Parliament and Council
Kunstig intelligens er en utfordring for Norge	Aftenposten	News article
Lack of guidance leaves public services in limbo on AI, says watchdog	The Guardian	News letter
Spesielt om regulatorisk sandkasse for ansvarlig kunstig intelligens	Datatilsynet	Report
3 Barriers to AI Adoption	Gartner	Article
Hello, World: Artificial Intelligence and its Use in the Public Sector	OECD Observatory of Public Sector Innovation	Working Paper

Table 5.2: Documents used for our data collection

Document studies provide a way of tracking AI development in the PS. As various drafts of documents are available, we can compare and identify changes within the sector. Accessible final reports were also used to obtain a clearer picture on how organisations operate in regard to AI adoption over time.

However, the way documentary data serves our research purposes should be considered carefully, as emphasised by Atkinson & Coffey (2004):

> *We should not use documentary sources as surrogates for other kinds of data. We cannot, for instance, learn through records alone how an organisation actually operates day-by-day. Equally, we cannot treat records—however 'official'—as firm evidence of what they report. [...] That strong reservation does not mean that we should ignore or downgrade documentary data. On the contrary, our recognition of their existence as social facts alerts us to the necessity to treat them very seriously indeed. We have to approach them for what they are and what they are used to accomplish* [92].

To do so, we examine the documents' position in the PS alongside the values assigned to them. The analysis of documentary data is therefore considered an important part of our thesis.

5.4 Data Analysis

Since our understanding of the domain takes place as a continuous process throughout our study, we chose a thematic content analysis as presented by Braun & Clarke (2006) to analyse our data from the interviews and document studies [72]. Braun & Clarke (2006, p. 79) define thematic content analysis as a method for identifying, analysing, and reporting patterns, also referred to as themes, from data. They further claim that this form of analysis is preferable when shedding light on the experiences, opinions and realities of the participants, something we deem necessary to obtain a lens for understanding their experiences with AI adoption. In this way, we could use the analysis both to reflect the reality of the participants, but also to have the opportunity to examine their perceived realities (Braun & Clarke, 2006).

1. Familiarizing yourself with your data Transcribing data (if necessary), reading and re-reading the data, noting down initial ideas.
2. Generating initial codes Coding interesting features of the data in a systematic fashion across the entire data set, collating data relevant to each code.
3. Searching for themes Collating codes into potential themes, gathering all data relevant to each potential theme.
4. Reviewing themes Checking if the themes work in relation to the coded extracts (Level 1) and the entire data set (Level 2), generating a thematic 'map' of the analysis.
5. Defining and naming themes Ongoing analysis to refine the specifics of each theme, and the overall story the analysis tells, generating clear definitions and names for each theme.
6. Producing the report The final opportunity for analysis. Selection of vivid, compelling extract examples, final analysis of selected extracts, relating back of the analysis to the research question and literature, producing a scholarly report of the analysis.

Table 5.3: Braunt & Clarke's Phases of Thematic Analysis (p.87)

By adopting this analysis approach, we can capture complex relationships within the field of AI adoption in the PS. The goal of our analysis is to identify themes to understand organisational readiness, AI, and the relationship between the two. This is far more than summarising the data. On the contrary, it is about interpreting and making sense of the gathered data. This analysis method can thus aid us in identifying themes to relevantly answer our research questions. We will do this by engaging in the six-stepped process presented by Braun & Clarke (2013), with the first phase of the thematic approach being familiarization of the data (Table 5.5).

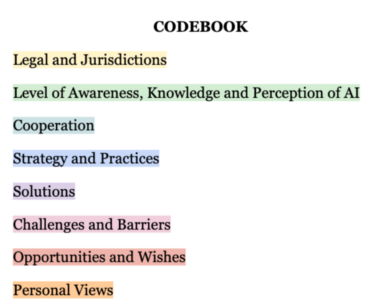
5.4.1 Phase 1: Transcription and Familiarizing with the Data

The first phase of data analysis concerns itself with transcription. The audio-recorded semi-structured interviews were transcribed verbatim for content analysis. As Roulston et al., (2003) notes, this process is time-consuming yet insightful as it provides a great overview of data [85]. The transcription process was two-fold; starting first with a rough transcription using the dictation function on Microsoft Word, and then proof-reading to manually transcribe and correct the data. This process of proof-reading the transcription initiated the activities of familiarization.

Before generating general codes, it is important to familiarize oneself with the data material. Braun & Clarke (2006) note that delving into the data by reading and re-reading them is crucial so that one is familiar with the depth and breadth of the content [72]. As we had transcribed and proof-read the interviews prior, we already gained some knowledge of the data. To continue the iterative process of familiarisation, we re-read the transcribed material, where each of the researchers noted down initial ideas and relevant quotes. We then went through the notes together before then writing short summaries of each interview to create an overview of the data. These summaries and notes aided us during the next step of generating initial codes.

5.4.2 Phase 2 and 3: Generating Codes and Searching for Themes

Phase two concerns itself of producing initial codes from the dataset in a systematic way [72]. As explained by Braun & and Clarke (2013), codes refer to relevant words or phrases within the data which can assist in answering the research question. In this study, we coded the data manually, since we did not come across softwares like Nvivo until we were too far into our data analysis. These codes were both data- and researcher-derived. Data-derived, also labelled as semantic codes, describe the explicit content, whereas researcher-derived codes, also known as latent codes, interpret the content to infer implicit concepts within the data. The utilised codebook and a snippet of the manual coding is presented in Figure 5.2 and 5.3.



CODEBOOK

Legal and Jurisdictions

Level of Awareness, Knowledge and Perception of AI

Cooperation

Strategy and Practices

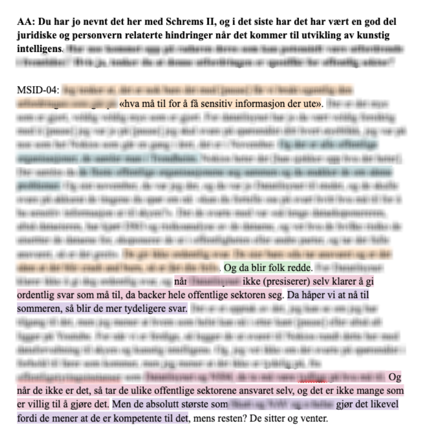
Solutions

Challenges and Barriers

Opportunities and Wishes

Personal Views

Figure 5.2: Top level themes of coding



AA: Du har jo nevnt det her med Schrems II, og i det siste har det har vært en god del juridiske og personvern relaterte hindringer når det kommer til utvikling av kunstig intelligens. [illegible]

MSID-04: [illegible] «hva må til for å få sensitiv informasjon der ute». [illegible] Og da blir folk redde. [illegible] når [illegible] ikke (presiserer) selv klarer å gi ordentlig svar som må til, da backer hele offentlige sektoren seg. Da håper vi at nå til sommeren, så blir de mer tydeligere svar. [illegible] Og når de ikke er det, så tar de ulike offentlige sektorene ansvaret selv, og det er ikke mange som er villig til å gjøre det. Men de absolutt største som [illegible] gjør det likevel fordi de mener at de er kompetente til det, mens resten? De sitter og venter.

Figure 5.3: Example of transcript and manual coding of MSID-04

Once we completed the data coding, it was time for us to move to phase three: looking for patterns within the dataset. Theme-based analysis allowed us to identify attributes which could be used to answer our research question. One way we identified relevant themes was looking at certain codes' frequency of appearance. Through our codebook, which guided our thematic responses, we organised similar statements and words which naturally created overarching themes. Finally, to contextualise and relate themes and codes to one another, we created a thematic mind map.

5.4.3 Phase 4 and 5: Reviewing and Defining Themes

Phase four of the analysis involves generating a thematic "map" based on the two levels of reviewing themes. During level 1, we examine whether the themes are appropriate in relation to the codes, whereas level 2 examines the themes to the rest of the dataset [72]. Through these levels, we were able to generate a thematic map and assess whether it reflects the holistic significance of the data [72]. To evaluate our themes, we re-read the transcribed material based on the new-found codes and themes we generated. During this iterative process, we noted desirable changes and discussed our understanding of the codes. This process resulted in a thematic map (Figure 5.4) which was the basis of phase 5.

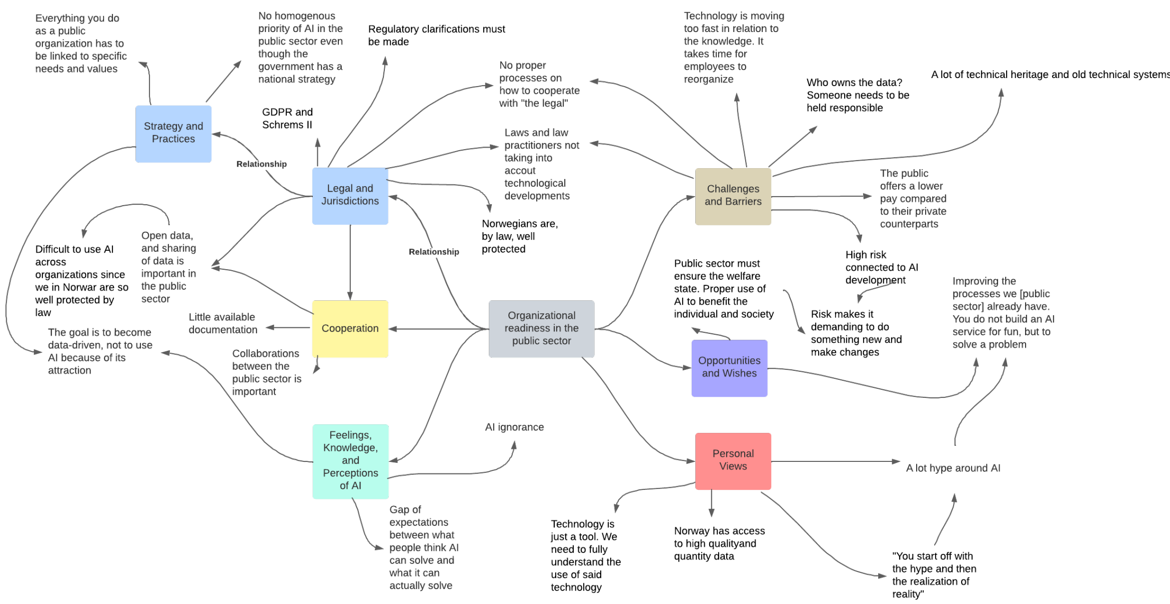


Figure 5.4: Map of our Thematic Analysis during phase 4

The next phase starts with our thematic map and pertains to the ongoing analysis of refining themes. We attempted to identify the essence of each theme, and the overall story they told. By examining aspects of data which were captured by the themes and how they related to each other, we were able to generate clearer definitions for each theme. Through this procedure, we derived a final thematic map for producing the report, as seen in Figure 5.5.

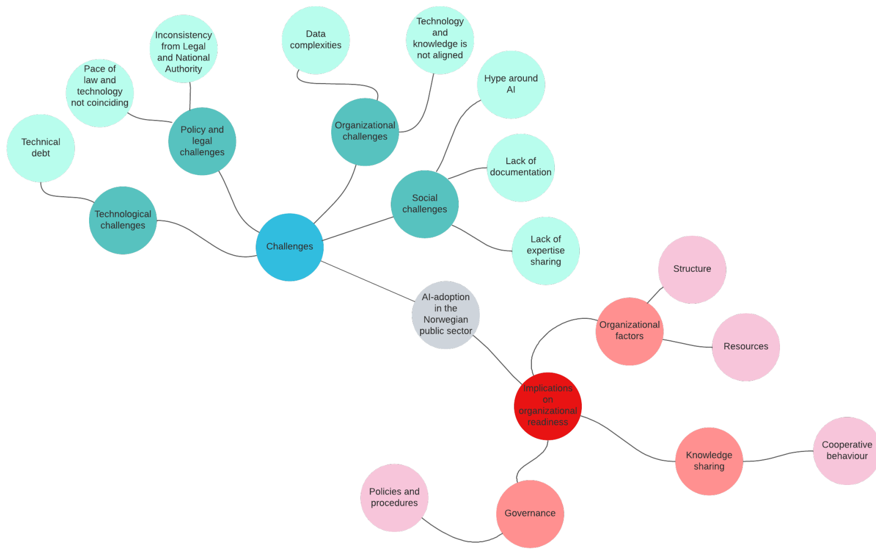


Figure 5.5: Map of our Thematic Analysis during phase 5

5.4.4 Phase 6: Reporting

The final step of our analysis, which is presented in Chapter 6, relates to reporting. Writing a report pertains to telling a story of the data by choosing vivid and convincing examples in a way that assures the reader of the value and validity of the analysis [72]. As we ended our analysis, validity, among other criteria of research quality, were vital aspects of research which needed continuous reflection.

5.5 Research Quality

The views on the criteria for sound interpretive research are numerous, since there are various approaches to interpretivism - each having its own epistemology [93]. To raise the quality of our thesis, we chose to follow Klein et al. (1999)'s seven principles for interpretive field research to assess this research quality [93]. These principles, as the term suggests, are not mandatory rules, but rather a proposition that serves as the foundation of our quality assessment. It is therefore incumbent upon the researchers of this thesis to reflect and discern decisions on whether the principles are applicable and appropriate. Since the principles are, to a certain degree, interdependent, we are not arbitrarily deciding on or ignoring principles [93]. While interpretive research is praised for its contextual depth, it is often criticised for its quality in terms of the result's validity and reliability.

Principle	Description	Application
1. The fundamental principle of the hermeneutic circle	This principle suggests that all human understanding is achieved by iterating between considering the interdependent meaning of parts and the whole that they form. This principle of human understanding is fundamental to all the other principles.	Iteration where we moved between the individual interviews, interviewees' answers to the questions, and the overall research problem of AI adoption in the PS.
2. The principle of contextualization	Requires critical reflection of the social and historical background of the research setting, so that the intended audience can see how the current situation under investigation emerged.	Collected documents on the context of AI in the Norwegian PS and interviewed people working in this specific context.
3. The principle of interaction between the researcher and the subject	Requires critical reflection on how the research materials were socially constructed through the interaction between the researcher and participants.	Reflects on the social interactions between researchers and participants by asking follow-up questions during the interviews, as discussed in Section 5.3.2
4. The principle of abstraction and generalization	Requires relating the idiographic details revealed by the data interpretation through the application of principles one and two to theoretical, general concepts that describe the nature of human understanding and social action.	Generalised from data to findings through thematic analysis, as presented in Section 5.4.
5. The principle of dialogical reasoning	Requires sensitivity to possible contradictions between the theoretical preconceptions guiding the research design and actual findings with subsequent cycles of revision.	Clarified our assumption through Chapter 2 where we describe the preconceived setting in which this study lies.
6. The principle of multiple interpretations	Requires sensitivity to possible differences in interpretations among participants as are typically expressed in multiple narratives or stories of the same sequence of events under study. Similar to multiple witness accounts even if all tell it as they saw it.	We included the different views in the field to gain a deeper understanding on the participants' experiences.
7. The principle of suspicion	Requires sensitivity to possible 'biases' and systematic 'distortions' in the narratives collected from the participants.	Did not pay attention to distortions

Table 5.4: Overall assessment of research quality based on Klein & Myer's Seven Principles for Interpretive Field Research (p.72)

Generally, the research quality is linked to the methods used and the validity of the generated findings. Evaluation and validation of qualitative research reference a variety of techniques, however, in this study, we adopt the opinions of those who argue that validity and reliability are appropriate terms within qualitative studies. In the broadest sense, these elements are applicable, with reliability describing consistency within the employed processes, while validity refers to the integrity of methods undertaken and the relationship's accuracy between the findings and data. Validity and reliability are thus vital concepts of credibility and trustworthiness in qualitative research. By carefully emphasising on these components, in addition to Klein& Myers's seven principles, we may enable quality and allow for good research. [94].

5.5.1 Validity

Validity in qualitative studies is characterised by the degree in which the obtained data is consistently examined to the point where the analysis becomes self-correcting, and the researchers can identify "when to continue, stop, or modify the research process" [95–97]. These mechanisms were incorporated into every step of our study: (i) ensuring compatibility between our research question and attained data; (ii) appropriate sampling; (iii) coding systems that were examined among the researchers; (iv) keeping detailed field notes and transcriptions. This way, we were able to determine when to pause the research process and hence strengthening the validity of our thesis.

Tjora (2017) states that the validity of a study can be strengthened by clarifying the research process and choices along the way [98]. By describing and complementing our data collection with interview guides and supplementing findings with direct quotes, we have attempted to illustrate a clear and logical process in our thesis. Therefore, the aim of our methodology was to present the completed process and enable transparency to invite others to the discussion as equals. This way, readers can evaluate the study's richness and rigour. Our methodology was thus chosen based on validity, rather for practical reasons [98].

Stability is another indicator of validity [99]. This measure concerns itself of data trustworthiness and whether observations derived from the data collection and analysis are repeatable [95]. To ensure data stability, we continuously reflected on the research objectives as to remain within the scope and domain of the study. Furthermore, stability engages with the findings' extent to focus on the inquiry without biases of researchers.

Biases of researchers, whether intentionally or not, can greatly affect the validity of a study. Humans behave and respond differently when observed, making the presence of the researcher indicative of the study's validity [100]. As suggested by Klein & Myer's third principle, information gathered during the data collection is produced as "*part and parcel of the social interaction of the researchers with the participants*" [93]. We must thereby recognise participants as equal interpreters, since they adjust their horizon according to the utilised concepts of AI-adoption. Where possible, we conducted follow-up interviews, as well as document studies, to ensure that themes devised in the initial interviews were reoccurring. This way, we could argue that nothing new emerged, and thus that our data was stable.

Stability of our interview data was enforced through audio recordings. In many cases, audio recordings can increase the validity of a study by providing opportunities for new interpretations as the researchers' understandings of the data develops [101]. This interpretive process progresses from a preliminary understanding of the fragments (i.e., sentences and words) to the whole and "*from a global understanding of the whole context back to an improved understanding of each part*" [93]. This harmony between the details and the whole aligns with the first principle of the hermeneutic circle, which describes our understandings of a complex phenomenon deriving from preconceptions and relations of the meanings of fragments. As we used "Nettskjema Diktafon" to record the interviews, this thesis was not dependent on the researchers' memory and their immediate interpretations. On the contrary, interviews could be replayed, and thus allow for deeper interpretations - enabling stability.

Consistency in the answers enables us to compare the degree of stability within our findings. Researchers' level of empathy and reflections on their comprehension of participants' issues is also crucial for measuring stability [95]. Our interpretive paradigm maintains the researchers' roles in the interpretation of knowledge. By understanding the context and the participants' perceptions, the researchers were able to negate or confirm the knowledge derived from the interviews. To achieve this understanding, a critical reflection of the background and environment which our participants operate in was deemed critical so that our readers can see how the Norwegian setting of AI-adoption has emerged. We primarily used documentary studies to provide information on the context.

5.5.2 Reliability

Reliability refers to research being verifiable and that data collection methods of the same study has similar conclusions [102]. As we adopted a qualitative research approach, our methodology argues that subjects construct knowledge differently. Hence, data remaining consistent across iterative investigations and with different informants is highly unlikely [95]. Regardless, qualitative research contests generalisations of human behaviour. Such a research approach focuses rather on comprehending the meaning of a phenomenon [96]. Data generated through this approach is thus dependent on the researcher, which makes achieving high reliability challenging. Qualitative approach refers therefore to dependability instead of traditional reliability.

Dependable data is fostered by allowing external audits during the research process [103]. Allowing external people to assess the accuracy, in addition to findings and conclusions, allows us to determine the dependability of the data. The findings, theoretical frameworks, and analysis were discussed with our supervisors, who then shared their thoughts while being critical to the researchers' interpretation to ensure validity. We also considered other sources concerning the studied phenomenon, however, as there are limits of resources within this domain, the added degree of reliability was limited compared to other research approaches (i.e., quantitative).

5.6 Ethical Considerations

Granted the significance of ethics in research in addition to the challenges surrounding conducting research, academic institutions and researchers alike are diligent to protect the safety and dignity of research subjects [104]. To maintain a focus on research ethics, several ethical aspects were considered to ensure that the thesis was conducted properly [105]. Furthermore, there were several ethical assessments which needed a call to attention. As Guillemin & Gillam (2004) point out, ethical dilemmas are reoccurring themes when conducting research, where both political and personal aspects of research should be considered and reflected upon throughout the process by practising continuous reflexivity [106]. In this chapter we explain the ethical considerations, both the formal aspects followed, as well as other ethical dilemmas that became prominent in the thesis, commonly called "ethics in practice"[106].

5.6.1 Processing of Personal Data

Prior to implementing the study, we applied to NSD (Norwegian Centre for Research Data). NSD is a national centre and archive for research data, and their aim is to make data on people and society available for research [107]. The University of Oslo's routine for research projects stipulates that all student and research projects that deal with personal data must apply for NSD in order to obtain an assessment of privacy [108]. NSD defines personal information as any information regarding an identified or identifiable individual [107]. For our application, NSD concluded that our research was not subject to notification, as it does not collect any directly identifiable or sensitive information. Following NSD's assessments and General Data Protection Regulation (GDPR)'s principles on legality, justice, and transparency (art. 5.1 a), participants received satisfactory information about the project and data processing.

5.6.2 Informed Consent

To safeguard informants' privacy, as well as ensuring legality, justice, and transparency, we obtained consent from all participants. However, the question of form of consent left us with an ethical dilemma. While written consent is common practice, Silverman (2009) notes that to foster a comfortable relationship between researcher and informant - which we deemed necessary in our unstructured interviews - highly formalised ways of requesting consent should be avoided [109]. Nevertheless, an ongoing ethical regard for informants should still be upheld. To sustain the participants rights, and promote comfort and trust, we deemed verbal consent appropriate for unstructured interviews. In support of this, Fritz (2008) illustrates that the strength of research lies often in the informality of the interview [110]. Participants were, verbally, informed on the purpose, methods, and intended use of the study, in addition to what their participation in the study entails to safeguard their privacy [111].

Written consents were also utilised, specifically prior to all semi-structured interviews. When creating the consent form, we utilised a template from NSD to ensure that any measures and guidelines were adhered to. Nevertheless, the consent form was naturally customised for our specific study. We also made sure to underline the voluntary nature of our study. Any participant is free to withdraw from the interview at any given, as well as ensuring anonymity of the informants.

5.6.3 Anonymity

The declaration of consent stated, among other things, that the subject can withdraw at any moment and that they will remain anonymous. To preserve the informants' anonymity, we attempted to limit the participants' personal information and presented the participants using pseudonyms and refrained to refer to the public organisations by name. As the organisational names did not add any value to the context and research, we thought it was best to exclude them from our study. We tried thus to omit and minimise the possibility of connecting information to people. Moreover, the audio recordings were encrypted and stored using "Nettskjema Diktafon" and will be deleted securely at the of the project.

Chapter 6

Findings

This chapter presents the empirical findings uncovered during the data collection and analysis. Our data collection and analysis reveals five key findings which we describe as challenges to illustrate the obstacles of AI adoption in the Norwegian public sector, respectively policy and legal, organisational, social, technological, and data challenges. This chapter is therefore divided according to the themes found in the analysis process, and highlighted text and subheadings correspond to conceptual categories belonging to the various themes. Here, anonymous quotes from our interviews in addition to quotes and findings from our document studies are highlighted.

The following table summarises the perceived challenges in the adoption of AI by several public organisations, divided into five categories: policy and legal, organizational, social, technological, and data challenges.

Challenge	Description	Characteristics
Policy and Legal	Perceived challenges related to domain experts from national levels not involving in AI development in the sector, in addition to law and regulations being unclear	Inconsistency from national levels
Managerial	Lack of necessary knowledge to adopt AI, making it difficult to reorganize. Absent commitment and prioritization from management to carry out technology changes.	Competence and understanding of needs and values are imperative to keep up with emerging technology
Social	Significant gap between hype and pessimism, which is further strengthened by the lack of shared documentation on the technology within the sector	No shared documentation on hyped technology
Technological	Incompatible technical infrastructure which makes it increasingly harder to integrate AI into the organisation	Large outdated and ineffective systems
Data	Adopting AI requires good data, however the public sector has limited access to the high-quality data which Norway possesses	Fragmented public sector, uncertainties on ownership, and strict regulations

Table 6.1: Summary of the findings

6.1 Policy and Legal Challenges: Inconsistency from National Authority

A common theme throughout our data analysis is the lack of consistency from national authorities. On a national level, policy is progressively centred around the potential of emerging technologies and their consequent benefits, as well as how to utilise public data. However, when emerging technologies such as AI catches the attention of the PS, issues related to privacy, data, and other legal topics arise to the agenda. In this agenda, a public organisation's mandate to protect the average Norwegian citizen's data is the focus. As specified by our participants, they are authorized to serve the public good and must therefore reckon with the Norwegian public's interests. Due to this, they must be tidy and handle these matters in proper ways to ensure that Norwegian data is operated well [5]. Although legal and national authorities push for an increased usage of AI, they require the public to follow legislation and frameworks to secure the privacy and security of Norwegian data.

> "*Information security and privacy must be on the agenda from the start. We must have a set of rules that makes it possible for the solutions to be dynamic and train on our data.*" (MSID-05).

Norwegian data is protected through a plethora of regulations. The Personal Data Act contains privacy principles that companies must adhere to and presents the general principle that individuals should control how data related to them is used [112]. One of the principles states that organisations must have a full overview of their processing of personal data and implement technical and organisational measures that ensure that the law is complied with. This means that each company must make important assessments on their own, before collecting and using personal information.

However, how to make these assessments has been an issue of concern for public organisations. MSID-03 explains that "*the privacy regulation that we supervise must be technology neutral.*", yet public organisations are struggling to base their assessments on these regulations, showcasing inconsistency between the legal regulations and the national requirements. National organs' limited aid in how to ensure legal access to data further complicates the adoption of AI in the public sector.

6.1.1 Lack of Guidance from National Level

As highlighted by the data analysis, regulation of AI, or lack thereof, poses concerns of uncertainty within the PS. Firstly, there is no official definition of what AI truly is, which brings about inconsistency among practitioners in the sector. The most popularised definition of the term in the public sector can be found in the national strategy for AI, and is based on AI HLEG's definitions. However, as this definition is a "*crude oversimplification of the state of the art*", in addition to the national strategy for AI needing adjustments and evaluations in line with technological and societal developments, national authorities have yet to declare it as an official definition [23]. Despite a working definition of AI, the PS are still misunderstanding the term, as stated by MSID-04:

> "*People are misunderstanding the term "AI" and what the technology actually entails. [...] What I've noticed [...] is that, usually, when people talk about AI, they mean ML. They are mixing the terms.*"(MSID-04)

Essentially, it is a goal for the government that the meanings of terms used in PS regulations stay consistent [5]. For regulatory and governing purposes, a shared definition of AI is the foundation for laws and policies to operate across the sector. In regulatory contexts, ensuring a reliable use of the term enables therefore clarity across the PS. In the absence of a common definition, uncertainty of how to tackle the emerging technology arises.

Additionally, lack of official standards reinforces the uncertainties. As exemplified by our informant MSID-06, "*we haven't had proper processes on how to cooperate with legal, and we haven't gotten clarifications on what data we are allowed to compile*". As the sector has no shared standards to follow, uncertainty tied to the legitimacy and justification of AI usage sweeps across the Norwegian PS. This unclear environment, which public organisations operate in, is slowing the process of AI adoption within the sector:

> "*Unanswered questions around the dark side of AI, I think it's holding them [the public sector] back. They are unasked and unanswered in the Norwegian context. There are regulatory clarifications that must be made.*" (MSID-00)

When discussing national authorities' role within AI, our informants expressed their apprehensions:

> *"The knowledge of these [public administrative] organs about this subject area [AI] has been very limited. These organs do not give proper answers. They just say 'you take responsibility and if it's a 'crash and burn', then it is your [the public organization] fault' and people [working in the public sector] obviously are frightened."* (MSID-04)

MSID-04 further notes how national bodies' "lack of knowledge" slows down the technological development within the sector:

> *"When the [national authorities] themselves are unable to provide answers that are needed, the entire public sector backs off. It is not clear from these [administrative] bodies what is needed and expected. [...] large parts of the public sector end up sitting and waiting since they are not getting the needed answers"* (MSID-04)

As public organisations are unable to get clear answers from the national level, the sector is unable to establish sound technological developments and governance. AI's increased complexities, in addition to the technology fundamentally impacting the way public services are provided, clear guidance on how to adapt their operations for AI is deemed necessary by our informants. With the lack of shared guidelines, decisions regarding AI is thus shut down immediately. This is further illustrated by our informants when discussing the process of adopting AI in their organisations:

> "*[...] then the answer for most decisions [for AI and AI-projects] will be "No". We lack basic guidelines for what we can and cannot do. There are unanswered answers and unasked questions.*" MSID-06

There has, however, been attempts from the national level to provide strategies and guidelines in the field of AI. One prominent example is the relatively new "National Strategy for Artificial Intelligence" provided by the Norwegian Ministry of Local Government and Modernisation's. In this strategy, authorities' roles "*facilitating business development, also with regard to AI*" has been highlighted as necessary for developing AI with respect to individual rights and freedoms [5]. It is further argued in the strategy that the government, along with administrative bodies, are obliged to "*give guidance to public agencies on how they can ensure access to data*" and provide "*guidance on responsible use of artificial intelligence in public administration*" [5]. Nonetheless, such attempts of guidance were seen as nothing but a mere "play for the gallery".

One prominent event highlighted by our informants to illustrate the "play for the gallery" occurred when DiFi invited them (i.e., organisations) to their offices. One of the aims for this visit was to get input from the organisations to aid in the development an AI strategy. Once the organisations went down to DiFi's offices, however, they quickly realized that the strategy had already been written:

> "*We felt that it was a play for the gallery, because they [DiFi] had pretty much finished writing [the strategy] before all of us [the organisations] came down to DiFi.*" (MSID-06)

> "*The [DiFi] strategy should have taken more principled clarifications about what we can and cannot do in relation to the legal, but it did not. If you make a mistake on the GDPR front, then you can have major consequences, especially for us in the public sector, which gives us anxiety about making mistakes.*" (MSID-06)

Although the attempts are commendable, guidelines for AI in the PS remain lacking. Frameworks from multi-disciplinary fields in the development of AI are scarce, which signals how AI-specific guidelines are necessary as Norway increasingly adopts these systems [113]. To further illustrate the need for guidance from the national level, a report presented by OECD explains how seven out of eleven Latin American respondents note insufficient guidance to be a strong or moderate obstacle [113]. This global sentiment is shared with our Norway-based informants:

> "*There is not enough guidance from the national level.*" (MSID-00)

The limited guidance can be seen in relation to the limited interdisciplinary knowledge of technology and jurisdictions.

6.1.2 Regulations not Considering Technological Development

The Norwegian government explains how technological developments will change the PS, and the pace of change will continue to accelerate [5]. These disruptions require regulations that encourage appropriate usage of AI in the public. However, AI is currently not recognized as a subject of law in national and international law and has thus no juridical personality and cannot be held liable [114]. This discrepancy between the pace of legislators and technology enhances fear that privacy is not covered properly:

> "*Challenges with legal authority that does not take into account technological develop-*

ment." (MSID-03)

The laws governing the processing of personal data are seldom designed in a way that allows for AI development. Our informants are hence urging legislatures to facilitate for the development of AI within a responsible framework. If the PS is to develop AI-models further, it will therefore be necessary for a clearer and distinct supplementary legal basis through legislation [114]. This phenomenon is further explained by MSID-03:

> "*In our national law, there are different legal basis of processing, and you [public organisation] must have one. You [public organisation] must be able to specify that your processing of personal data is based on certain laws, right? [...] The most common legal basis for the public sector is called '6-1 f' which states that we process data by virtue of exercising public authority. This basis applies for almost the entirety of the Norwegian public sector, but to use it they [organisations] must refer to a supplementary legal basis. [...] They must refer to a national law other than the GDPR [...]. And then you encounter a problem which is that many of those laws, national laws, were written at a time where AI did not exist, right?*" (MSID-03)

> "*[...] a change in the law most probably needs to happen as there must be legislative work done. [Public organizations] cannot sit and do it for obvious democratic reasons, so something must happen in the Storting, right?*" (MSID-03)

AI leads to new ways of processing personal data, which were not considered when the laws were first formulated [114]. With current technological developments, our informants expressed how contemporary terms can disappear within a few years, making technology-neutral legal provisions necessary. It is also seen as necessary for legal provisions to refrain from stating that human case officers should solve tasks, as to enable the tasks being automated and solved by any upcoming IT systems.

> "*[...] technology neutrality [...] the principles and guidelines it [the law] lays down should be applicable to new technology*" (MSID-03)

> "*And then we have to get a set of rules and regulations that makes it possible for the solutions to be dynamic.*" (MSID-08)

While there is no shared definition, the many AI-terms are unclear and shifting. As emphasised by our participants, the shifts and technology-laden laws results in less applicable regulations.

6.2 Managerial Challenges: Managing Competence

Competence and expertise poses as significant challenges according to our informants. To emphasise, these managerial challenges are related to the public sector's management practices - in particular top management support and other strategic activities.

Building New Environment: Professionals or Enthusiasts?

When asked how AI development has been in their organisations, one interviewee notably indicated that the enthusiasts, who were allowed to experiment and test different technologies, have been the driving force behind AI development:

> *"It's been a "emerging strategy", as we call it. People are beginning to do [practice, perform, work] so. It has been passionate and enthusiasm based all along - [there has been] no strategy. No one has denied it [enthusiasts' experiments], and no one has put a stop to it. You have mainly got the resources you have needed and taken the time you have actually taken, so we have been able to expand on the learning experience we have had so far"* (MSID-07)

Another interviewee compared AI projects to research projects that are being conducted in an experimental setting. Due to the need of different expertise and the emergence of several clarifications, AI projects differ from previous projects, and thus requires a new environment with people who are engaged in research:

> *"[AI projects are] a research project rather than a development project. AI projects are a little different because you need a little different competence and a little more interdisciplinary [lens] due to several clarifications. It's a bit different, and it gets more experimental [...] We need to build a new environment with people who are interested in research* " (MSID-01)

As it was further emphasised by MSID-01, building a new environment for AI will contribute to scientific understanding as well as improving the existing solutions.

However, the topic of building new environments has been recognised as a challenge in certain organisations. This problem is faced when organisations introduce new technological projects, for example AI, that necessitate relevant expertise and skills. This issue is typical in environments where a certain domain's technology is heavily reliant on the experienced professionals like radiology. In fact, a survey done by Gartner (2019) showed that 56% believe that learning new skills will be essential to do both existing and newly created jobs [115]. Businesses and IT leaders acknowledge that skills will be a challenge, as AI may alter the skills required for completing AI tasks. As the technology progresses beyond research settings, the routines of solving problems will change. One interviewee emphasised this point by offering the following thought:

> *"A recurring theme is that we are unable to free professionals [...] The question is: "Are they the best resources to be able to carry out such a project? Are they the most willing to change? Are they the ones who have the most expertise in new technology?" I don't think so [...]"* (MSID-08)

Additionally, the obstacle of freeing professionals is underpinned in the differing resource allocation between the public and private sector:

> "*Another thing that separates the [private and public sector] is [...] how high salary they [people with AI competence] are offered for the competence needed to run AI. It is a high demand on this expertise in the market today. The private sector offers a much higher salary for that expertise than we [public] do.*" (MSID-07)

> "*Data scientists are probably the most sought after at the moment. Or probably aligned with IT architects. [...] So the recruitment in the public sector [...] those skilled people [...] you do not get to have them for a long time before a private organisation steals them away*" (MSID-06)

Including the updated technologists, the enthusiasts, who are engaged in research when reckoning with new technology is thus seen as vital by our informants as they struggle to recruit people with the right skill and competence.

Due to the lack of AI expertise, organisations make error of judgements by selecting skilled professionals over younger and inexperienced technologists. The terms "experienced" and "inexperienced" refer to knowledge in a certain discipline in this context. The ideal approach, as they further noted, is to build a connection between the professionals and the updated, dedicated, and young technologists. The interviewee highlighted this view, by saying:

> *"We choose not to use them [younger ones] because they know so little [inexperienced]. They are so fresh and stuff, and that is a classic [mistake] which we often do in these projects [...] The ideal would have been to connect the younger [technologists] and older experienced [experts] because technology is a competence. It's about technology, too."* (MSID-08)

Ultimately, organisations face a conundrum in which they must consider whether to build a new environment, including the professionals, the enthusiasts or a combination of both groups, when dealing with new technologies, such as AI.

Technology and Understanding Not Aligned

In response to the topic of how far the organisations have progressed in the work with AI, several interviewees stated that organisations' understanding of AI's benefits and use in the workplace is not aligned with the advancement of technology. The premise that the pace between the technology and understanding must be the same in order to use the technology (i.e., why and how it benefits the organisation and the end users) is held in high regard. Many struggle due to limited research and AI expertise. The non-alignment issue is regarded as a challenge to AI adoption in the organisations as it slows down the development. One interviewee depicted this challenge by illustrating that the technology accelerates fast, but the understanding is too slow.

It is important to gain a balance between these two parameters. One interviewee suggested a distribution as a key to their organisation's success with AI projects:

> *90% is about value-creating measures, which means "why do we do it here?" And 10% is the technology. Technology is just a tool - an accelerator. We need to fully understand the use of said technology - why and how AI can help us and the end users.* (MSID-04)

Furthermore, the highlighted challenge can be found across a wide range of Norwegian organisations, particularly in the PS. According to MSID-04, the challenge arises because of the time it takes for employees to restructure:

> *"The challenge is that in the Norwegian public sector, it takes time for employees to reorganize [...] whether it is about learning or individuals having too much to do."* (MSID-04)

Management must "*determine the solution to the problem in order to ensure that employees have the appropriate competence and understanding of the technology before it is deployed in the workplace*" (MSID-07), as highlighted by one interviewee. Employees will reorganise their work processes when new technology, such as AI, is introduced to the workplace. When it comes to understanding the change in the organisation, it is critical that the management's understanding is always ahead of the employees. As another interviewee indicated, it necessitates the "*management's attention and prioritization to carry out the changes*" (MSID-08). By that, the management provides the essential understanding, ensuring that employees will not use much time on reconstructing their work processes.

6.2.1 AI Ignorance: Unawareness of Needs and Values

Throughout the interviews with our informants, it became evident that ignorance is one of the challenges to employing AI. There is a concern of finding the right domain or the right use case for deploying AI due to uncertainties, as many interviewees expressed. One interviewee acknowledged this as a challenge they currently face:

> *[...] The biggest challenge we have right now is ignorance and going from having a need for it [the problem] and being able to say: "And here is actually the solution to that need".*

> *[...] And after that part [defining the need and solution] is solved, there is also such a gap of expectations that can be challenging because even if you think - "alright, AI can be the solution to this" - it is not guaranteed that it is actually true.* (MSID-01)

Moreover, a prominent concern which emerged from the interviews was the difficulty in describing what the AI solutions provide. The interviewees explained that they "*have not fully understood what it means to manage an AI solution yet*" (MSID-01), and that they are "*unable to properly explain themselves what the solution gives them*" (MSID-04). One particularly expressed the "*struggle of telling the outside world what they could actually contribute and operationalise it, quite concretely*" (MSID-05). This concern is related to the lack of understanding of AI among those who "*have only read it*", as one interviewee indicated:

> *"I noticed that in every project we have had, or that they do not have an understanding of what AI is because they have only "read it" - it's a buzzword"* (MSID-04)

As a matter of fact, a survey done by Gartner (2019) showed that 42% are not fully understanding AI benefits and use in the workplace [115]. For business and IT leaders, quantifying the benefits of AI projects poses a considerable challenge [115]. As the interviewee MSID-01 indicated, AI is not always the most optimal solution for a particular problem.

Likewise, it is also observed in the working paper *Hello, World: Artificial Intelligence and its Use in the Public Sector* (2019) by OECD Observatory of Public Sector Innovation, that supports the interviewees' remark. The issue of developing such emerging technologies (e.g., AI) can be risky, as one often "*starts with solutions and then look for problems for the technology to solve*" [116]. Governments and the public organisations alike should seek to understand and grasp the needs of citizens, businesses, and everyone else who might engage with or be impacted by the AI-based solution. With this awareness of needs, the governments and public organisations may determine whether AI-based solution - or other solutions - is the optimal solution to achieve specific objectives. As such, an AI-based solution must always be linked to specific needs and use cases. The majority of the interviewees agreed on this remark, where one participant expressed:

> *"We have to take advantage of the opportunities and have an understanding of possibilities. You do not start [an AI project] until you see which domains have needs. You have to start with needs and processes. One must get an understanding of why and how AI can help, and it must always be linked to a value. [...] Everyone can use the technology, but what matters is how they use it right. And then, we are back to "what value does it provide to adopting this technology?" There are far too many people who have adopted a lot of technology without knowing why [...] and think "this is cool, we have to do this". One must start thinking about value - what business value?"* (MSID-

04)

Awareness of needs and values were emphasised as an essential part of adopting AI which needs more attention as it is, as of now, still lacking.

6.3 Social Challenges: Artificial Intelligence or Artificial Ignorance?

The public organisations in this study express a wide range of concerns related to social challenges which are connected to societal norms and attitudes towards AI. We will dive deeper into these challenges - respectively the lack of expertise sharing and documentation, the hype around AI, and finally the high risk connected to AI development.

6.3.1 Lack of Expertise Sharing and Documentation

As mentioned in Section 2.2, the Government launched the national strategy for AI in January 2020, in which it will, among other things, "*facilitate cooperation and exchange of experience and best practice for AI in both central and municipal administration*" [5]. The Government will establish an advisory body and a regulatory sandbox, as well as being receptive to requests from public and private enterprises. One of the measures was to establish a regulatory sandbox for responsible AI. Shortly after, the sandbox for AI was established in the autumn of 2020, and 2021 was the first operational year [117]. The regulatory sandbox has the goal to "*promote the development of innovative AI solutions that, from a data protection perspective, are both ethical and responsible*" [118]. They have the ambition to assist individual organisations in ensuring compliance with relevant regulations and the development of privacy-conscious solutions. So far, Norwegian Data Protection Authority has completed and published exit reports for several projects, including NAV, Secure Practice, and AVT. These reports offer a summary of the process and conclusions in each project, including findings and the road ahead. By that, an arena is created where the public and private sector can build competence and gain insight in important fields such as legal, technological, and social. Similarly, by delving deeper into the issues of the organisations, Norwegian Data Protection Authority will gain greater competence and understanding, which is critical for providing guidance in a fair and competent manner. One interviewee indicated the importance of sharing expertise as the following:

> *"It is important to establish arenas where you can share experiences with AI. Open data is important in the public sector. In the private sector, they are very good at sharing data, so for example oil and gas they have API.equinor.no, where they try to make the energy sector better and better. Everything is tied back to the data, that's the basis for artificial intelligence"* (MSID-04)

Another one argued:

> *"Establishing a type of network and collaboration arenas where we can share experiences around AI is terribly important"* (MSID-08)

Many interviewees, whilst agreeing on the importance for expertise and documentation sharing, also expressed the lack of sharing. This distinction is particularly apparent and frustrating for the organisations:

> *"There is no documentation on how to do things, or how things have been done in the past. There is little documentation available on gains from operations, we know little about how well it will work."* (MSID-08)

Considering the lack of documentation, the organisations are utterly dependent on testing. "*We need to test as much as possible*", was mentioned by several interviewees.

As supposed by one interviewee, other countries are further ahead in their thinking because they learn from their experience. However, the fact that other countries are further ahead in AI adoption as opposed to Norway poses as a non-issue. This is illustrated by our interviewee,

> *It's more [that], other countries are more mature around the thinking around this for taking more conscious choices maybe than we are now. But [. . .] I do think that Norway, if we manage to get the right people around the table, we can really do this properly in a way that other countries might be able to do this so that we might be a slight catch up* (MSID-00)

The lack of available documentation in Norway that public organisations can learn from poses as a source of frustration among our participants. One interviewee argues that the world is changing rapidly, and many companies still have unsolved questions:

> *"I think that's very important that we do try to remember this that "yes, the world moves quickly" but we're still very much learning here... Many countries are standing back now and asking the questions we didn't asked... But I think many are standing back and asking questions. But I think until we get to that point, you know, we need a certain maturity "*

6.3.2 Hype Around AI

The hype around AI was a recurring theme during our interviews. The interviewees referred to AI as a "*buzzword*" (MSID-09), which the organisations, as of today, are adopting:

> *"Before, AI was just a buzzword, but now there is more implementation! We are using it!"* (MSID-04)

"AI is a buzzword. Before the hype was "data mining" and now it is "AI". It's the same technology - "Same thing, new wording" (MSID-09)

The hype around AI is currently flourishing and has become extraordinary deafening. There are massive assumptions on what AI can do and the outcomes of it. Despite the lack of research within AI and awareness of the needs and values in the respective organisations, AI is portrayed as an attractive technology that must be adopted. The buzz and trends associated with AI leads, according to our participants, to the technology becoming overhyped, and subsequently be held to unrealistic standards. As an interviewee stated:

"There's a power here to change things that we haven't been able to do in many many years, and that's really attractive but also at the same time scary. And I think [...] it's been much more attractive to start with [the attraction] before we really started understanding this [technology] and that's the hype right, because 'wow we can actually do this, we can do huge transformations, and wow [...] we can do health systems, we can predict you know disease, we can prevent disease, we can prevent crime, we can all these different things' which [...] I think support the hype. I think that's what builds the hype. But I hope quite soon we're going beyond the hype and get more realistic. [...] You start off with the hype and then the realization of the reality. I'm hoping we're getting more realistic." (MSID-00)

The overhype of AI originates from the private sector, as expressed by the interviewees. As of today, AI is easier and more adopted in the private sector compared to the PS, which the majority of the interviewees agreed on. As opposed to the private sector, the PS has several questions which they have to consider, which is slowing down AI adoption. It is argued as follows:

"The public [sector] has so many questions that we need to consider - what's the meaning for universality, what's the meaning of citizen relationships, what's the meaning of democracy" (MSID-00)

Given the hype's vast amounts of assumptions, our informants are urging for a deeper understanding and consideration of the consequences of the hyped technology's.

6.3.3 High Risk Connected to AI Development: Fear of the Unknown

Since AI is portrayed as the "it" technology - noteworthy and exceptional-, the surrounding hype has enticed firms and organisations to adopt it. Many organisations are tempted to follow the success stories of AI adoption, where the technology itself has been the driving factor behind the success. Based on the lack of expertise and research in AI, our participants have emphasised that considerable risk may result in serious consequences that affect, for instance, users and society. On the journey to grasping and adopting AI, one thing is certain — there will be uncertainty. Our interviewees are particularly concerned with the uncertainty of results, which were much discussed in the interviews. One interviewee described it as follows:

> *"The risk in a [AI] project is great [...] and the result is uncertain [...], which affects the willingness to take the risk or prioritise such a measure. We focus on reducing uncertainty. We must be aware of the risks involved in the components we use [...] There is a quite a lot of risk and uncertainty associated with AI methods, which may do something about choosing not to prioritise it."* (MSID-01)

Because the risk is considerable in some circumstances, the employees are trained to hold the risk as low as possible. Another interviewee argued as follows:

> *"We are very concerned about risk in our environments. They are procedurally controlled and work constantly to have as low risk as possible. The introduction of new technology involves risk. There is a risk that things may go wrong when we use them again. So, it's always scary to do something new. It's in the spinal cord all the time that the risk should be as low as possible always, that is what our professionals are trained for. It makes it a little demanding to do something new and make changes."* (MSID-08)

Another common theme which reoccurred throughout the interviews is related to the risk in the PS. The PS is politically controlled, making AI adoption more complicated than in the private sector [5]. The responsibility level to the PS is different to the private sector, as they are concerned and must consider the major issues that might impact the PS. As the PS involves both the individual and society, the PS must "*apply the least possible pressure to society*", which the interviewees expressed throughout the interviews.

One interviewee stated particularly:

> *"What makes Norway quite unique is the relationship of trust between the citizens and the authorities, but also businesses. It is important for us as an agency that what we do must always be transparent. We depend on the trust of the people. We must ensure a welfare society."* (MSID-07)

Proper digitisation and the correct use of new technology can benefit the individual and society. However, as it is identified in the interviews, the path of AI adoption in the public sector is perceived as uncertain due to the risk which could potentially affect the individuals and society.

Moreover, technologies that follow similar patterns to AI, such as cloud computing, were mentioned and discussed in the interviews. The participants drew on the historical evolution of cloud computing, and highlighted the similar trajectory in which AI is following. One of our interviewees described cloud computing's associated challenges as a reoccurrence, and illustrated how AI may follow the same path as cloud services:

> *[...] In the past, people [about cloud platforms] said that "we are not going there [the technology takes us] because of security concerns", but then it has been realized that technology is the future."* (MSID-06)

6.4 Technological Challenges: Technical debt

Some interviewees highlight perceived challenges related to the the public sector's technological portfolio. Most of these technological challenges are related to technical debt, as one interviewee expressed:

> "*The data warehouse was simply not properly taken care of [...] and was technically lagging behind as well. So, the alternative now is to turn off the data warehouse and buy some servers and push the data into them [the new servers]. But that's not an option. To close a data warehouse is business critical in every possible aspect, especially in relation to operations in the organisation. So it is not an option.*" (MSID-06)

The root of this technical debt is argued to be related to lack of a professional environment for technological development:

> "*It was clear after a while that we had no best practice on how to develop these systems. It was these "fiery souls"[enthusiasts] who sat there and were allowed to experiment - which lead to this "homemade" system.*" (MSID-06)

In software development, technical debt (also known as tech debt) refers to the implied cost of additional rework incurred as a result of choosing short-term solutions over long-term ones [119]. It can be defined as a gap between the optimal technical solution and the current solution, meaning that the solutions are incomplete, overly complicated, and outdated, preventing effective operation, administration, and development.

Due to the outdated IT systems used in public organisations, the expense of constructing new systems is enormous. One interviewee recognised the massive cost of building new systems in their organization, stating:

> *We have a lot of large systems. It costs a lot of millions, hundreds of millions to build new systems over time. If so, it may be an challenge in the future that we are constantly lagging behind on the system technology side[...] I have worked here in many years. I see how rotten these systems are [...] We must have extra funding when we build these systems. We are talking about something like the collection. We are talking about billions to build such a system* (MSID-07)

to which a colleague responded,

> *The size [of the systems] makes it definitely difficult to keep up with the technological.* (MSID-06)

It becomes apparent that the technical debt is a crucial challenge for implementing new systems, in which it requires a huge amount of resources and funding that the organisation might not be able to provide.

6.5 Data Challenges: Complexities of Data

As stated by the Norwegian Data Protection Authority's report, large data streams can be utilised to achieve societal benefits [117]. Such benefits are achieved by analysing data and finding patterns and relationships. Norwegian Data Protection Authority further emphasises that «*AI can make a difference. While traditional analysis methods rely on being programmed to find connections and links, AI learns from all the data it sees. The computer systems can therefore constantly respond to new data and adapt their analysis, without human intervention* » [114].

Despite the praised possibilities unlocked by the emerging technology, it is agreed among our informants that to realise these capabilities, AI must be used in a responsible way. In the national AI-strategy, the protection of intellectual property is deemed as an important step towards ensuring responsible AI development [5]. The government wishes for organisations to make competent decisions along the process of AI adoption and have a conscious approach to data.

Data serves as the fuel for AI. The more data used training the systems, the more accurate the predictions. AI development does not only demand high quantities of data, but also a high quality of data:

> " *[...]to get good, advanced analysis you need good data*" (MSID-01).
>
> "*Data is almost like gold that we must learn to exploit*" (MSID-07).
>
> "*I always call data for our treasure chest*" (MSID-06)

Data being described by the PS as the fuel of AI, gold, and a treasure chest illustrates an era where data changes the way knowledge is produces, and where communication is based on the collection and processing of data. This era thus introduces questions of challenges related to organisations' use of data. During our data collection and analysis, we discovered three main issues: quality of data, data ownership, and regulations of data.

6.5.1 Access to High-Quality Data

The Norwegian PS produces large amounts of data in its case processing and exercise of authority. The produced data is an important source of innovation, research, and business development, and in the last ten years, Norway has made a significant effort to make this public data available and shared [120]. However, AI-systems are only as "intelligent" as the data from which they learn.

For decision-making systems, data volume and data quality are important for systems to be able to make accurate decisions. According to the government, data quality, which refers to whether the data can be used for its intended purpose, is highly prioritised at policy level based on the contention that bad data equals bad results. As such, sufficient data quality is seen as important for the Norwegian PS. When discussing the role and importance of data with our informant, they highlight the unique situation which Norwegian public organisations operate in. Evidently, Norway has extensive data registers of high quality, which enables many opportunities:

> "*What sets Norway apart from many other countries is the access to good data, that is, the access to population data that goes back many decades. The quality of them is very high.*" (MSID-03)

The state registers information about individuals, companies, and enterprises on a large scale, which forms the basis for accumulated knowledge about welfare, work, business, and the population's behaviour and composition over time. It is therefore believed that the data registers contains answers to many of society's future challenges and solutions [120]. The high-quality register in Norway constitutes a comparative advantage which should be maintained.

However, having vast amounts of high-quality data does not necessarily mean you have direct access to it. As illustrated by one interviewee, the fragmentation of functions and competence between different public organisations results in different interpretations of what can be shared. The PS in Norway is somewhat fragmented in 358 municipalities, 70 executive agencies, and 16 national ministries [113]. On organisational level, we find high degrees of autonomy and strict boundaries [114]. Consequently, when data collection occurs in the PS, it is often fragmented, where different departments operate in silos. One informant further stated that the challenge of accessing and analysing data stems in the challenge of cracking "*the silos in the data*" (MSID-09). Thus, these different interpretations can hinder cooperation between the various organisations. Often a big data approach assumes that one has access to all the data deemed necessary, however this is not the case in the PS.

> "*[...] and retrieving data from other [public organisations] for analysis. To collaborate with others [in the sector]. So not necessarily that we sit and build it [AI systems] on our*

> *own [...] but for example with the sector as a whole*" (MSID-01)

As emphasised by out informants, high data quality makes it easier to automate and streamline, but it is also important to understand that data quality inevitably becomes better by sharing.

6.5.2 Data Ownership

Our informants suggest that public agencies cannot solely leverage technologies; they need to consider several dimensions around ownership of data:

> "*Someone must own the data and be held responsible for taking good care of where it is used*" (MSID-04)

Data is collected in many ways across a wide range of objects and people. This can range from personal data in the health care system or data from sensor technology. When discussing this topic with our informants, a repeated concern from the participants was "*Who should own the data?*" - Is it the actor who collected data, or is it those who have reported and produced the data in various ways, meaning the data subjects, who are the owners of the information the data contains? Since AI is commonly used to predict, it is important to decide who is in control of the data, and who should be held responsible for the data and the algorithms:

> "*You need good data, and one must have control over that data, and understand the context of use. I'm worried about when the data goes outside our "property" and suddenly is shared with other private actors. We need to gain control over how our data is used at all times.*" (MSID-07)

One interviewee specified how this responsibility should be placed in the management:

> "*The algorithm cannot be responsible. It [the algorithm] is not the one we can hold accountable if things go wrong. So, there must be a type of leader then who is responsible*." (MSID-08)

Other participants, however, explain how the ownership should lie with the data subjects themselves. The importance of data ownership presents an opportunity to build trust. Ensuring the users' ownership over their own data builds trust between them and the public organisations which enables them to be part of the process in which their data is part of:

> "*That aspect of trust [...] I think is way more important than people realize, and [...] there is a reason why things work pretty well here [in Norway] and do not work at all in the US for example. [...] and it's pretty much all about that trust between the individual and society*." (MSID-03)

"*Because it is very important that we, as a public agency, that what we do must always be transparent. We are dependent on the trust of the population [...] that people are not thinking that we are abusing their data and private information*." (MSID-06)

Since the Norwegian public sector is described as highly digitised and benefits from high levels of trust from citizens, our informants expressed the need to maintain this trust [113]. Strategies for increased data sharing must in any case relate to the existing legal framework for ownership and control [5].

6.5.3 Regulation of Data

Along with the Personal Data Act, GDPR and Schrems-II has had direct effects on AI adoption on organisational levels:

"*We have GDPR which slows down a lot [of the processes] when we start getting down on individual level. We have tons of information and data but there are limitations on what we actually can put together because they have been collected for different purposes. [...] Everything related to GDPR is very strict.*" (MSID-06)

"*Something that came not so long ago is the Schrems-II verdict which is very demanding [for data usage in the organisation]*" (MSID-08)

By engaging in these international and national laws for data protection, the government ensures that Norwegian citizens, and consequently their data, are offered protection and rigorous control:

"*In Norway and the EU, there are many laws that must be complied with. In Norway, we are incredibly protected when it comes to privacy.*" (MSID-03).

Data must be seen in relation to fundamentals of culture and competence. As described by our informants, data cannot be used creatively without a solid foundation:

"*What we often find important [...] is having a well-formulated problem and having the data. [...] It must be rooted in the management and organisation and the employees must be involved for it all to be legal*" (MSID-06)

Chapter 7

Discussion

This chapter will first answer the RQ by studying the main findings of this empirical research in relation to Organisational Readiness for Digital Innovation in Section 7.1. Following that, Section 7.2 will enlighten the key learning points our thesis made by discussing our current research findings in connection to the existing literature on the PS and AI and organisations, and ultimately present the suggestion of a re-conceptualised organisational readiness model as an extension of the existing readiness construct. Lastly, we will present the contribution our thesis provides to the research field and to the practitioners - respectively Section 7.3 and Section 7.4.

7.1 Challenges of AI Adoption

To recall, the research aim of this thesis is to explore challenges of AI adoption in the Norwegian PS and their impact on organisational readiness. This section will therefore answer our RQ, formulated as:

> *What are the challenges that impact the organisational readiness for AI innovation of the Norwegian public sector?*

When we earlier identified the AI adoption challenges in Section 6, we noticed a relationship between our empirical findings and the *Organisational Readiness for Digital Innovation* theory. To understand the challenges' impact on organisational readiness for AI adoption in the Norwegian public sector, we will discuss our findings in relation to the theory's seven relevant dimensions, namely the seven organisational readiness factors. We will thus answer the RQ in two steps: firstly discuss the perceived challenges of AI adoption in the context of Norwegian public sector, and secondly discuss the challenges' implications for the organisational readiness of the sector. To do so, we have divided the following subsections according to the key findings in Chapter 6, respectively Policy and Legal, Managerial, Social, Technological, and Data challenges.

To provide an overview, the following matrix summarises the relationship between the readiness factors and associated AI adoption challenges. Note, the N/A fields denote that our findings have no relationship with the a priori model of organisational readiness.

	Policy and Legal	**Managerial**	**Social**	**Technological**	**Data**
Resources	N/A	Difficulty balancing between technology-updated employees and experienced employees when building new environments for AI development	N/A	Lack of flexibility of (re)configuration	N/A
Culture	N/A	N/A	Lack of expertise sharing. High risk regarding AI development which enables fear of the unknown. Employees' adaption skills are low since they are trained to hold the risk as low as possible	N/A	N/A
Strategic	N/A	Management lacking understanding of technology, and thus struggle to communicate with the employees on relevance.	N/A	N/A	N/A
Innovation Valance	N/A	N/A	The hype around AI leads to discrepancy between their high positive expectations and the disappointing reality	N/A	N/A
Cognitive	N/A	Difficult to reorganize and adapt due to their limited knowledge. Unawareness of needs and values	N/A	N/A	N/A
Partnership	N/A	N/A	N/A	N/A	N/A
IT	N/A	N/A	N/A	Instability in enterprise and IT infrastructure caused by technical debt	N/A

Table 7.1: Matrix describing adoption challenges in relation to organisational readiness. The perceived challenges are represented on the X-axis, while the organisational readiness factors are represented on the Y-axis.

7.1.1 Policy and Legal Challenges

When conducting this research on AI adoption, it became evident that the PS faces challenges concerning policy and legal areas. Challenges in policy-related and legal areas highlight the reinforcing uncertainties of national authorities' inconsistency and the unclear legal basis. Since the domain experts from national levels are not involved in AI development, in addition to laws and regulations being unclear, this poses as a challenge for the PS as public organisations are heavily reliant on the national level's guidance for developing AI.

Given the absence of readiness factors concerning governmental intervention in Lokuge et al.'s (2019) readiness construct, discussing policy and legal challenges' impact on organisational readiness is questionable. Despite our findings demonstrating that reliance on the regulations and rules is significant for the PS, the current readiness construct has not taken governmental intervention as a readiness factor into account. When considering the policy and legal challenges' impact on the organisational readiness of the PS, it is difficult to infer the direct relationship between the challenges and the readiness factors. Thus, this offers critical evidence that calls for an extension of the current readiness construct, implying the need to introduce a readiness factor for highlighting governmental interventions' role in AI adoption. This will be further discussed in Section 7.2.

7.1.2 Managerial Challenges

Our findings show that the PS faces managerial challenges in the journey of adopting AI. The challenges related to the managerial practices demonstrate that competence and understanding of the technology, needs, and values are imperative to keeping up with emerging technologies, such as AI. As the management's commitment and prioritisation to carry out technological changes is absent, it constitutes a challenge for the PS when adopting AI for three distinct reasons. Firstly, our findings show that management's lack of AI comprehension might reinforce the slow development of AI adoption in organisations, making it hard for the Norwegian PS to adopt AI. Second, our findings illustrates how the understanding of AI within public organisations is currently not aligned with the technology's pace. The imbalance between the rapid technological changes and the insufficient understanding of AI reinforces unclear purposes and goals caused by the top managements' inability to fulfil their role of emphasising and understanding the technology, poses a challenge for organisation's capabilities to adopt AI. Third, our findings reveal that managements struggle to communicate with the employees on relevance caused by the lack of understanding of technology. This results in the difficulty of balancing between technology-updated employees and experienced employees when building new environments for AI adoption. Thus, based on our study, top management's crucial role of continued commitment, involvement, and support for AI adoption and the need for AI to be anchored in management is critical for the journey of AI adoption. However, as delineated from our findings, this top management support is, for now, absent.

Managerial challenges impact the PS's readiness in three ways: the PS's resources, cognitive, and strategic readiness. Firstly, the difficulty of balancing between technology-updated employees and experienced employees when building new environments for AI development implies the lack of flexibility of human resources. This, in turn, has an impact on the *resource readiness* factor, which finds human resource flexibility to be crucial for becoming organisational ready. As described by Lokuge et al. (2019), resource readiness emphasis the resources' flexibility to change the assemblage of IT to the rapidly changing markets. Since the PS has no shared understanding on technological objectives and its alignment to business values, the flexibility of the human resources may be halted which, in turn, impacts the organisational readiness of AI adoption.

Second, the challenge of reorganising and adapting to new technologies, in addition to the unawareness of needs and values, impacts the *cognitive readiness* factor as AI adoption necessitates knowledge of the technology in order to be organisational ready. As previously mentioned, the imbalance between these components (i.e., understanding and technology) is a challenge for the adoption of AI as it reinforces unclear purposes and goals - further facilitating the limited understanding of the technology's purpose. This limited understanding can be seen in connection to top managers diverting their attention away from AI, and thus developing insufficient knowledge on the technology and its usage [10]. Top managements' inability to fulfil their role of emphasising and understanding the needs and values in regard to the technology poses as a challenge for the organisation's capabilities to adopt AI, which in turn impacts the organisation's readiness for AI adoption.

Third, the imbalance of the rapid technological changes and the insufficient understanding of AI is related to management's lack of understanding of technology. Due to poor understanding of technology and strategy miscommunication from the top management, this elicits an unclear plan of action which, in turn, facilitates unclear guidelines for AI adoption, which ultimately impacts the strategic readiness factor. [10].

7.1.3 Social Challenges

In this thesis, social challenges refer to attitudes, assumptions, and understandings which affect AI adoption in the Norwegian PS. The social force for AI adoption lies, as asserted by the informants, in the cooperation between organisations and the assumptions of what AI can achieve. However, as there is limited cooperation within the sector in addition to varying attitudes and assumptions of the technology, the PS becomes increasingly reluctant to adopt AI. These values of public organisations alludes to attitudes and assumptions towards AI which discourages value creation. Such challenges therefore impact the PS's readiness in two ways, namely the sector's cultural readiness and innovation valance, which we will discuss in relation to the social challenges.

The findings of this study highlight, first and foremost, the shared concern of high risk around AI among public organisations preventing the adoption of AI. In particular, the empirical findings of this study show that the high risk is due to "black-box" characteristic of the AI and its related uncertain outcomes, which enables fear of the unknown. Additionally, it is found that employees are trained to hold the risk as low as possible due to the underlying strategy to not take unsolicited risks. This is consistent with the Lokuge et al.(2019)'s construct of organisational readiness, which demonstrates that, among other things, low-risk aversion fosters digital innovation. Given the moderate risk associated with digital innovations and the impossible outcome of complete failure [10], avoiding any potentially risky innovation leads to the resistance of adoption. Because public organisations prefer not to employ AI due to the high risk, this assertion concurs with the empirical evidence and hence impacts the organisational readiness through the factor of *cultural readiness* factor.

The organisational readiness for digital innovation theory divulges further that sharing ideas in a connected workplace will have positive effects on digital innovation. In line with this, the findings of this study demonstrate that expertise sharing and documentation are beneficial for the whole sector. Aligned with the findings' emphasis on expertise sharing and documentation, the current national AI strategy is urging for cooperation and experience sharing in the PS. Because of the lack of expertise sharing between public organisations, which the empirical evidence revealed, this type of challenge is thus impacting *cultural readiness*. With the absence of collaborative work within the sector, organisations are unable to work interdisciplinary, and thus challenges AI adoption as it relies on the integration of different perspectives, such as domain and IT.

Furthermore, Lokuge et al. (2019) articulate that *innovation valance* enhances organisational readiness by fostering a positive attitude toward digital innovations. Employee attitude, in particular, is crucial as it promotes open-ended creativity, which is a fundamental driver for digital innovation. The empirical finding of this study reveals immediately that the hype around AI is a common concern that is currently flourishing within the public sector, originating from the private sector. Considering the significant issues related to human rights, discrimination against vulnerable groups, and democracy, the public sector is unable to mirror the AI advancements in the private sector. There are fewer challenges to consider in the private sector, and hence the public sector requires a different approach and sets of questions. This unveils that the increasing hype may be held to unrealistic standards, leading to a discrepancy between their high positive expectations and the disappointing reality. As such, this empirical evidence reaffirms that *innovation valance* is fundamental for organisational readiness and that the hype thus impacts the organisational readiness for digital innovation.

7.1.4 Technological Challenges

Our findings show that the technological challenges impacting AI adoption are related to technical debt. Given the PS's large outdated systems that had been developed by amateurs, organisations were technically lagging behind as the existing system were overly complicated and prevented effective operations. The size of these systems and their associated technical debt makes it difficult to keep up with the technological pace. To adopt AI, organisations must therefore reconstruct these enormous systems. However, reconstructing these systems is a complex task. Firstly, since reconstructing such systems are highly expensive, having the necessary resources and funding is crucial. Secondly, since the systems in the PS were developed without a best practice, they tend to be overly complicated, incomplete, and entangled. Since these systems are not fragmented, introducing new innovation requires a replacement of the whole system, instead of a fragment of a system. Based on these two technological challenges, we will further discuss how they impact the organisational readiness through the factors of resource and IT readiness.

This finding of technological challenges aligns with the a priori model of organisational readiness for digital innovation (previously mentioned in Section 4) by Lokuge et al. (2019), which found *Resource readiness* as fundamental for organisational readiness. Because of the outdated systems in public organisations and the lack of resources to update the systems to respond to the rapidly emerging technologies, this challenge impacts resource readiness that emphasises the flexibility of configuration and reconfiguration of its resources. The outdated systems are an attribute of public organisations' infrastructure, and subsequently their resources, which AI is reliant on. With rigid IT resources, which characterizes the PS, the sector are unable to follow the technological change as they are constantly falling behind the rest of technological environment. As such, this unveils that the lack of flexibility of (re)configuration plays a significant role in PS's readiness to adopt AI.

Connected to the flexibility of the IT resources, the empirical findings show that technical debt affects the strength of public organisations' IT portfolio - both enterprise systems and IT infrastructures. This ties well with *IT readiness* that highlights the importance of stability of the enterprise and IT infrastructures in increasing the innovation capacity of digital technologies and leading innovation. Due to the instability caused by technical debt, this particular issue impacts organisational readiness for AI adoption through the factor of IT readiness. As the IT portfolio is described as unstable, little can be done to adopt AI successfully. As a result, the technological challenges, precisely lack of flexibility of (re)configuration and technical debt, have an impact on the organisational readiness for adopting AI in the Norwegian public sector.

7.1.5 Data Challenges

Our findings show that the data challenges related to access to high-quality data, regulation of data, and data ownership are limiting AI adoption in the PS. The data challenges underline the fragmented public sector, uncertainties on ownership, and strict regulations. Such challenges are of relevance when adopting AI, as AI adoption requires good data. However, the public sector has limited access to the high-quality data that Norway possesses and is reliant on regulations (e.g., GDPR) and Schrems-II, making it challenging to adopt AI.

This study has verified that data has a significant impact on AI adoption. However, given the current readiness construct by Lokuge et al. (2019), such challenges impacting organisational readiness are questionable, as our empirical findings cannot ensure a direct connection with the current readiness construct. While data appears to be significant for AI adoption in the PS, the current construct has not taken data into consideration. Thus, this finding goes beyond the existing model and needs to be considered as a readiness factor.

7.2 Public Sector's Readiness for AI

Through our discussions in 7.1, we have illustrated the Norwegian PS's perceived AI adoption challenges that may impact the sector's organisational readiness. However, out of the five perceived challenges this thesis identified, two of them, namely data and policy and legal challenges, had no direct impact on Lokuge et al. (2019)'s organisational readiness framework. Given Lokuge et al. (2019)'s aim of generalisability and parsimony of their framework, factors such as government legislation were omitted [10]. However, as we are exploring the research context of PS, context-specific factors may aid us in understanding the challenges that impact the Norwegian PS's organisational readiness. Contingent to our interview based research design and applied method of document studies and literature review, we therefore argue for an extension of the organisational readiness framework by transferring it to a sectoral level - highlighting the perceived challenges from the PS's perspective.

Considering AI's attributes and challenges, adoption of AI suggests a high implementation complexity, which differentiates it from the adoption of other traditional technologies. [31]. Given the various ways in which AI is required to approach problems due to their high computational ability, availability of relevant data, and algorithms [4], the technology impacts sectors in differing ways. Subsequently, AI enables varying adoption purposes, such as organisations' objectives for specific use cases. As such, adoption requires an understanding of AI as a technology as well as an assessment of organisations' readiness for AI. Comprehending readiness, specifically the readiness factors, in relation to AI may strengthen the possibility of a successful adoption, and is thus crucial to leverage AI's capabilities. With this, AI's characteristics demands an exploration through readiness factors.

By extending our understanding of organisational readiness framework based on our discussions on policy and legal (Section 7.1.1) and data challenges (Section 7.1.5) to include both AI and PS-specific characteristics, we attempt to provide a better understanding of the challenges that may impact the organisational readiness of the Norwegian PS. We will discuss these two key factors, or better called: the key learning points of our thesis, in greater detail in Section 7.2.1 and Section 7.2.2. Finally, we will round off this chapter by extending the organisational readiness framework to better suit our AI and PS-specific research setting in Section 7.2.3

7.2.1 Government Interventions

As an extension from literature on political, legal, and policy challenges, this thesis has verified a need for supervision from national and legal levels [45]. In line with Sun et al.'s observations on marked uncertainty, our findings suggest an increase in uncertainty within the PS which is rooted in the lack of official AI definition, as well as a lack of official standards. With no shared or clear understandings on what AI entails, or how to employ it, the sector becomes reluctant to the adoption of AI. As delineated by our informants, the absence of a clear environment for AI adoption holds the sector back - resulting in a slower process of AI adoption.

Although prior research has emphasised on national and legal challenges' impact on AI adoption, what they have been unable to demonstrate is the root for these challenges. As corroborated with Sun et al.'s meso-level challenge, our findings suggests that an absence of a shared definition on AI leads to uncertainty. However, we further discovered that the lack of definitions, as well as guidelines, is tied to policy-makers equal lack of knowledge. With public administrative bodies having limited knowledge on AI, they are unable to provide proper guidelines for the PS.

On a micro-level, the foregoing literature identified challenges regarding the absence of legal regulations of AI. Following the nature of AI wherein the technology replaces decision-making procedures, the public need rules on how to connect AI with the legal system of accountability. In accordance with previous studies, our findings further support the idea of AI's unrecognisable juridical personality. In contrast to earlier literature, however, evidence of the relationship between technological development and law has been detected in this study. With laws not enabling AI development due to them being technology-laden, rather than technology-neutral, the PS are facing a challenge which they can only overcome through government interventions.

7.2.2 Data Governance

The need for collaborations within the sector is embedded in Norway's large data streams [121]. Compared to other governments who struggle with insufficient databases, Norway produces and stores vast amounts of data which poses as a necessary source for innovation and the root of AI training. Moreover, researchers have argued that the high quantity and quality of Norwegian data registers constitutes a comparative advantage in an international context which should be maintained and exploited to unlock the technology's potential [121, 122]. However, Norway sitting on this data does not necessarily mean that the PS has direct access to it.

Access to data, and knowledge on how it can be used, is increasingly becoming a prerequisite for decision-making, and developing public goods [5]. Data accessibility is thus necessary in order to facilitate value creation in what the government calls a data driven economy. However, as both our findings and previous research on adoption has highlighted, the fragmentation of the PS, and consequently the fragmentation of data, has fostered an inaccessibility of data in the Norwegian setting [113]. The lack of shared arenas for data sharing is rooted in the ethical challenges of balancing data sharing and privacy as the PS must supervise with laws and regulations.

Another challenge for the sector relates to ownership of data, which is aligned with the literature on AI adoption [45]. When data is produced by several actors, there is often ambiguity about who can share and is responsible for data or which actors it must be clarified with. As there are different practices and ambiguities, a number of paradoxes arise regarding the distribution of data [55]. As illustrated by Berente et al., feeding AI all types of data within and beyond organisational bound gives rise to questions on data ownership [55]. With no clear answer to the challenge of data ownership, emerges the inability of proper AI adoption.

Management's resistance to data sharing is described by Sun et al. to be a key obstacle for adopting AI in the PS [45]. Since data is viewed as a valuable asset, like our findings support, managers are reluctant to share them with the rest of the sector and would rather own these "values" for themselves. Although Norwegian public organisations view data as a "goldmine", our findings links the lack of data sharing to the lack of arenas for collaborations rather than reluctance from managers. Distinct to thePS, data sharing is a prerequisite to develop more seamless public goods, wherein increased sharing can contribute to innovative and effective delivery of services. Given the lack of collaboration with the rest of the sector in terms of data, expertise, and document sharing, the PS are unable to gain deeper insight and competence to adopt AI. This combination of findings and literature supports the conceptual premise of emphasising data governance's role in the adoption of AI, which as of now is impacted by data challenges.

7.2.3 Extension of Readiness Framework

Figure 7.1: Organizational readiness for AI adoption at sector level. An extension of Lokuge et al.'s organisational readiness construct.

One approach of studying technology adoption within organisations is by employing the theoretical framework of readiness. By using this lens in relation to this study's five identified perceived challenges and the theory's underlying assumption that certain factors can impact the readiness, we recognised two key learning points, or better called two divergent factors, which enabled the researchers to re-conceptualise the priori model in regard to the PS. As our findings specify external factor's role for public organisations, we would argue for extending the theory's underlying assumption to include uncontrollable factors such as government interventions. Furthermore, with the challenges accompanying AI's characteristics of data, it can be conceivably suggested from our discussion that these context-specific characteristics can aid us in understanding the challenges of AI adoption and their implications on organisational readiness of the PS. Moreover, since our findings reveal that the perceived challenges had no impact on the *partnership readiness* factor and had no direct relationship, we can argue for omitting this particular factor from the extension of readiness framework. As a result, we have developed an extension of the organisational readiness framework for the PS by adding *Government Intervention* and *Data readiness*, and excluding *partnership readiness* in hopes for it to bring actionable insight for the PS.

7.3 Contribution to Research

This thesis provides contributions to the research field in two ways. First of all, the main contribution of this study is to the emerging literature on AI adoption challenges. Due to

AI's attributes (i.e., data), prior research suggests that adoption of the technology poses different challenges in comparison to other traditional technologies [45, 50]. These challenges include insufficient database sizes, lack of quality data, and absence of data integration and standards [45], which this research has confirmed. As discussed in this thesis (Section 7.2.2), these challenges can be seen in connection to the national level's limited knowledge, and consequently, their limited guidance. While the public sector is in need of guidance, in terms of shared definitions and guidelines, from the national level, AI proves difficult to regulate due to its ambiguity associated with data [55]. We are therefore encountering a dilemma where AI cannot be properly regulated due to its pervasive nature, and the public sector cannot adopt AI without clear regulations. This extended knowledge presents a new understanding of AI adoption challenges in the research field, which highlights a paradoxical cycle.

Secondly, this study contributes to the research of organisational readiness by recognising two context-specific factors, wherein one is related to the foundation of AI (i.e., data), while the other illustrates the attributes of the PS (i.e., government intervention) [10]. These two factors pose as context-specific to an otherwise generalised framework to understand this thesis' identified AI adoption challenges and their implications on organisational readiness. The identified extensions may be considered meaningful as they can promote a scientific discussion. The discussion can, for example, be about the differing challenges and their associated implications on organisational readiness between the public and private sector, or explore the challenges across different industries in the same sector.

7.4 Contribution for Practice

This research's insight into perceived challenges for AI adoption within the PS may be of interest to practitioners in the PS. Given the extension of the framework of organisational readiness (Figure 7.1, we identify a need to prioritise guidelines and data development. The AI-specific (i.e., data governance) and PS-specific factor (government intervention) illustrates how AI systems only are as good as the data which they are built on. With limited access to high-quality data and no guidance on how to use the data, AI cannot provide its promised benefits. Before delving into AI and the adoption of it, top management must therefore focus on data governance, whereas policy-makers are urged to devise shared guidelines and definitions of AI. Given the dynamism and uncertainties characterising the nascent phase of AI adoption in the PS; establishing shared definitions and standards may limit, or perhaps prevent, some data and policy and legal challenges associated with AI adoption. A practical contribution is thus to prioritise the development of AI guidelines and data governance, rather than adopting AI for the sake of AI.

Another contribution of this thesis is that the pace between technology and regulations should be taken into account when commencing the adoption of AI. AI leads to novel ways of processing data which were not considered when national laws were formulated. Since AI requires the processing of large amounts of data - often personal data -, the PS need clear legal requirements for the adoption of AI which may be difficult to explicitly derive from the national laws. A legislative process, including rounds of consultations between PS and national authorities, could therefore ensure a supplementary legal basis for the adoption of AI in the PS.

Furthermore, arenas for knowledge sharing are advocated to encourage collaboration and the exchange of experience in the public sector. Although the government issued a goal to facilitate cooperation and exchange of experience and best practices for AI in both central and municipal administration [5], our empirical findings reveal that the frustration among the public organisations is due, among other things, to the lack of expertise sharing and documentation. Since Norway is still in the nascent phase of AI adoption, characterised by high risk and uncertainties, AI has not yet matured enough to document the gains or the best practices, and many questions remain unsolved. It is important to remember that the PS is still learning and asking unanswered questions. To promote AI in such environments where the PS is still in its nascent phase, it is therefore necessary to pose questions collectively, in order to establish arenas where knowledge, expertise, and experience may be shared.

Chapter 8

Conclusions

In this thesis, we have investigated the perceived challenges that impact the organisational readiness for AI innovation in the Norwegian public sector. The objective of this study is to contribute to the research field by exploring AI adoption and challenges in the PS from a perspective of organisational readiness. By using the theoretical lens of organisational readiness for digital innovation by Lokuge et al. (2019), we were able to identify the perceived challenges impacting the Norwegian public sector's readiness. The results suggest that three of the five identified challenges, namely managerial, social, and technological, impact Lokuge et al.'s framework of organisational readiness through factors such as resources, culture, strategy, innovation valance, cognitive, and IT. However, two challenges, i.e., policy and legal and data, had no direct impact on the original framework, despite these challenges being key aspects of AI adoption in the public sector. This resulted in this study's re-conceptualised organisational readiness framework to include two context-specific factors, namely data and government interventions, and exclude the partnership factor. Given that the readiness factors are the cause of the latent construct of organisational readiness, we can conclude that the Norwegian public sector's organisational readiness is fully derived by these factors (i.e., resource, cultural, strategy, data, governance intervention, IT, innovation valance, and cognitive). With this research, we aimed to provide the public organisations with insight on the challenges that impact their organisational readiness for AI adoption.

8.1 Further Research

The findings of this research open up interesting questions for further research. To further enrich and build upon the findings of this study, we propose some focal points that can contribute to the AI domain in PS.

Firstly, it would be necessary to test the validity of the extended readiness framework. This study has solely looked into AI adoption and has been conducted in the Norwegian public sector. As the extended readiness framework is validated on a small portion of the public sector, a re-examination of this framework is necessary for improving validity. This can be done by testing it with a greater sample size and in diverse settings, contexts, and timelines.

Secondly, while this study primarily focuses on the PS in Norway, a study in other countries would contribute to a more in-depth understanding of the relationship between regulations and laws and AI. It would be of relevance to shed light on how other countries have addressed this problem and how different regulative frameworks - based on different legislative systems - address AI. Future research may thus investigate the dynamism between other countries' regulations and laws and AI.

Thirdly, one can delve into determine the relative importance of each factors of the extended readiness framework. As it was defined earlier, readiness is conceptualised as a degree of readiness. This study has not answered the weight of each factor, as our scope is limited to the challenges that impact the organisations' readiness. It would be insightful to investigate certain factors that increase the readiness. Further research which puts more focus on the degree to which the factors have an impact on organisational readiness is therefore suggested.

Lastly, more research on the interrelation between factors and challenges might be possible. Our study has focused on challenges impacting the organisations' readiness rather than the factors. It would be interesting to look into the relationship between factors and challenges, as well as the underlying mechanisms causing such relationships.

8.2 Limitations

There are two limitations of our study that require attention in future studies. First, our sample of participants are mostly public organisations that have advanced significantly in their use of AI. This may have influenced our findings, which demonstrate a smaller degree of perceived challenges of AI adoption and a stronger willingness and ability to solve than is likely to be reflective of most public organisations implementing AI.

Second, the theoretical framework of organisational readiness was identified late in the process. As we adopted an inductive approach, the identified themes in our obtained data were generalised into relevant theories - theory of readiness. Because of this trajectory, we never asked our informants directly about concepts within the readiness theory. As a result, our research might lack useful insight which can potentially only be recognised through a deductive approach - by starting with a relevant theoretical framework.

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Appendix A

Interview Guides

A.1 Interview Guide for Organisations

Intervju Guide - Organisasjoner

Med forbehold om endring.

Først og fremst, takk for at du tok deg tid til å delta i dette intervjuet.

Vi er to masterstudenter ved UiO, Institutt for Informatikk, som for tiden skriver en masteroppgave innen AI i offentlig sektor. Målet med dette intervjuet er å få mer innsikt i muligheter og begrensninger som offentlig sektor har innenfor kunstig intelligens, samt hvorfor utvikling av kunstig intelligens går tregt. All informasjon er anonymisert.

Intervjuet vil finne sted ved videokonferanse (Teams / Zoom) og vil bli tatt opp lydopptak for transkripsjonsformål. Vi bruker mobilappen Nettskjema Diktafon for å ta lydopptak, og opptaket blir umiddelbart kryptert på telefonen og man kan aldri lytte til opptak i mobilappen.

Intervjuet er delt i 6 deler - vi starter med **oppvarmingsspørsmål** hvor vi blir bedre kjent med deg. Så går vi over til spørsmål om din **organisasjon og dens overordnede mål og offentlig forvaltning**. Og så går vi nærmere inn på **status, utfordringer og muligheter** mtp. AI i din organisasjon. Og til slutt vil du få muligheten til å kommentere eller diskutere noe vi ikke har tatt opp hvis du ønsker det.

Oppvarmingsspørsmål

Vi starter litt med oppvarmingsspørsmål for å få ballen til å rulle litt.

1. Hva er rollen din/ansvarsområdet ditt i organisasjonen?
2. Hva jobber du med i organisasjonen din?

Spørsmål om organisasjon og overordnede mål og offentlig sektor

1. Hva er visjonen deres innen digitalisering og kunstig intelligens?
    a. Har dere en overordnet strategi når det gjelder dette feltet?
2. Hva føler du skiller din organisasjon fra andre organisasjoner i offentlig sektor mtp. bruk av kunstig intelligens?
3. Hvor høyt er kunstig intelligens prioritert i din organisasjon?
4. Hvordan er arbeidet med kunstig intelligens organisert i din organisasjon? (Hvem er ansvarlig for kompetanse, modellering av AI, R&D, etc)

   a. Hvorfor er arbeidet organisert på denne måten og hvorfor har organisasjonen valgt å sette ansvaret her?

5. Hva tenker du er potensielle årsaker/grunner til å bruke kunstig intelligens i din organisasjon? Kunne du utdype årsakene/grunnene?

6. Hva tenker du er hovedmålet med en AI-drevet offentlig sektor, eller i dette caset ?

   a. Hvorfor tenker du at dette er hovedmålet?

   b. Vil du si at dette hovedmålet gjelder for din organisasjon også?

For å bli bedre kjent med dere som organisasjon, skal vi stille noen spørsmål om nåsituasjonen deres (hvor dere ligger hen i utvikling av KI), utfordringer eller begrensninger dere har møtt på, og hvilke muligheter dere har eller ønsker å få.

Status / nåsituasjon

1. Med tanke på status - hvor langt har organisasjon din kommet i arbeidet med kunstig intelligens? Hvilken fase er dere i for øyeblikket?

   a. Hva planlegger dere for øyeblikket å bruke kunstig intelligens til?

   b. Hvilke områder har dere tatt i bruk KI? Hvor bruker dere KI?

   c. Har dere et prosjekt innenfor AI-området som du vil fortelle oss?

2. Hva slags type form av kunstig intelligens har dere brukt i organisasjonen?

3. Kunne du fortelle hvordan det har vært å utvikle kunstig intelligens i organisasjonen deres?

   a. Kunne du fortelle oss utfordringer i et spesifikt prosjekt eller noen spesifikke prosjekter?

4. Har dere brukt kunstig intelligens for å helautomatisere prosessen(e) eller som støtte-verktøy?

Utfordringer

Mtp utfordringer….

1. Hva ser du på som **den** største utfordringen ved anvendelse av kunstig intelligens i din organisasjon?

    a. Kan du gi oss et eksempel i et prosjekt der dere har møtt på denne utfordringen?

    b. Hvorfor anser du denne utfordringen som den største utfordringen?

    c. Hvordan takler/dealer dere denne utfordringen?

    d. Er utfordringen fremdeles en begrensning i dag? Hvorfor/hvorfor ikke?

    e. Tenker du at denne utfordringen er spesifikt for offentlig sektor? (Gjelder det kun offentlig sektor) Hvorfor/hvorfor ikke?

2. Er dere flere utfordringer som dere møter på?

Muligheter

Mtp muligheter og ønsker …

1. Hva slags type kunstig intelligens hadde dere ønsket å bruke? Har du et eksempel på hvilket området/prosess dere hadde brukt den type AI i?

    a. Hvorfor ønsker dere å bruke kunstig intelligens der?

    b. Hvorfor har dere ikke brukt kunstig intelligens der?

2. Har dere tanker om å helautomatisere prosesser?

    a. Hvorfor/hvorfor ikke?

    b. Har du et eksempel på en prosess som dere ønsker å helautomatisere?

Avslutning

Vi nærmer oss slutten av intervjuet nå.

1. Er det noe du ønsker å diskutere om eller ta opp?

2. Er det noe du ønsker å legge til avslutningsvis?

3. Har du noen dokumenter eller data relatert til det vi diskuterte i dag som du kan dele med oss?

A.2 Interview Guide for Researchers

Interview Guide - Forsker

Med forbehold om endring.

Først og fremst, takk for at du tok deg tid til å delta i dette intervjuet.

Vi er to masterstudenter ved UiO, Institutt for Informatikk, som for tiden skriver en masteroppgave innen AI i offentlig sektor. Målet med dette intervjuet er å få mer innsikt i muligheter og begrensninger som offentlig sektor har innenfor kunstig intelligens, samt hvorfor utvikling av kunstig intelligens går tregt. All informasjon er anonymisert.

Intervjuet vil finne sted ved videokonferanse (Teams / Zoom) og vil bli tatt opp lydopptak for transkripsjonsformål. Vi bruker mobilappen Nettskjema Diktafon for å ta lydopptak, og opptaket blir umiddelbart kryptert på telefonen og man kan aldri lytte til opptak i mobilappen.

Intervjuet er delt i 6 deler - vi starter med **oppvarmingsspørsmål** hvor vi blir bedre kjent med deg. Så går vi over til spørsmål om din **forskningen din**. Og så går vi nærmere inn på **status, utfordringer og muligheter** mtp. AI i din organisasjon. Og til slutt vil du få muligheten til å kommentere eller diskutere noe vi ikke har tatt opp hvis du ønsker det.

Oppvarmingsspørsmål

Vi starter litt med oppvarmingsspørsmål for å å få ballen til å rulle litt.

1. Hva er rollen din/ansvarsområdet ditt?
2. Hvordan ser en typisk arbeidsdag ut for deg som en forsker?

Spørsmål om forskning

Kunne du fortelle litt om forskningen din innen AI?

(Oppfølgingsspørsmål hvis relevant): Har vært litt forskning angående adopsjon av AI og dets relaterte utfordringer og potensialer. Har dette blitt diskutert i forskningen din? Hvordan da?

Nåsituasjon i Norge og offentlig sektor (hvor de ligger hen i utvikling av KI), utfordringer eller muligheter du har forsket på eller har tanker over

Status / nåsituasjon

Hva tror du er hovedmålet eller hensikten med å bruke AI i offentlig sektor? Hvorfor tror du det er hovedmålet?

Hva tror du er de potensielle årsakene til å bruke AI i offentlig sektor?

Når det gjelder AI i offentlig sektor, hva mener du skiller offentlig sektor fra andre private organisasjoner, så vel som andre land?

Etter din mening, hvor langt har Norge kommet i arbeidet med AI? Hvilken fase er Norge i for tiden?

(oppfølgingsspørsmål hvis relevant) Hvor lang tid tar det før Norge er i neste fase?

Utfordringer

Prompt: Sammenlignet med USA, Kina, Russland og til og med Storbritannia, ligger Norge bak når det gjelder distribusjon av AI i offentlig sektor (ifølge noen forskere/personer).

Hva anser du som det vanskeligste ved å implementere AI i norsk offentlig sektor? Og hvorfor tror du denne utfordringen er den mest utfordrende?

Prompt: Mangel på kunnskap når det kommer til AI og regulering av AI som gjør offentlig sektor mer "redde" for å adoptere AI.

Hvorfor tror du det er det? Har du sett denne trenden i forskningen din før?

Prompt: Data. På den ene siden har vi folk som ikke, under noen gitte omstendigheter, ønsker å dele dataene sine overhodet. Mens vi er på det motsatte av spekteret, har vi folk som ønsker å dele ALT.

Hva synes du om disse divergerende meningene? Og hvordan skal det offentlige takle det?

Muligheter

Mtp muligheter og ønsker …

1. Hva slags type kunstig intelligens hadde dere ønsket å bruke? Har du et eksempel på hvilket området/prosess dere hadde brukt den type AI i?
    a. Hvorfor ønsker dere å bruke kunstig intelligens der?
    b. Hvorfor har dere ikke brukt kunstig intelligens der?
2. Har dere tanker om å helautomatisere prosesser?
    a. Hvorfor/hvorfor ikke?

b. Har du et eksempel på en prosess som dere ønsker å helautomatisere?

Avslutning

Vi nærmer oss slutten av intervjuet nå.

1. Er det noe du ønsker å diskutere om eller ta opp?

2. Er det noe du ønsker å legge til avslutningsvis?
3. Har du noen dokumenter eller data relatert til det vi diskuterte i dag som du kan dele med oss?

A.3 Mixed Interview Guide for Researchers and Organisations

Interview Guide - Researcher and Organization

First of all, thank you for taking the time to participate in this interview.

As you already know, we're two masters students at UiO who are currently working on a master's thesis in AI in the public sector. The aim of this interview is to gain more insight into the opportunities, challenges and constraints that the public sector face, as well as why the development of AI is slow. All information is anonymized

The interview will take place at Zoom, and audio recording will be recorded for transcription purposes. We will use an app called Nettskjema Diktafon to record audio, and the recording is immediately encrypted on the phone. We cannot listen to the recordings in the app.

OPPVARMINGSSPØRSMÅL

Could you tell us a bit about your background?

What does your typical working day look like? What's your work assignments???

—

So what's [organization]'s vision when it comes to AI and digitization? Do you have an overall strategy?

What do you think is the primary goal or purpose of using AI in the public sector? Why do you think that's the primary goal?

What do you think are the potential reasons for using AI in the public sector?

When it comes to AI in the public sector, what do you believe distinguishes the public sector from other private organizations, as well as other countries?

How would you describe the technology culture in Norway, especially in the public sector?

To what extent would you say that AI is a priority in the Norwegian public sector, and why?

<u>CURRENT STATUS??? AND CHALLENGES IN THE PUBLIC SECTOR</u>

In your opinion, how far has Norway come in the work of AI? What phase is Norway in at the moment?

(oppfølgingsspørsmål hvis relevant) How long will it take for Norway to be in the next phase?

Compared to the US, China, Russia and even the UK, Norway is behind when it comes to deployment of AI in the public sector (according to some scholars/people).
What do you consider to be the most difficult aspect of implementing AI in the Norwegian public sector, like what is the biggest challenge of using AI in the public sector? And why do you think this challenge is the most challenging?

Do you think this challenge is specific to the public sector or is it a general challenge? Why?

Are there other challenges besides those you have mentioned?

Prompt: Lack of knowledge when it comes to AI and regulating AI which makes the public sector more "anxious" of implementing AI.
Why do you think that is? Have you seen this trend in your research before?

Prompt: Data. On one side, we have people who do not, at any given circumstance, want to share their data whatsoever. While on the opposite of the spectrum, we have people who want to share EVERYTHING.
What do you think of these diverging opinions? And how should the public sector tackle it?

Lately, there have been a number of legal, regulation and privacy related barriers when it comes to developing AI.
So we were wondering if something has appeared on the horizon/radar that could be potentially challenging in the future? If so, do you believe this challenge is specific to the public sector?

The organizations we have talked to have mentioned a lot of regulations and legal barriers, which have been an obstacle for developing AI in their environments.
Do you believe there's a relation between the challenges you mentioned and the challenges regarding regulations? Are there any relations between the challenges? If not, have you noticed any overlap between the other challenges?
H:

<u>AVSLUTNING</u>

We're getting close to the end of the interview.

Is there anything else you'd like to discuss or add before we wrap up?

Do you have any documents or data you'd want to share with us about the topics we've discussed today?

Appendix B

Consent Form and Information Letter

Vil du delta i forskningsprosjektet

"AI in the Public Sector"?

Dette er et spørsmål til deg om å delta i et forskningsprosjekt hvor formålet er å undersøke muligheter og begrensninger kunstig intelligens har i offentlig sektor. I dette skrivet gir vi deg informasjon om målene for prosjektet og hva deltakelse vil innebære for deg.

Formål
Forskningsprosjektet gjennomføres som en del av vår masteroppgave ved Institutt for Informatikk, Universitetet i Oslo (UiO). Formålet med prosjektet er å undersøke muligheter og begrensninger kunstig intelligens har i offentlig sektor. Masteroppgaven har som mål å gi innsikt i hvorfor utviklingen av kunstig intelligens i den norske offentlig sektoren går treigt.

Hvem er ansvarlig for forskningsprosjektet?
Institutt for Informatikk ved Universitetet i Oslo er ansvarlig for prosjektet.

Hvorfor får du spørsmål om å delta?
Utvalgt er basert ut ifra utvalgskriterier som samsvarer med prosjektets målsetning. Dette betyr ansatte på ledernivå med innsikt i overordnende kommunikasjonsstrategier, forskere, og koordinatorer som jobber med daglig drift og videreutvikling blir spurt om å delta i prosjektet.
Til prosjektet er det regnet med at ca. 4-6 personer vil bli intervjuet.

Hva innebærer det for deg å delta?
Hvis du velger å delta i prosjektet, innebærer det at du deltar i et dybdeintervju. Det vil ta deg ca. 45 minutter.

Dybdeintervjuet inneholder spørsmål om bakgrunnen din; nåsituasjon, begrensninger og utfordringer, og fremtidsplaner og utredning om bruk av kunstig intelligens i organisasjoner; tanker og meninger om utfordringer ved bruk av AI i offentlig sektor. Dine svar fra dybdeintervjuet blir registrert elektronisk. Vi vil også ta lydopptak og notater fra intervjuet.

Det er frivillig å delta
Det er frivillig å delta i prosjektet. Hvis du velger å delta, kan du når som helst trekke samtykket tilbake uten å oppgi noen grunn. Alle dine personopplysninger vil da bli slettet. Det vil ikke ha noen negative konsekvenser for deg hvis du ikke vil delta eller senere velger å trekke deg.

Ditt personvern – hvordan vi oppbevarer og bruker dine opplysninger
Vi (Ahlam og Mai Julie) vil bare bruke opplysningene om deg til formålene vi har fortalt om i dette skrivet. Vi behandler opplysningene konfidensielt og i samsvar med personvernregelverket. Navnet og kontaktopplysningene dine vil vi erstatte med en kode som lagres på egen navneliste adskilt fra øvrige data. Dataen ligger kryptert med passordbeskyttelse, det vil si kun individer med tjenstlig behov får tilgang. Vi vil lagre dataen lokalt på våre maskiner med en backup på harddisk. Det er kun vi som vil ha tilgang til lydopptaket fra intervjuet, og etter transkriberingen vil disse filene slettes.

Hva skjer med opplysningene dine når vi avslutter forskningsprosjektet?
Opplysningene anonymiseres når prosjektet avsluttes/oppgaven er godkjent, noe som etter planen er 01.12.22. Ved prosjektslutt anonymiseres datamaterialet (navnelisten slettes).

Hva gir oss rett til å behandle personopplysninger om deg?

Vi behandler opplysninger om deg basert på ditt samtykke.

På oppdrag fra Institutt for Informatikk ved Universitetet i Oslo har Personverntjenester vurdert at behandlingen av personopplysninger i dette prosjektet er i samsvar med personvernregelverket.

Dine rettigheter
Så lenge du kan identifiseres i datamaterialet, har du rett til:

- innsyn i hvilke opplysninger vi behandler om deg, og å få utlevert en kopi av opplysningene
- å få rettet opplysninger om deg som er feil eller misvisende
- å få slettet personopplysninger om deg
- å sende klage til Datatilsynet om behandlingen av dine personopplysninger

Hvis du har spørsmål til studien, eller ønsker å vite mer om eller benytte deg av dine rettigheter, ta kontakt med: Institutt for Informatikk ved Universitetet i Oslo ved:

- Mai Julie Nguyen, student på master i informatikk: digital økonomi og ledelse (e-post: maijn@ifi.uio.no)
- Ahlam Aatif, student på master i informatikk: digital økonomi og ledelse (e-post: ahlamaat@ifi.uio.no)
- Miria Grisot, masterveileder og Førsteamanuensis (e-post: miriag@ifi.uio.no)
- Vårt personvernombud: UiOs personvernombud Roger Markgraf-Bye (e-post: personvernombud@uio.no)

Hvis du har spørsmål knyttet til Personverntjenester sin vurdering av prosjektet, kan du ta kontakt med:

- Personverntjenester på epost (personverntjenester@sikt.no) eller på telefon: 53 21 15 00.

Med vennlig hilsen

Miria Grisot (Forsker/veileder)	Mai Julie Nguyen & Ahlam Aatif (Masterstudenter)

Samtykkeerklæring

Jeg har mottatt og forstått informasjon om prosjektet *AI in the Public Sector*, og har fått anledning til å stille spørsmål. Jeg samtykker til:

☐ å delta i dybdeintervju
☐ å bli tatt opp lydopptak

Jeg samtykker til at mine opplysninger behandles frem til prosjektet er avsluttet

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(Signert av prosjektdeltaker, dato)

Elektronisk samtykke

Hvis du har lyst til å delta i studien, kan du svare på denne e-posten og inkludere teksten under i ditt svar.

«Jeg har mottatt og forstått informasjon om prosjektet «AI in the Public Sector». Jeg samtykker til å delta i et intervju og til at mine opplysninger behandles frem til prosjektet er avsluttet.»