Artificial Intelligence in Norwegian organizations

An exploratory study of challenges in AI adoption

Merethe Sjøberg

SUPERVISORS

Tom Roar Eikebrokk
Leif Skiftenes Flak

University of Agder, 2019
Faculty of Social Sciences
Department of Information systems

PREFACE

This master's thesis completes my master's degree in Information systems at the University of Agder and marks the end of a four-year long crazy journey which includes a bachelor's degree in IT and Information systems and a now a master's degree in combination with a full-time job as an IT project manager.

The journey has been long and hard, but it has also enabled me to accomplish things I never thought possible.
Being able to write this thesis, study and get to know one of the most interesting technologies I know and the challenges it brings has been one of the most rewarding challenges I have ever taken on.

To mark the end of this journey I would like to thank people who have meant a lot to me during the course of my studies and the completion of the thesis.

First and foremost, to my supervisors Tom Roar Eikebrokk and Leif Skiftenes Flak, thank you both for wanting to be my supervisors – I could not have asked for a better team to guide me through this. Thank you for the discussions, the laughs, the positive feedback and the late-night emails.

To my mom for letting me empty my brain, for the food and hugs you have given me when I have needed them the most.

To my dear Kasper, for believing in me, being my eternal sparring partner and sticking by me through this crazy journey.

And finally, to all my friends who have stuck with me through my limited social life and to my amazing colleagues, thank you for cheering me on.

Merethe Sjøberg

Merethe Sjøberg

ABSTRACT

In a fairly recent survey from Microsoft which evaluates the state of Artificial Intelligence in multiple European countries, it is found that Norway is lagging behind in the adoption and utilization of Artificial Intelligence.

The report shows that Sweden has invested six times as much as Norway in artificial intelligence in the last 10 years, and Denmark even 13 times more.
And while our neighboring countries – Denmark and Sweden – have already launched their national strategies for Artificial intelligence, the Norwegian government by the Ministry of Local Government and Modernization has yet to launch the Norwegian strategy at December 19th, 2019 which has been announced to be launched in 2019.

At the time this study was started there was no Norwegian research on this subject or any research on what the reasons can be for why Norway is lagging behind in utilizing Artificial intelligence.

Using an explorative and descriptive approach, this study aims to answer the following research question:

"What challenges can impact Norwegian organizations' adoption of Artificial Intelligence?"

The study aims to be a starting point for trying to understand the phenomenon and the contribution of the study are multiple implications for further research as well as implications for practice.

The research process consisted of creating a theoretical foundation based on literature from other countries which highlight challenges that may impact adoption of Artificial Intelligence.
A survey was performed as an online questionnaire which was distributed to respondents through purposive- and snowball sampling, and ended up being completed by 123 respondents.

The results show that the main challenges that can have an impact on adoption of Artificial intelligence in Norwegian organizations are related to knowledge about AI, GDPR and its regulation of use of data and security concerns.

The study presents implications for further research such as "Has GDPR put an extra damper on the adoption of AI in Norwegian organizations?" and implications for practice by highlighting that the Norwegian Government has to put Artificial Intelligence on their agenda to a larger extent and that there must be a focus in sharing knowledge regarding AI if we want to increase the adoption of AI in Norwegian organizations.

TABLE OF CONTENTS

TABLE OF FIGURES

LIST OF TABLES

1 INTRODUCTION

Ever since IBM Watson, beat a man who had won Jeopardy 70 times back in 2011 (Gabbatt, 2011), artificial intelligence has received substantial focus and become a technology that increasingly influence our daily lives.

Artificial intelligence or AI for short, is a set of technologies such as machine learning, deep learning, computer vision and natural language processing, that allow machines to simulate human intelligence by processing data, learning from that data and improve over time without human intervention (Wang & Preininger, 2019).

Although the example of IBM Watson did happen in the 21st century, the term "artificial intelligence" is not new. It has its origin from the early 1940's but was not made official until 1956 by John McCarthy and Marvin Minsky (Haenlein & Kaplan, 2019).

All over the world companies are investing in AI technology and the discussions concerning human replacement and the impact on the world economy if they do is not stopping the investments.

In Norway organizations such as Telenor and Kongsberg Digital are investing heavily in AI research and development and the Norwegian government is participating in multiple international forums that are working to create strategies and guidelines for artificial intelligence in the EU, OECD and the Nordic Council of Ministers (Regjeringen.no, 2019), to mention some.

Although this may make Norway seem like a country who is in the forefront of AI investments, several surveys show that Norway actually falls far behind compared to other Scandinavian and even European countries.

A recent report from Microsoft (Ernst & Young LLP, 2019)investigating the state of AI in Europe, shows that Norway is lagging behind the other Scandinavian countries in terms of utilization of AI and the investment in the technology. The report shows that Sweden has invested six times as much as Norway in artificial intelligence in the last 10 years, and Denmark even 13 times more. While our neighboring countries – Denmark and Sweden – have already launched their national strategies for AI (The Danish Government, 2019; Government Offices of Sweden, 2018), the Norwegian government by the Ministry of Local Government and Modernization has yet to determine the Norwegian strategy. The plan is for the Norwegian strategy for Artificial Intelligence to be launched in 2019, but as of December 19th, 2019 it has not yet been launched (Regjeringen.no, 2019).

A recent report by NyAnalyse for EVRY (NyAnalyse, 2019) surveyed close to 24% of Norwegian municipalities (100 of 422) and found that 20% of the municipalities asked said that they have initiated at least one project that involves AI or "new solutions for automation" within the last year. 20% say that they have initiated 2-3 projects and only 4% say more than three. When generalizing to all the municipalities, this shows that about 10% of all the Norwegian municipalities have initiated some sort of project to automate, either through AI or other automation technologies.

Artificial intelligence in the context of this study does not only mean technology that replaces humans entirely, but also AI that is implemented in the organizations as support for humans or as additions to other technology for new business areas.

We currently have no clear understanding of what types of challenges Norwegian organizations are experiencing or consider having a potential impact, therefore this study will try to investigate the question:

"What challenges can impact Norwegian organizations' adoption of Artificial Intelligence?"

1.1 Motivation and Research Contribution

There are two major motivational factors for this project.
The first one being my interest in disruptive technologies – the other being my interest in how technology impacts society and business.

With artificial intelligence being one of the areas that interest me the most, because of its history and technological potential and possible impact on society, I knew that this had to be the topic of my thesis.

A discussion with Leif Skiftenes Flak, head of Centre for Digital Transformation (CeDiT) at the University of Agder in Southern Norway, put me on the path of researching the state of Artificial Intelligence in Norwegian organizations. I started searching for literature both in the academic databases, but also from more commercial sources and found nothing that could give a picture of how AI was being adopted and used in Norway. I came across multiple reports from different companies that show that Norway is way behind other Scandinavian and European countries in term of adopting AI, and I started wondering why.

Discussions with my coworkers and friends in the technology industry helped the idea mature more, as one of my coworkers pointed out that clients had said *"We need AI, but we don't know what to with it"* and my friend telling me that he was struggling with implementing AI in one of his applications for his company because *"I don't understand how it works, no seems to be able to explain it to me or prove that the output is correct!"*

Some more discussions with my supervisors led me to investigate if challenges from other studies are also applicable to Norwegian organizations.

As there is no research on what challenges surrounding adoption of AI are, this study aims to contribute to the understanding of the topic.
The study is of an exploratory and descriptive nature and only scratches the surface of the topic, and the challenges experienced can only be described and presented on a very high level without making any conclusion of why the organizations are experiencing these challenges.

The objectives of this study is to get an initial overview of challenges that can potentially impact adoption of AI and to use this information to suggest topics for further research.

This thesis is structured in the following way:

First the literature review and method used to create the theoretical foundation for this thesis is presented. The literature review provides an overview of the different challenges that have been experienced by others and that may have an impact on adoption of AI in Norwegian organizations. The next chapter provides an overview of the research methodology used in this study, before the results of the research are presented followed by a discussion and conclusion based on the results.

2 LITERATURE REVIEW AND THEORETICAL FOUNDATION

This chapter presents the theoretical foundation of the study.
First the method for literature review is presented. The method describes the procedure for collecting and reviewing research articles and other relevant literature.

Second, a definition of artificial intelligence in the context of this study is presented followed by the literature that makes the theoretical foundation.

At the end of the chapter a concept matrix is presented to give an overview of authors of included literature and the concepts they touch upon.

2.1 METHOD FOR LITERATURE REVIEW

The theoretical foundation for this thesis was created through a literature review. The aim of the review is to uncover challenges
According to Kitchenham and Charters (2007) a literature review is a type of secondary study that follows specific rules and guidelines to provide fair and unbiased results.

The theoretical foundation was further used to create the surveying tool used to collect primary data and is described further in the research methodology chapter.

The approach for the literature review is adopted from Webster and Watson (2002) which in its simplest form can be described as a three-step approach:

1. **Literature search:** Search for relevant literature using leading databases, journals, conferences and predetermined keywords
2. **Backward Search:** Look into the references and citations used in the articles found in step 1 for other relevant literature
3. **Forward Search:** Identify articles relevant citing the key articles found in step 2

Webster and Watson (2002) highlight that a lot of the research in the field of Information systems tend to be focused on just a small sample of scientific journals, and thus gives a limited view of the topics in question. Because Artificial Intelligence is not only a topic of interest for the Information Systems community, I decided to not limit my search to specific journals.

The process for the literature search did not apply to the definitions of artificial intelligence, as the definitions were very unclear or limited in most of the research literature found.

Keywords in search:

The literature search was performed using the following search strings in all databases;

(TITLE ("artificial intelligence" OR "AI") AND TITLE ("challenges" OR "barriers"))

(TITLE ("cognitive computing") AND TITLE ("challenges" OR "barriers"))

For forward / backward search I looked for sources in the reference lists in some of the larger articles for titles with the keywords; “AI” or “Artificial intelligence” and “challenges” or “barriers”.

The reasoning behind using Artificial intelligence and cognitive computing as search terms was to try to get a balance between the different technologies that AI consists of and find challenges related to AI as a whole concept.
To simplify the search and make the amount of articles manageable, the decision was made to only search in the title of the articles.

SOURCES FOR LITERATURE

To perform the literature review I searched the online databases Scopus and ScienceDirect with the search terms defined further down in this chapter, forward-backward search and also included some articles from a previous course during my master’s program.

The table below shows the number of documents from each source in the very beginning of the study.

Table 1 - Total number of documents per source

Source	Number of results

Scopus	240
ScienceDirect	13
Forward-backward search	27
Articles from previous course	5
Total	***285***

INCLUSION CRITERIA

The following criteria were used to decide whether or not an article should be included in the review or not:

- Journal articles and conference proceedings
- Published between 2015 – 2020
    - A lot of research exists on Artificial intelligence from the 1980s. However, the study aims to understand current challenges and an assumption is made that newer literature is more relevant as AI has recently become more democratized than it was back in the 1980's.
- Full text document available
    - To understand the context of the challenges mentioned in the literature, it was necessary to have the entire document available
- English language
- Approved publication source in NSD (Norwegian Centre for Research Data)
- Relevance of content – described in more detail below.

Inclusion and exclusion based on relevance:
As this project focus on AI on an organizational level in terms of implementation of AI, articles that discuss topics such as AI development on a technical level, ethics on a philosophical level and articles concerning challenges experienced in collaboration between humans and technology have been excluded.

The relevance of an article was evaluated in two steps; 1) Relevance of abstract and 2) Relevance of main text.

The reasoning behind this is that this study focuses on the reason why organizations choose to implement AI or not and what challenges they have faced or consider to be relevant for them in terms of implementation and reasons why such initiatives may not be successful.

The table below describes the process and number of documents remaining after each inclusion / exclusion criteria has been applied.

Table 2 - Literature review - elimination process

Step	Exclusion/inclusion process	Remaining documents

1	Total number of documents based on search	285
2	Removal of duplicates	179
3	Relevance of abstract	94
4	Full-text available / English language	49
5	Source verifications according to NSD	32
6	Relevance – main text	20

2.2 DEFINING ARTIFICIAL INTELLIGENCE

Defining artificial intelligence is challenging as there is no official and agreed upon definition of Artificial intelligence (AI) (Sun & Medaglia, 2019). However, Davenport and Ronanki (2018), who are well known in the field of artificial intelligence define AI as a type of technology used to automate processes, provide cognitive insight and decision support through data analysis and cognitive engagement through for example machine-learning chatbots.
The term "Artificial Intelligence" is not new. It actually has its origin from the early 1940's but was not made official until 1956 by John McCarthy and Marvin Minsky who were the first to use the term during a conference (Haenlein & Kaplan, 2019).

Kapland and Haenlein (2019) further define artificial intelligence as a system's ability to correctly interpret external data, learn from it and to use what it's learning to achieve specific goals and tasks through flexible adaption (Kaplan & Haenlein, 2019). Simply put, it is a computer code that, in various degrees, is able to learn from data and make its own decisions.

Davenport and Ronanki classify AI systems into three different groups based on how advanced they are:

1. **Analytical AI:** This group of technologies is the most common, and is what most companies who have applied AI, is using. This technology learns from historical data to make predictions about the future.
2. **Human-Inspired AI:** This group of technology not only has the cognitive intelligence like Analytical AI, but also has emotional intelligence. This means that the technology is able to recognize and understand human emotion and include them and take them into consideration when making decisions.
3. **Humanized AI:** This group of technology is not yet available and may not be for an unforeseeable future. This is the group of technology that we often hear about in the media when talking about "the robots taking over". Humanized AI has not only the cognitive and emotional intelligence, but also the social intelligence. Its self-awareness and self-consciousness will enable it to mimic human behavior and experience the world like humans. One example from the pop-culture being the movies "Terminator".

Taking Davenport and Ronanki's the definition further, AI technologies can also be divided into four main categories that can be applied in organizations today:

1. **Machine learning** – Machine learning (ML) might be the most well-known category of AI, as it forms the basis for most AI technologies. ML is a technology that enables computers to be taught how to analyze data, identify patterns that are not necessarily obvious, classify and make predictions based on the data they are fed and also improve over time without explicit instructions programmed into it (Loucks, Hupfer, Jarvis, & Murphy, 2019).
2. **Deep learning** – Deep learning is a more advanced part of machine learning and used by most AI systems. It builds on a conceptual model of the human brain – neural networks – which consists of multiple layers; An input layer, multiple processing layers and an output layer (Loucks, Hupfer, Jarvis, & Murphy, 2019). While Deep learning learn based on data like machine learning, the process of *how* it creates the output it does, is usually like a black box and thus difficult to explain (Haenlein & Kaplan, 2019).
3. **Natural language processing (NLP)** – NLP is technology with the ability to listen, speak, write, read and understand human language (Marr, 2019). One of the most common applications of this technology is chatbots that many companies use in customer service (Loucks, Hupfer, Jarvis, & Murphy, 2019).
4. **Computer vision** – Computer vision is a systems ability to extract meaning and intent from visual elements (Loucks, Hupfer, Jarvis, & Murphy, 2019).

AI has a wide range of application possibilities and these application areas keep on growing as the technology keeps getting more powerful (Duan, Edwards, & Dwivedi, 2019). Some of the major benefits of AI include cost reduction, increased productivity and efficiency and improved decision making and forecasting (Pavaloiu, 2016; Dwivedi, et al., 2019). Although the potential benefits of AI are many and many organizations are aware of what AI can bring to the business they still refrain from implementing it (Schlögl, Postulka, Bernsteiner, & Ploder, 2019)

2.3 CHALLENGES IN ADOPTING ARTIFICIAL INTELLIGENCE

Implementing AI can be extremely challenging and there are a number of factors that can impact the outcome of an AI investment (Duan, Edwards, & Dwivedi, 2019). Although the definition of success is subjective and can vary widely from business to business, there are some challenges that organizations may consider to be barriers of such magnitude that they simply choose to not invest in cognitive technologies such as AI.
Duan et al. (2019) stresses that identifying critical success factors, bottlenecks and barriers is essential to succeed.

One important note is that although there are challenges that organizations may face, or even consider to be deal breakers, the stakeholders within an organization may have different opinions as to what the challenges are and the impact they have (Sun & Medaglia, 2019).

The challenges found in the literature have been categorized into four main categories. These categories were frequently mentioned in the literature and have therefor been adopted into this study. The table below provides an overview of the areas of challenges found in the literature.

Table 3 – High level overview of areas of challenges

CHAPTER	CATEGORY	CHALLENGES
2.2.1	***Technological challenges***	Security Transparency and explainability
2.2.2	***Data challenges***	Data availability Data sharing and integration Unstructured data Data quality Data bias Data origin and domain
2.2.3	***Organizational challenges***	Strategy Change Knowledge and resources Cost of AI
2.2.4	***Societal challenges***	AI governance Legal challenges Privacy Ethics Trust

The following literature review provides further insight into these groups of challenges.

2.3.1 TECHNOLOGICAL CHALLENGES

One category of challenges that organizations may experience are technological challenges. The challenges include issues such as safety and security and lack of transparency and explainability.

SECURITY

AI security and safety is an issue that more and more organizations understand the criticality of, and it can also become a major challenge for many organizations.

The potential exposure of data to outsiders or people who are not authorized to access the data is one issue that many organizations struggle with. Technology connected to the internet can be an easy target for cyber-crime such as theft and misuse (Pavaloiu, 2016; Holzinger, Kieseberg, Weippl, & Tjoa, 2018) and even technology and data that is well protected can be vulnerable to outside threats (Shaw, Rudzicz, Jamieson, & Goldfarb, 2019). Information security is extremely important the consequences of an attack can be catastrophic. Not only can it harm the organizations reputation with the consequences that may bring, but it can also – in the worst-case scenarios – cause loss of human lives. These examples are seen in the healthcare industry, where hacking of devices can impact patients directly by hackers overtaking tools used by surgeons, or retraining diagnostics systems to recommend incorrect treatment of patients (Iliashenko, Bikkulova, & Dubgorn, 2019).
Sun and Medaglia (2019) found that there is a concern that if foreign companies were allowed to collect and store data such as health data through the use of their technology it could make a country more vulnerable to for example biological warfare.

(Wirtz, Weyerer, & Geyer, 2019) highlights that safety in terms of AI does not just concern information security, but also security in general.
Safety in AI is also about protecting the AI from manipulation from the outside such as adversarial attacks – which Wang and Preininger (2019)defines as the process of constructing data that can confuse machine learning models which in turn can result in incorrect decisions.
These adversarial attacks are however not just a threat from the outside but can also be coming from the organization's own employees. If they are unhappy with the decisions made by the AI that can cause them to for example lose status or that they feel like they have been treated in an unfair way, they can adjust their behavior and decisions and thus confuse the system as the system cannot protect itself from adversarial attacks and behavior like a human would (Tambe, Cappelli, & Yakubovich, 2019).

AI is sensitive to changes and may learn negative behavior from its environment and it is important that the AI can learn without the outcomes becoming serious threats themselves. Perc, Ozer and Hojnik (2019) stresses that AI should follow Asimov's Laws of Robotics:

1. A robot may not injure a human being, or through inaction, allow a human being to come to harm
2. A robot must obey the orders given by human beings except where such orders would conflict with the first law
3. A robot must protect its own existence as long as such protection does not conflict with the first or second law.
4. A robot may not harm humanity, or by inaction, allow humanity to come to harm

Knowing which security measures are sufficient and most reliable to protect the data and the AI can be a challenge. It is important that the AI is created and protected in a way that makes it resilient toward threats from the outside. Not only in terms of the protection embedded in the technology, but also determining who is responsible for making sure everything is protected as well as it possibly can and who is responsible is an incident should occur (Pavaloiu, 2016; Iliashenko, Bikkulova, & Dubgorn, 2019). However, there is an issue for organizations in the SME category and public sector to provide the necessary amount of security as they usually have more financial constraints (Dwivedi, et al., 2019).

TRANSPARENCY AND EXPLAINABILITY

AI has by many been described as a "black box" because there is no transparency into how the algorithms are written and how decisions are made, and how the output impacts humans and our society (Sadeghi, 2017). In some cases, the way the AI achieves its results is even unknown to the developers who wrote it (Shaw, Rudzicz, Jamieson, & Goldfarb, 2019). There are essentially four reasons why there should be some transparency into how AI works; Justification, control, improvement and discovery (Dwivedi, et al., 2019). Without a clear and obvious way of describing how the technology really works it can be difficult to justify the implementation of it. Especially in industries that are heavily regulated or where the public has expectations to transparency and explainability, and require a clear description or need an understanding of how decisions are made (Davenport & Ronanki, 2018; Dwivedi, et al., 2019; Tambe, Cappelli, & Yakubovich, 2019; Holzinger, Kieseberg, Weippl, & Tjoa, 2018; Duan, Edwards, & Dwivedi, 2019).

Transparency is also a challenge in regard to the severe consequences output from an AI can have. The algorithms describe a way to process data that eventually produce an output such as for example patient diagnosis or patient treatment plans. Not being able to explain the algorithms means there is no guarantee that the output is correct or that it can be trusted (Dwivedi, et al., 2019).

Although the final decision in many cases are made by a trained human professional the lack of transparency in how the AI works can be a major challenge in terms of validating the outcome (Raaijmakers, 2019) and fixing problems with the algorithms or data if there are issues (Sun & Medaglia, 2019; Wang & Preininger, 2019).

Since we do not in many cases know how the algorithms work it can be difficult to justify the AIs ability to generalize (Thesmar, et al., 2019). Meaning it may not be possible to confirm that AI trained on certain datasets from one country, business or even from one type of organization can be applicable to other countries, businesses or organizations (Wang & Preininger, 2019).

On the flipside, the need for some transparency into how the AI works can lead to oversimplification which in turn can have its own challenges (Raaijmakers, 2019). The core of AI is to detect patterns that humans cannot (Yu & Kohane, 2019) – or that would require an enormous amount of human resources to do.

Raaijmakers (2019) claims that attempting to explain and summarize how this pattern-detection happens might be close to impossible when speaking to a non-technical person. It will also add the risk of leaving important information out. This information may be crucial to further knowledge creation but also to the accuracy of the outcomes if we were to create simpler data models for processing.

2.3.2 Data challenges

One reason for the increasing success, development and use of AI is the massive amount of data that is generated every single day (Dwivedi, et al., 2019).
Data is the core of artificial intelligence (Wirtz, Weyerer, & Geyer, 2019), and that of course means that data is also the main challenge of using AI. The data challenges are typically related to quality, quantity, origin, standardization and database development, to mention some (Sun & Medaglia, 2019).

DATA AVAILABILITY

Challenges in regard to the amount of data becomes especially obvious when training brand new AI. The technology is dependent on massive amounts of data to learn, and dependent on continuously growing amounts to improve and produce outputs that are relevant (Tarafdar, Beath, & Ross, 2017; Tambe, Cappelli, & Yakubovich, 2019).

In many fields however, there has not been a focus on collecting data, which means there is little data to use for training the AI. This makes training difficult. This issue is mentioned especially in areas where Deep Learning is being used (Wang & Preininger, 2019; Sun & Medaglia, 2019) or in other areas where certain events do not occur very often (Tambe, Cappelli, & Yakubovich, 2019). The size of the organization and its domain is also a factor that can impact the amount of data an organization has available as smaller organizations in general may not have access to as much data as larger organizations (Tambe, Cappelli, & Yakubovich, 2019; Dwivedi, et al., 2019) This does, however, not mean that the technology cannot use the smaller amounts of data to detect patterns , but not having large amounts of data means that an organization do not benefit from the analysis in the same way they would if they had large amounts of data (Tambe, Cappelli, & Yakubovich, 2019)

On the other end of the scale there is a challenge that comes with having large amounts of data; Schlögl et al. (2019) found that some organizations have collected sufficient amounts of data to be able to achieve the benefits of AI, however, they do not know what to do with all the data they possess.

DATA SHARING AND DATA INTEGRATION

Data integration and data sharing is the combination of multiple data sets, such as for example demographic data and clinical data from multiple sources and is considered to be the foundation of artificial intelligence (Sun & Medaglia, 2019; Wirtz, Weyerer, & Geyer, 2019).

This is however one of the most challenging issues and what makes the implementation of AI very difficult (Davenport & Ronanki, 2018). Many organizations, especially in the public sector, are reluctant or unwilling to share data (Dwivedi, et al., 2019), such as hospitals being unwilling to share patient data with another hospitals about the same patient (Sun & Medaglia, 2019) or sharing data with third parties, partners or a central data repository for analysis (Holzinger, Kieseberg, Weippl, & Tjoa, 2018).

Another issue is sharing and integration of data from multiple systems within an organization It is common for organizations to have different systems serving different purposes. The systems may come from the same or different vendors, but they all have the possibility of storing data and it can be challenging to share data across these systems. Because the data might be built on different types of technology and therefore stores today to in different formats and are there for it often not compatible with each other. Tambe et al. (2019) also found another issue that a lot of organizations face in terms of sharing data is internal political battles where departments do not want to share data in fear of losing control and power. This may of course be a violation of privacy, but even if the data is anonymized it can result in the original owner giving up control of the data and thus risk losing data that is of great value. This means that the organizations have to make sure that the data cannot be further distributed (Holzinger, Kieseberg, Weippl, & Tjoa, 2018).

Most AI especially in critical industries such as healthcare require large amounts of integrated, relevant and good quality data as well as continuous data growth. The lack of this may become a barrier for adoption of AI (Sun & Medaglia, 2019).

DATA QUALITY AND UNSTRUCTURED DATA

Another challenge that is mentioned in the literature are the difficulties surrounding unstructured data such as images, video and audio. The lack of structure in this type of data is challenging for the AI technology to process and that when such data is processed the AI cannot work without human involvement (Sun & Medaglia, 2019)

Unstructured data also impacts the data quality, and Dwivedi et al. claims that organizations that have collected a lot of unstructured data also run a risk of having very low-quality data. Data quality, or the lack of it, can become one of the biggest problems for an organization when adopting AI (Dwivedi, et al., 2019).

Data integration means using data from different sources, which in turn means that there most likely will not be a common standard for the data. AI is only as smart as the data it is provided to learn from (Wirtz, Weyerer, & Geyer, 2019; Shaw, Rudzicz, Jamieson, & Goldfarb, 2019; Sun & Medaglia, 2019) and how useful data is depends on the quality (Dwivedi, et al., 2019). Yu and Kohane (2019) calls it the “garbage in–garbage

out-rule”.
Low quality data can lead to inaccuracies or failure of output, which in turn can lead to poor decision-making and even financial loss (Wirtz, Weyerer, & Geyer, 2019; Dwivedi, et al., 2019) and AI needs data in formats that it can process. Which means that the data needs to be cleaned and structured (Tarafdar, Beath, & Ross, 2017).

The issue of data integrity is usually an issue when using data from a third party or other external sources, but it can also be a problem inside an organization.
Inside the organizations there can be a lack of data standards which means that data is collected and stored in different formats (Sun & Medaglia, 2019)
Some data may be collected on physical paper, stored locally or just be information that someone in the organization keeps in their heads. It can be in formats such as PDF or other text-format documents, pictures or picked up from information channels such as social media (Tarafdar, Beath, & Ross, 2017).

Dwivedi et al. (2019)says that one of the biggest issues we have with AI systems is that the systems function well if they have well defined conditions for how to process data but they do perform well in regards to variances and nuances in data, which is a problem. Their ability to generalize outside of the area that they are trained in will usually fail.

DATA BIAS

As mentioned, artificial intelligence and the outcomes it generates are only as good as the data used to train it (Shaw, Rudzicz, Jamieson, & Goldfarb, 2019). Predictive algorithms are fed historical data and base their decisions on what has happened in the past, which may have inherent bias (Bartoletti, 2019). If the AI is trained on data which contains an overload of one type of data or is incomplete – for example a lot of data regarding one type of gender or race - the AI, which job is to identify hidden patterns in data, will start “favoring” one gender or race over the other and thus generate bias results (Yu & Kohane, 2019; Thesmar, et al., 2019; Dwivedi, et al., 2019; Shaw, Rudzicz, Jamieson, & Goldfarb, 2019; Tambe, Cappelli, & Yakubovich, 2019).

This issue is also called AI discrimination in some cases, as the bias in the data can lead to inequality and unfairness (Wirtz, Weyerer, & Geyer, 2019).

Another and more serious issue that data bias leads to is that the AI may not pick up on the same issues in some sets of data as it will in others.
Wang and Preininger (2019) mentions especially the use of image recognition in healthcare, where if the AI has more data on for example white or dark colored skin, it may not be able to pick up on abnormalities in the skin in the same way and thus perform better on one skin color than another.

Data bias can have serious consequences and it is therefore important to carefully consider both the data input and the data output when using AI (Thesmar, et al., 2019)

It is also important to note that bias does not only come from the datasets entirely, but humans can also create bias. It can happen whilst training the AI and judging the decisions it makes (Raaijmakers, 2019) or even through the creation of the AI itself. Dwivedi et al. (2019) highlights that AI is created by humans who all have inherent opinions, preconceived judgements, ethics and so on that impact how the programmers think something should work.

DATA ORIGIN AND DOMAIN

Where the data originates from also has an impact the outcomes of the AI. Off-the-shelf-technology is trained on large data sets and what data the AI is trained on can impact the relevance of the outcomes which may not be relevant from one organization to the other, even if they are in the same industry (Sun & Medaglia, 2019; Wang & Preininger, 2019).

A hospital will need technology that is trained on relevant data related to health care and medicine, while a manufacturer will need data related to its industry and domain (Tarafdar, Beath, & Ross, 2017).

Sun and Medaglia (2019) also found that the geographic and ethnical origin of the data is relevant in healthcare. Their study in Chinese healthcare showed that the "off-the-shelf" tool, IBM Watson, is trained on data mainly from North American patients. This means that due to racial differences the data which the AI is trained on cannot be generalized to the Chinese people.

Identifying the right data for the AI to be trained on is therefore critical (Tarafdar, Beath, & Ross, 2017).

2.3.3 ORGANIZATIONAL CHALLENGES

Dwivedi et al. (2019) found that organizations need to have a focus on developing and maintaining their information assets if they want to succeed in exploiting AI inherently. But the organizations technological readiness may cause a gap between digitalization and digital transformation, which is crucial for organizations to succeed on their AI journey. As a consequence, it is difficult for organizations to define what they want to do and how to do it when it comes to adopting AI (Dwivedi, et al., 2019)

STRATEGY

The organization's strategy, or lack thereof, can be a challenge for many organizations when attempting to adopt artificial intelligence.

Adoption of AI has the potential to have a massive impact on an organization. Not only does it impact the way organizations perform their daily operations and change the way people work, but there is also the potential to replace humans entirely. Artificial intelligence is designed to perform tasks that require human cognitive abilities and although, in most cases, the technology is not implemented to replace humans, but to support them in their day to day tasks, it is not unlikely that people become redundant and that lay-off's can be a result of automation (Pavaloiu, 2016).

For organizations to succeed with their AI initiatives, it is critical that they have clearly defined goals and a clear and defined strategy for how to achieve those goals, and a plan for how to utilize and distribute their resources in the process (Davenport & Ronanki, 2018; Sun & Medaglia, 2019).

CHANGE

AI is disruptive in many ways and having an organizational culture that inhibits innovation and exploration can be a contributor as to why many organizations do not pursue artificial intelligence (Sun & Medaglia, 2019).

AI may be implemented in parts or stages of processes such as for example data collection or data analysis or be able to autonomously execute an entire process from data collection to action based on decision through data analysis (Dwivedi, et al., 2019). Changes to processes and the way people work is often inevitable when implementing AI, but it is also one of the biggest challenges that organizations are faced with when implementing AI (Schlögl, Postulka, Bernsteiner, & Ploder, 2019).

The amount of AI enabled automation will impact human performance. The introduction of artificial intelligence into the workplace can reduce the workload on humans and allow them to spend their time on other tasks by redesigning the work processes (Dwivedi, et al., 2019). However, Yu and Kohane (2019) found that it is critical that the business processes and workflows are redesigned in such a way that it prevents what they call decision-making passivity or "alert fatigue". Decision-making passivity means that the human is relying too much on that technology or lets it make decisions without human supervision. Alert-fatigue is on the other side of the spectrum, where the human working with the AI is skeptical of the outcome of the AI and make changes to the result and thus reduce the benefits of the technology (Yu & Kohane, 2019; Dwivedi, et al., 2019).

Schlögl et al. (2019) found that the biggest challenge organizations were facing during implementation of AI was the human resistance to the technology – or more precisely; the process changes that were required. Although the organization's intention behind implementing the technology was not to replace employees and reduce the head count, but rather to compliment the human workers to for example increase productivity.

Resistance toward the changes that AI introduce into organizations is not uncommon and one of the challenges many organizations struggle with. The wide range of application of AI creates fear of changes to the way employees work or even fear of job loss as AI often take over boring and repetitive tasks that humans used to do (Schlögl, Postulka, Bernsteiner, & Ploder, 2019; Dwivedi, et al., 2019; Pavaloiu, 2016; Wirtz, Weyerer, & Geyer, 2019). Artificial intelligence is predicted to take over millions of jobs in the future as it progresses, and the loss of jobs happens in many different industries. The massive impact on so many industries causes insecurities that can cause people to overestimate the potentially negative consequences of AI and underestimate the advantages (Dwivedi, et al., 2019).

The resistance to AI is not just caused by the workflow changes that organizations have to introduce to benefit from AI but can also be a result of people's fear of losing their status and relevance (Schlögl, Postulka, Bernsteiner, & Ploder, 2019; Sun & Medaglia, 2019) and that attitudes toward the AI is important to succeed (Duan, Edwards, & Dwivedi, 2019)

KNOWLEDGE AND RESOURCE CHALLENGES

Lack of knowledge about AI is twofold: One side is missing out on the benefits of artificial intelligence because there is limited knowledge of the values and business advantages that it provides. And the second being the illusion that AI is some magical tool that can solve almost any problem that humans cannot (Sadeghi, 2017). The hype surrounding AI can cause people to invest in the technology and, by lack of knowledge of the capabilities of the technology, end up having too high expectations and thus be disappointed when the technology cannot deliver as expected (Sun & Medaglia, 2019; Davenport & Ronanki, 2018).

The unrealistic expectations that the hype creates can become a problem and cause the AI initiatives to fail completely and it is crucial that organizational leaders and people with decision-making power realize the limitations of AI (Tarafdar, Beath, & Ross, 2017).

Knowing what the different types of technologies are and fully understand their abilities and limitations before implementing is critical to succeed with adoption and to avoid negative consequences further down the line and the waste of time and money by overestimating the abilities of the technology or implement tools that are not cut for the tasks in hand (Davenport & Ronanki, 2018; Duan, Edwards, & Dwivedi, 2019; Schlögl, Postulka, Bernsteiner, & Ploder, 2019). It is possible that the lack of knowledge among decision-makers cause them to deem AI as unfit for their organization and therefore not adopt it at all (Iliashenko, Bikkulova, & Dubgorn, 2019) Both the perception of the complexity of AI (Schlögl et al., 2019) or the perception of AI as a "dangerous" technology (Iliashenko, Bikkulova, & Dubgorn, 2019) can result in decisionmakers opting out of AI.

In general, organizations have three options when they are looking to implement AI (Tarafdar, Beath, & Ross, 2017); They can choose to develop their own systems and tools, buy from vendors or use and adapt open-source tools. But whichever alternative they choose there is one very important thing they need to do: They need to make sure they choose the right tool. To be able to succeed with implementing AI it is important to know what type of technology to use for your purpose as not all tools are suited for the job in hand (Davenport & Ronanki, 2018; Tarafdar, Beath, & Ross, 2017). Not all cognitive technology is created alike and not all sort of tools are suitable for all kinds of tasks. Some focus on simple and narrow tasks while others focus on entire suites of tasks or specific domains (Tarafdar, Beath, & Ross, 2017). Davenport and Ronanki (2018) claim that an organization with a good amount of knowledge concerning AI are more likely to be able to evaluate whether or not the technology is suited for the job, which vendors are the preferred ones and how quickly the technology can be implemented. They also claim that automation projects that are highly ambitious have proved to be less successful than smaller and more manageable projects.

Knowledge about the technology is not the only knowledge executives or high-level management need to succeed. It is also important that there is a thorough understanding of the business processes in the organizations and which ones are appropriate for automation either partly or entirely. Although organizations may learn more about this with some experience, the lack of knowledge can cause them to invest in inappropriate technology or to have unrealistic expectations (Tarafdar, Beath, & Ross, 2017).

SKILLS

To succeed with artificial intelligence, organizations need to have a clear vision of what they want to achieve and also understand which requirements need to be in place in order to achieve their goal. This means that there needs to be people involved in the AI initiatives who understand the functional and technical sides of the organization itself and the technology that is being implemented. However, this is often missing (Dwivedi, et al., 2019).

Having the right resources with the correct skills and competence available to handle the technologies is one of the biggest challenges that organizations struggle with when it comes to implementing and using AI.

Having these skills available does not necessarily mean hiring additional resources or replacing employees with new ones, but can mean retraining existing employees and upskilling them so they are able to understand the new technologies and work with them (Davenport & Ronanki, 2018; Pavaloiu, 2016; Dwivedi, et al., 2019). But it can also mean hiring new personnel like machine-learning engineers to help interpret output or adjust data models and train the system (Raaijmakers, 2019). Having all these skills in-house can be a challenge, and will sometimes require companies to go outside their own organization to find the competence needed to be able to experience progress (Davenport & Ronanki, 2018).

AI comes in two different shapes, one being open-source and the other being "off-the-shelf" tools that are supplied by vendors. The two are very different and require two different sets of skills and expertise. Open-source tools require people with strong technical skills and understanding who have the ability to program and configure and make sure the tool is fitted to the context in which it is going to operate. Vendor-supplied tools on the other hand, are usually controlled, upgraded and optimized by the vendor itself and its team of specialists and support functions and does not require the organization to hire this type of expertise themselves (Tarafdar, Beath, & Ross, 2017).

RESOURCES

Recruiting the right people with the right set of talents and skills to work with AI is one of the biggest challenges in organizations when it comes to AI strategy (Dwivedi, et al., 2019).

AI application is increasing at a mind blowing pace and exponentially the need for AI experts and specialists globally (Wirtz, Weyerer, & Geyer, 2019)
One of the reasons being that the required resources need interdisciplinary skills, meaning technological skills but also domain skills such as for example healthcare or law enforcement (Sun & Medaglia, 2019; Raaijmakers, 2019). Not having the expertise and skills available for the desired AI initiatives puts the breaks on AI development (Wirtz, Weyerer, & Geyer, 2019).

COST OF AI

Sun & Medaglia (2019) found that some of the hospitals they interviewed for their study said that they had high expectations for increased profit when they implemented IBM Watson, but have yet to see any. Artificial Intelligence does not come cheap, and cost of AI is one of the biggest and most critical challenges organizations can face when wanting to adopt AI and it is important that organizations make a thorough evaluation of the financial feasibility of implementing AI, meaning the cost of the AI and what can really be expected in terms of increased revenue and profit (Wirtz, Weyerer, & Geyer, 2019).

AI requires a lot of resources. The tools and hardware that is used to process and use data, as well as train the AI creates heavy workloads for the hardware, which in return sets requirements for data processing power. Also – the use of data from multiple sources within an organization also creates an additional cost of moving the data. This cost can for some organizations discourage them from implementing AI (Iliashenko, Bikkulova, & Dubgorn, 2019) In the public sector the cost of AI falls into the public budgeting. The funding for paying for the technology and subsequent resource needed may not be available (Shaw, et al.,2019).

The technology itself is not the only cost-driver. The choice of tools to implement is a determining factor for cost as well (Tarafdar, Beath, & Ross, 2017). Many organizations do not have the expertise needed to develop, adapt and get the most out of the AI, which means they will need to either hire AI experts or upskill their existing employees. Wirtz et al. (2019) points out that AI experts are a scarce resource, and that the high demand for this expertise also increase the cost of these resources in terms of higher salaries.

The high cost of AI can force organization with limited financial resources to abandon the idea of adopting artificial intelligence entirely (Dwivedi, et al., 2019)

2.3.4 SOCIETAL CHALLENGES

AI GOVERNANCE

AI governance refers to the ability manage AI through collections of regulations and laws that are in place to control the technology and its impact on society and humans The wide range of application that AI has also cause it to be impacted by a great deal of regulations concerning data, algorithms, infrastructure and even humans to mention some (Wirtz, Weyerer, & Geyer, 2019).

Governance can be one of the most challenging aspects of AI. One reason being that there is a lack of a common definition and shared standards for how AI should be used and evaluated (Sun & Medaglia, 2019; Duan, Edwards, & Dwivedi, 2019) and another being that it is often not given the attention and priority it needs in many organizations due to its complexity and lack of transparency, which makes it difficult to understand the algorithms and consequences of its decisions and actions (Wirtz, Weyerer, & Geyer, 2019). As artificial intelligence has a huge impact on society and holds many risks it is important to have proper and sufficient AI governance in place.

Governance is important to be able to determine responsibility and accountability, ensure fairness, mitigate risks and ensure that AI is beneficial. Governance is not just an organizational concern, but also important on a national. National AI governance provide guidelines and legislations to regulate the use or Artificial intelligence which organizations must align with when adopting AI and sets requirements for organizational AI Governance (Sun & Medaglia, 2019; Dwivedi, et al., 2019; Wirtz, Weyerer, & Geyer, 2019; Guan, 2019; Bartoletti, 2019).
Perc et al. (2019) says that it is important that both the industry and government is involved in the process of determining governance and regulations, to preserve the democratic principles.

Governance of data is a main aspect of AI governance and thereby also one of the challenging aspects of AI governance. The use of AI requires enormous amounts of data, which leads to data being collected and store in many ways by many different actors for many different purposes. AI governance is an important factor in controlling why the data is collected, if there is consent for the collection and what the data is use for and also ensuring that the decisions that is made by AI technology is the right one and that is follows the applicable rules and regulations (Dwivedi, et al., 2019).

RESPONSIBILITY AND ACCOUNTABILITY

One of the most important tasks of AI Governance is to determine who is legally responsible, accountable and liable when the AI cause harm, such as for example when a self-driving car run a person over and kills them (Wirtz, Weyerer, & Geyer, 2019; Dwivedi, et al., 2019). Dwivedi et al. (2019) stresses that the more powerful the AI technology is, the more important it is to properly define responsibility and accountability.

Wirtz et. al (2019) point to what they call a "responsibility gap" which is what happens when the AI learn and change, as is should, but end up defying human control. In their research they found that the opinion regarding responsibility is divided and that there is yet to be any agreement on how to really handle it.

While some people argue that humans cannot be held accountable for the AIs actions and behavior when it defies human control, others argue that humans are always responsible for the harm and consequences is cause because humans the" responsibility gap" is created through human decisions when developing the technologies (Wirtz, Weyerer, & Geyer, 2019). In some countries it is currently illegal for an AI to make final decisions as the AI itself is just a machine and is unable take responsibility for its actions. This means that all final decisions has to be made by humans, and unfortunately the extra use of human resources to make the decisions and sign off can potentially inhibit the adoption of AI in some organizations (Sun & Medaglia, 2019).

Dwivedi et al. (2019) suggest that cooperation, joint operation and shared roles between organizations and departments can make the responsibilities even more unclear and challenging to define.

LEGAL CHALLENGES

There is almost no legal area that does not apply to artificial intelligence. AI creates a lot of new legal challenges which can become extremely challenging for many organizations to handle and comprehend such as the high potential of misuse of data which can have severe consequences for humankind (Sadeghi, 2017). The challenges concern privacy, safety, bias, fairness, responsibility and lack of transparency in areas such as human rights, labor law and tax law, to mention some (Perc, Ozer, & Hojnik, 2019; Bartoletti, 2019).

One of the biggest legal challenges that organizations now face is the EU's General Data Protection Regulation (GDPR), which has a huge impact on organizations and how they collect, store and use data. Data is essential to AI but due to GDPR organizations are no longer allowed to collect, store and process data without the person of which the data belongs gives his or her consent and this can cause the AI to not receive the data it needs to produce value in for example the marketing industry (Dwivedi, et al., 2019).

GDPR states that individuals have the right to not be subjected to a decision made entirely through automation and also has the right to an explanation of the decision making process and possibility to challenge the decisions made (Dwivedi, et al., 2019). The right to an explanation causes major challenges for AI as it is in many cases, especially through machine learning and deep learning, sometimes almost impossible to explain how the decisions are made (Dwivedi, et al., 2019; Davenport & Ronanki, 2018; Tambe, Cappelli, & Yakubovich, 2019), but to satisfy the legal requirements it is critical that the AI provides and audit trail to show how decisions are made and to log who is doing what to what data (Dwivedi, et al., 2019; Bartoletti, 2019)

Other laws such as laws against discrimination become applicable for AI as data bias may cause unfair decisions and outcomes (Dwivedi, et al., 2019). Fairness regulated in many other laws such as labor laws, where for example employers are responsible for making decisions about hiring someone in a fair manner, which can be problematic if AI used in the hiring process contains bias (Tambe, Cappelli, & Yakubovich, 2019)

PRIVACY

Large scale data collection and data analytics represents a threat to the individual's right to privacy (Perc, Ozer, & Hojnik, 2019; Bartoletti, 2019) and there is a need to ensure an appropriate relationship and balance between data collection and privacy (Sun & Medaglia, 2019).

Privacy in terms of AI concerns protection of humans' privacy, data and technology and resources that are connected to an online network and that the data is treated in compliance with the laws and regulations that apply (Holzinger, Kieseberg, Weippl, & Tjoa, 2018; Wirtz, Weyerer, & Geyer, 2019). In 2018 the new General Data Protection Regulations (GDPR) was imposed by the European Union (EU) and applies to all countries in the EU and European Economic Area (EEA) and all countries that operate in these countries. GDPR sets entirely new regulations for what sort of personal data that can be collected, by whom it can be collected, for what purpose and for how long it can be stored and for how long (Schlögl, Postulka, Bernsteiner, & Ploder, 2019).

The use of artificial intelligence can potentially have a great impact on a person's privacy and thus makes the protection of privacy one of the most important tasks in terms of AI. But it is also one of the biggest challenges that organizations can face (Dwivedi, et al., 2019) as it requires both a change in policies as well as technical security measures built into that assistants to protect its an insurer privacy and safety for the securing the data (Holzinger, Kieseberg, Weippl, & Tjoa, 2018; Iliashenko, Bikkulova, & Dubgorn, 2019)

The protection of privacy also comes with a different challenge, as a principle for privacy as little data as possible should be collected (Bartoletti, 2019), which in turn limits the amount of data that organizations have available for processing. GDPR requires organizations to ask for consents from the person that they are collecting data from. A "general consent" is not sufficient, and the consent must be obtained specifically to process the data for a certain purpose (Wirtz, Weyerer, & Geyer, 2019). Because of this, many organizations experience that they do not get benefits from the data they collect as they would want to. In addition to this, GDPR also gives the individual the "right to be forgotten" which means that a person can demand that all data related to them as a person must be deleted (Tambe, Cappelli, & Yakubovich, 2019). Although it is possible to overcome that privacy challenges and by anonymizing data so that it is no longer possible to identify the person who provided the data, the methods for anonymization may cause the results to be distorted (Holzinger, Kieseberg, Weippl, & Tjoa, 2018).

The use of third-party datasets may create another challenge, as particularly rich data collected from sources such as social media and wearable devices combined with the existing data can make it possible to triangulate datapoints and thus identify the individuals that data has been anonymized for which in turn violates the person's right to privacy, creates the needs for more advanced anonymization (Thesmar, et al., 2019; Shaw, Rudzicz, Jamieson, & Goldfarb, 2019)

Another challenge from GDPR is that it no longer allows for the use of technology from vendors the store data in countries that are not part of the EU or EEA, which again can be a barrier for the adoption of artificial intelligence in European countries (Schlögl, Postulka, Bernsteiner, & Ploder, 2019).

ETHICS

The goal of ethics in AI is to guarantee the safety of humans and human interests and is a critical part of artificial intelligence (Guan, 2019; Dwivedi, et al., 2019)

According to Wirtz et al. (2019) ethics in AI has two aspects; 1) How ethical it is to develop certain technologies considering their potential consequences and 2) how to embed ethics into the technology itself during development. Another important consideration is that AI has to take into consideration social norms and standards such as honesty and loyalty (Wirtz, Weyerer, & Geyer, 2019) and the human value system – with factors such as dignity, respect, compassion and fairness and consider whether or not it should decide in favor of the elderly, less fortunate or children, depending on context (Dwivedi, et al., 2019). Defining ethics for machines and embed them into the technology is extremely challenging (Dwivedi, et al., 2019; Wirtz, Weyerer, & Geyer, 2019).

Thesmar et al. (2019) use a theoretical example where algorithms use medical data to predict the potential of future illness to help decide the insurance premium on health insurance. While a person who, according to the predictions, is likely to get sick in the future and thus would want insurance, it might be difficult for that person to get insurance, as they are high risk and the insurance premium would go up making it expensive for them to get the insurance and thus leaving them worse off.
With AI acting the way it does by learning and adapting, there is a risk that is might create its own value system and frame of reference that is not compatible with the human one. This can be especially challenging when a decision made by a system stripped of human values, emotions and social norms is different from when it is made by a human as it can have severe consequences for a decision (Wirtz, Weyerer, & Geyer, 2019).

Guan (2019) stresses the reality of the double effect principle in AI in which an well intended action can have harmful consequences, such as the example above. This means that the technology has to factor in the environment it operates in and what impact and cost its decision will have on society (Dwivedi, et al., 2019).

TRUST

Research show that people's attitude toward AI is context dependent. People will in general be positive to AI as long as it does not affect them, their safety, privacy, employment or health directly, but if the technology does not delivery what people expect it to, their positive attitude toward AI may change. This also applies to cases where unemployment for some leads to increase in profit to others (Wirtz, Weyerer, & Geyer, 2019).

The most advanced AI, such as deep learning, are incredibly difficult to understand and in some cases, no one even knows what the algorithms do (Dwivedi, et al., 2019). In health care, the lack of patients trust in AI can actually make the adoption of AI very challenging. Not being able to explain the algorithms leads to patients not trusting the outcomes of the AI (Yu & Kohane, 2019), but also the need for doctors to interact with the AI and support the decision making causes concern (Sun & Medaglia, 2019).
In addition, the lack of regulation or uncertainties related to regulations and governance of AI can lead to people being concerned for the legitimacy of AI in certain sectors such as health care (Sun & Medaglia, 2019).

Schlögl et al. (2019) found that people are reluctant to put their trust in tools and features provided by certain foreign providers such as Apple and Amazon who are not under the EUs GDPR legislation. The main concern is the sharing of data and lack of ability to protect the data and the use of commercial providers. These factors cause concern for the data being misused or even stolen and used for purposes it was not collected and to which people have not given their consent or that their input can be manipulated at a later point (Holzinger, Kieseberg, Weippl, & Tjoa, 2018; Sun & Medaglia, 2019).

Table 4 - Literature overview - Concept Matrix

		Technological challenges		Data challenges						Organizational Challenges				Societal challenges				
Author and year	Year	Security	Transparancy & explainability	Data availability	Data sharing & integration	Data quality	Bias	Data origin and domain	Unstructured data	Strategy	Change	Knowledge	Cost	Governance	Legal challenges	Privacy	Ethics	Trust
Yu & Kohane	2019		✓			✓	✓				✓							✓
Wirtz et al.	2019	✓				✓	✓				✓	✓	✓	✓		✓	✓	✓
Wang & Preininger	2019	✓	✓	✓			✓	✓										
Thesmar et al.	2019		✓				✓										✓	
Tarafdar et al.	2017			✓		✓		✓				✓	✓					
Tambe et al.	2019	✓	✓	✓	✓		✓								✓	✓		
Sun & Medaglia	2019	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓		✓
Shaw et al.	2019	✓	✓			✓	✓	□					✓			✓		
Schlögl et al.	2019			✓							✓	✓				✓		✓
Sadeghi	2017		✓									✓			✓			
Raaijmakers	2019		✓				✓					✓						
Pavaloiu	2016	✓								✓	✓	✓						
Iliashenko et al.	2019	✓										✓	✓			✓		
Holzinger et al.	2018	✓	✓	✓												✓		✓
Guan	2019													✓			✓	
Dwivedi et al.	2019	✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓
Duan et al.	2019		✓								✓	✓		✓				
Davenport & Ronanki	2018		✓		✓					✓		✓			✓			
Bartoletti	2019						✓								✓	✓	✓	

Perc	2019	✓											✓	✓	✓			

3 RESEARCH METHODOLOGY

This chapter describes the research methodology used in this study to try to bring more insight into the research question *"What challenges can impact Norwegian organizations' adoption of Artificial Intelligence?"* as well as the reasoning behind the chosen research method used.

The chapter is structured in the following way:

First the research approach is presented, followed by the methods for collecting and analyzing data and finally the research ethics applied to this study.

3.1 RESEARCH APPROACH AND STRATEGY

The study is an exploratory and descriptive study which aims to explore and describe the challenges that can impact the adoption of Artificial intelligence in a Norwegian context.

Because there is no previous research from a Norwegian context to build on, relevant literature from other parts of the world like China, America and other parts of Europe was used to build the theoretical foundation for this study. The challenges found in the literature that is said to have an impact on adoption of AI, may or may not apply to a Norwegian context, and the lack of previous studies makes an exploratory study relevant. An exploratory study entails applying the theory to a Norwegian context and see whether or not it is in fact relevant (Oates, 2006).

The literature has formed the basis for the questions used in the questionnaire used in this study. Theories and other information from the study has been used to shape the questions. In addition, the author has applied her knowledge and previous experience from her work as a consultant in the IT industry serving clients from both private and public sector to shape questions with the information found in the literature.
A deductive approach means using existing theories and applying them and an inductive approach is to use the data or categories of data in the literature to shape new theories and applying them to a new context (Oates, 2006).
Both a deductive and inductive approach require the researcher to keep an open mind, as being too committed to a certain theory or applying his or her own prejudice and opinions can have negative impacts on the study such as overlooking important factors (Oates, 2006).

The short timeframe available to execute this study made a quantitative approach through a survey in the form of an online questionnaire the most appropriate and realistic method to collect data. An online questionnaire allows for collection of standardized data from a large population in a short amount of time (Oates, 2006).

3.2 RESEARCH DESIGN

The figure below is a visual representation of the approach to collect, process and analyze data.

The project was divided into different phases; planning, preparation and execution. The planning phase consisted of the search for and review of relevant literature. In this phase the different concepts found in the literature was categorized and the concept matrix presented in the literature review was created.

During the preparation phase the questionnaire was created, pre-tested and piloted and an initial group of respondents were detected.

In the execution phase of the project, the data collection was performed though a snowball sampling method, the data analysis was completed, and the study was finalized.

Throughout all the phases I worked on writing and structuring the report.

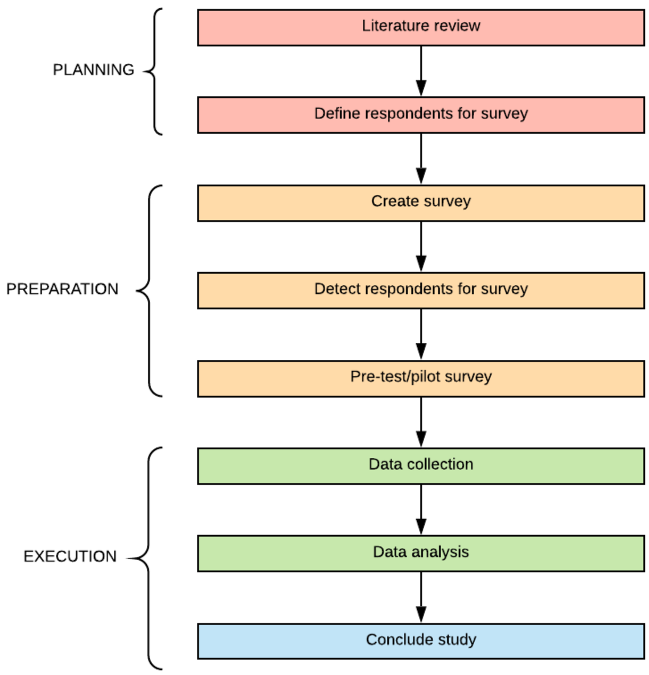


Figure 1 - Research design

3.3 DATA COLLECTION & ANALYSIS

This chapter gives a description of the method for data collection, sampling and data analysis.

3.3.1 QUESTIONNAIRE

Oates (2006, p. 93) describes a survey as a systematical and standardized way to gather the same kind of data from a large group of people or events and look for patterns in the collected data. A survey can be performed in many ways, one of them being questionnaires which is the method of choice for this thesis.

For the study a self-administered online questionnaire was created, which is a type of questionnaire where the respondents answer the questions without the researcher being present.
According to Oates (2006) questionnaires are especially useful when you want to:

- collect data from a large number of people
- collect standardized data
- collect short and uncontroversial data from people

A lot of time and effort went into the creation of the questionnaire used in this survey. The tool "SurveyXact" was used to create the questionnaire. SurveytXact is an online surveying tool developed by Rambøll that is available to students at the University of Agder.
The questionnaire was created in multiple iterations where the author's supervisor, Tom Roar Eikebrokk, was consulted. Feedback from was used to make adjustments.

As the target audience for the survey was Norwegian organizations the questionnaire was created in Norwegian to avoid misunderstandings.

The questionnaire was created based on the theoretical foundation in Chapter 2. The challenges found in the literature was shaped into questions for the respondents to answer – by rating the question or statement on a Likert-scale as to what extent something was relevant or important for their organization in regard to adopting AI.

The use of Likert-scales is commonly used to analyze attitudes and how these attitudes can be divided into different categories. But it does not allow an analysis of how much of a difference there is between the different categories (Gripsrud, Olsson, & Silkoset, 2010) If you ask a question about the importance of privacy, you cannot differentiate between "important" and "very important" in the same way as if the question was "how much money do you have in the bank". If someone answers that they have $400 dollars in the bank and another one said $500 – you know that the difference is $100.

In the questionnaire, the first questions were used to define which groups of respondents were answering the survey.
The groups define where the organizations stand in terms of adopting AI.

Appendix A – Questions and sources show the questions that were used in the survey (with adjustments for each group of respondents) and the sources from the literature where the concept was mentioned.

While Appendix B – shows the questionnaire in full.

The respondents were also asked to supply any additional information about challenges they may have considered to impact adoption or that they had experienced during implementation. The answer was to be supplied in a free-text field.

VALIDITY AND RELIABILITY

Oates (2006) says that it is important to consider the questionnaires content validity in terms of content and construct.

Content validity refers to assuring that the questionnaire covers the domain of research in a well-balanced way. The questionnaire and the questions it contained was created based on the research literature found in Chapter 2, this also includes the definition used in the questionnaire.

Construct validity refers to assuring that the questions actually measures what we want them to measure, and nothing else. To assure construct validity the questionnaire was tested before being distributed to the respondents.

PRE-TEST AND PILOTING

To ensure that valid and reliable data is collected, it is important to construct the questionnaire carefully. The questionnaire contained many different routings dependent on the respondent's answers which made it important to make sure that the routings were correct and that the questions were understandable in all of them.

PRE-TESTING

In addition to testing the questionnaire during development through multiple iterations, the questionnaire was pre-tested.
The pre-test was performed by sending the questionnaire to two people who work in the domain of Artificial intelligence and business development, but who do not belong in the target population – Norwegian organizations (Oates, 2006).

The testers were informed that the potential respondents may be people with very little technical competence in terms of AI and feedback on the terms used would be especially valuable. Such feedback included that the terms used were actually correct, whether they were too difficult to understand from a non-technical perspective and to make sure that there were no ambiguous or unclear questions or terms used.
Based on the feedback, some adjustments were made to simplify some of the questions, as the testers pointed out that some of the wording used could potentially be too technical for people who do not have the technical competence in AI.

PILOT

After making the changes suggested by the people with domain knowledge, the questionnaire was piloted. Piloting means getting some people to answer the questionnaire as if they are real respondents (Oates, 2006). Three people who were not in the target group to answer the questions were asked to answer as if they were. These people work in HR, banking and software development.

They were asked to provide feedback on whether the questions were difficult to understand and answer, or unclear in any way, if the setup made sense, how long it took them to finish and if there were any spelling mistakes that should be corrected.

PRIVACY

To ensure that people respond honestly to the survey, it was decided to make the survey anonymous. This made sure that the study does not violate the General Data Protection Regulation (GDPR) in any way by collecting personal data from any respondents.
To further support anonymity, the level of identification was limited to sector, industry and role title of the respondent.

3.3.2 SAMPLING FRAME AND SAMPLING METHOD

As the study aims to try to understand and describe the challenges that Norwegian organizations experience in regard to AI, the decision was made not to limit the survey to certain industries, sectors or specific roles in the organization. The population for the survey is all organizations in Norway that have either started using AI or is currently in the process of implementing AI or organizations that have not started using AI.
The target group for the questionnaire were people who have participated in the evaluation of AI for their organization, participated in development or implementation projects within their own organization or people who are responsible or have a say in terms of introducing new technology and tools into their organization.
This includes roles such as CEO, CTO, CIO, COO or equivalent as well as project managers, business developers and data analysts but can also potentially include a wide range of other roles which is not always obvious. Technology is no longer just the responsibility of the IT department as it has traditionally been and there is therefore a chance that many different roles can be involved in AI initiatives and thus be able to answer the questionnaire.

Quite a large number of respondents was required in this study to be able to generalize. To find these respondents two types of non-probability sampling methods were used in combination. One being so called "purposive sampling" where potential respondents in the target group were hand-picked (Oates, 2006). This was then combined with Snowball sampling. Snowball sampling is a method used in many research areas such as medical and social studies to uncover "hidden" populations (Johnson, 2005) or gain access to respondents that are not obvious (Oates, 2006). The core of this sampling method is for the researcher to use their social network to find respondents through referral made by other respondents. Due to this, snowball sampling is also known as "chain referral sampling" (Crouse & Lowe, 2018). The two methods were used in combination in the way that the respondents found through purposive sampling were asked to either share the survey with people considered relevant, or to refer to other potential respondents. The author's social network on LinkedIn and personal network was used to get in touch with relevant respondents either by having network connections share the survey or share contact information so the potential respondents could be contacted directly.

3.3.3 DISTRIBUTION METHOD

The questionnaire was distributed through email and through my social network. SurveyXact offers the possibility to send out emails through the tool, but to limit the risk of the emails ending up being stopped by spam filters or the respondent to delete the email as it may look like a mass-distribution, this tool was not used.
All emails were sent from the author's student email-account provided by the University of Agder.

The social network was reached through LinkedIn-posts and the network was asked to share the post and the link to the questionnaire as described in the snowball sampling method.

The email was distributed through:

- 67 emails – of which only 16 confirmed that they had responded to the email
- 30 direct messages on LinkedIn
- 3 posts on LinkedIn that was shared by network connections 19 times

3.4 RESEARCH ETHICS

Although research can be value to the public, it can also cause harm. And this is why it is important to consider the consequences of the research – short term and long term.

It is important to keep within the boundaries of laws and other regulations, as well as protecting the individual against any potential harm caused by the research.

The Norwegian National Research Ethics Committees (2016) have made some guidelines for research ethics that I will follow in this project. Some of the areas that I find particularly important are listed below:

- It is important to **protect the individual**'s right to privacy, his or her dignity and reputation.

- It is the researcher's responsibility to make sure that the participants have been adequately **informed** about the research study they are participating in. This includes the purpose, the intended use of results and the potential consequences of participation.
- Consent must be obtained from the individual if personal data is being collected. The **consent must be given** freely and explicit and be made on an informed basis. The individual may at any point in time before the project has been completed with draw their consent without any negative consequences for them.
- It is the researcher's responsibility to ensure **good citation practice** and **avoid plagiarism**
- The researcher is responsible to ensure **scientific integrity**. Meaning making sure that the data presented in the project are real data and that research subjects have not been misled in any way.

This project has been approved by The Norwegian Centre for Research Data and satisfies the demands of the European General Data Protection Regulation (GDPR).

4 ANALYSIS AND RESULTS

This chapter presents the results and analysis from the survey used to answer the research question:

"What challenges can impact Norwegian organizations' adoption of Artificial Intelligence?"

The survey was distributed to respondents found through purposive and snowball sampling which is described in Chapter 3 – Research methodology.
Data collection was started on November 1st 2019 and was completed on November 27th 2019.

First the characteristics of the respondents are described, followed by the results from the survey. In addition to presenting the top challenges and impacting factors that the respondents have reported, the standard deviation of the different answers was calculated to understand to what extent the respondents agree on the different topics.

4.1 CHARACTERISTICS OF RESPONDENTS

The total number of people reached in this survey (people who clicked the link which generates a respondent instance) was 564.

Out of the 564, 122 people completed the survey, and 112 people only partially completed the questionnaire by answering only a couple of questions – with one exception. One respondent partially completed the survey by leaving only one question unanswered. As the missing answer was to the respondent's role within the organization, I decided to include these results into the completed group – which makes the total number of respondents 123.

This gives a response rate of roughly 22%.

The chart below shows the distribution of respondents across sector.
For this survey, academia and non-profit organizations were treated as separate sectors.

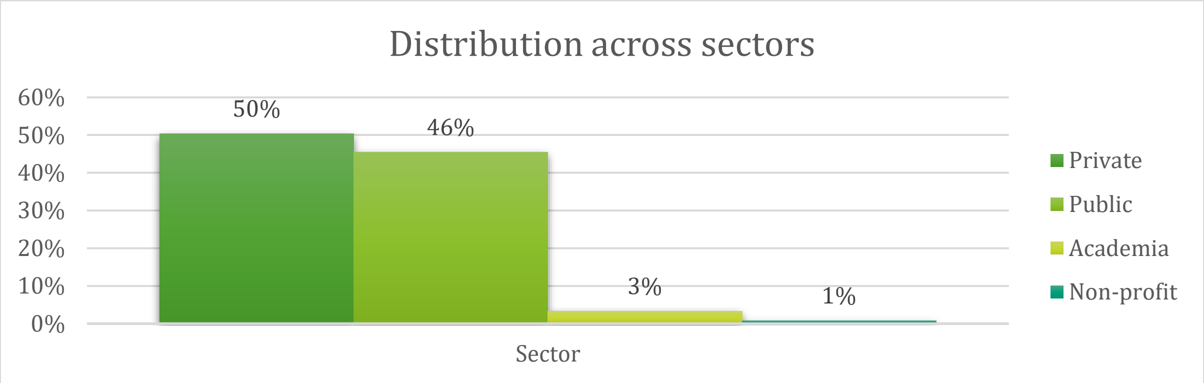


Figure 2 - Distribution of population across sector

The respondents were also asked to answer questions about which industry they belong to and the number of employees in their organization (referred to as size).
The industries and the ranges used for number of employees were inspired by Statistisk Sentralbyrå (Statistics Norway) but the number of ranges and industries have been reduced for convenience (Statistisk Sentralbyrå, 2019).

As the public sector is one of the larger groups of respondents, it is natural that a large group of the population belongs to public administration.

The figure below shows the distribution of respondents in numbers across industries.

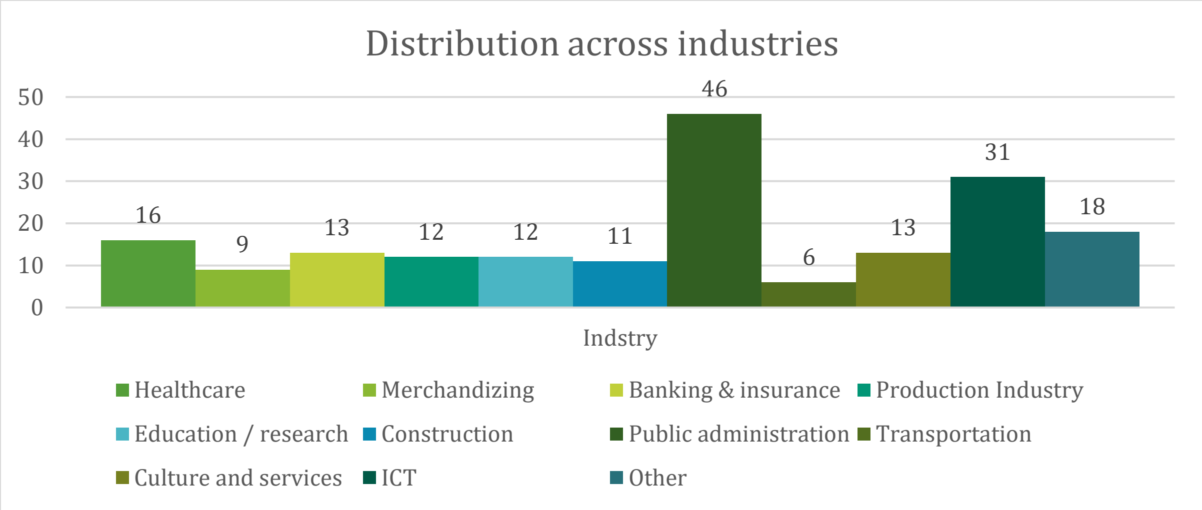


Figure 3 – Respondent distribution across industries

The majority (52%) of the respondents come from organizations with more than 500 employees, followed by 25% from organizations ranging from 100-499 employees. The figure below shows the distribution of respondents across the size of organizations in terms of number of employees.

Figure 4 - Respondent distribution across organization size

4.1.1 RESPONDENT DEMOGRAPHICS

Table The table below shows the demographic data for all the respondent who completed the survey.

Table 5 - Demographic data - All respondents

Dimension	Sample (N)	Frequency (%)
Total no. of respondents	**123**	
Sector		
Private	62	50.4%
Public	56	45.5%
Academia	4	3.3%
Non-profit	1	0.8%
Industry		
Healthcare	16	13.0%
Merchandizing	9	7.3%
Bank & Insurance	13	10.6%
Production Industry	12	9.8%
Education/Research	12	9.8%
Construction	11	8.9%
Public administration	46	37.4%
Transportation	6	4.9%
Culture and services	13	10.6%
ICT	31	25.2%
Hotel and restaurant	0	0.0%
Other	18	14.6%
Size (no. of employees)		
0-9	7	5.7%
10-49	11	8.9%
50-99	10	8.1%
100-499	31	25.2%
>500	64	52.1%

4.1.2 GROUPS OF RESPONDENTS

The questionnaire had some initial questions that the respondents were to answer before being routed to the appropriate set of questions about factors and challenges that impact the adoption of AI.

The respondents from the survey represent three different categories;

- The ones who have adopted AI
- The ones who are in the process of implementing AI

- The ones who have not adopted AI

The group who have not adopted AI was divided into three subgroups, based on another question where they were to consider how likely it is for their organization to adopt AI at the current time.

The table below gives a description of the different groups and subgroups, and the group names will be used in the following text for simplicity.

Table 6 - Groups of respondents

Group name	**Description**
Group 1 – Yes	Respondents who answered that their organization has adopted Artificial Intelligence.
Group 2 – Implementing	Respondents who said that their organization is in the process of implementing AI in their organization.
Group 3 – No	Respondents who answered that they have not adopted AI.
***Subgroup 3A* –** Evaluating	The group of respondents who said that they have not yet adopted AI, but they are in the process of evaluating it.
***Subgroup 3B* –** Not considered but likely to adopt	Respondents who have not yet considered AI but think that it might be relevant for them for adopt AI.
***Subgroup 3C* -** Not considered and unlikely to adopt	Respondents who have not yet considered AI and who says it's unlikely relevant or not relevant to adopt AI.
Subgroup 3D – Not adopting	This group consists of the ones who have decided not to adopt AI.

Figure 5 shows the distribution of respondents across the three main groups.

27% reported that their organization has implemented AI, 13% reported that they are in the process of implementing and the remaining 61% reported that they have not implemented AI.

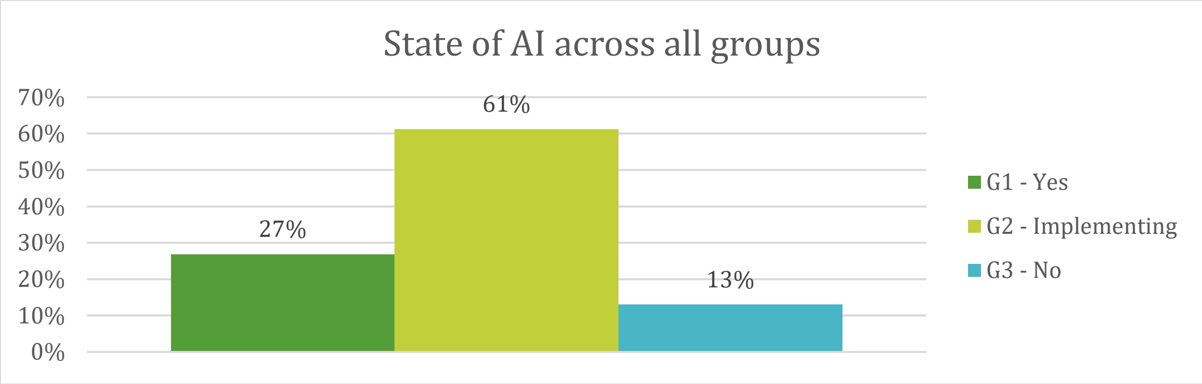


Figure 5 - State of AI across sample

The distribution across subgroups of the respondents in Group 3 is shown in figure 6 below. As the figure shows, the majority of respondents were found in Group 3A and 3C. Group 3D – not adopting – consists of only one respondent.

The total number of respondents in Group 3 was 74.

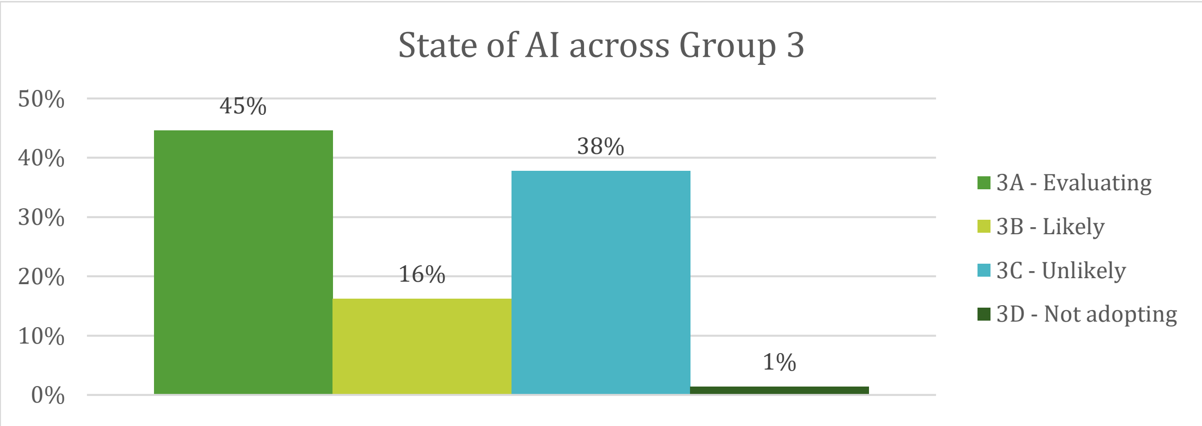


Figure 6 - State of AI across Group 3

4.2 Survey results

The following chapter presents the findings from the survey.
The results are presented in subchapters for each group. First the demographic data of each group of respondents is presented, followed by the top challenges that are considered to potentially have an impact or has had an impact on adoption of AI.
The mean and standard deviation of the results from the survey was calculated in the statistics tool SPSS to try to get an overview of the degree of agreement on the different topics.

Not relevant

In the questionnaire the category "*not relevant*" was used as an alternative answer. A free-text box was included in the survey for respondents to provide information about challenges that were not covered by the questionnaire.
Many respondents used this box to inform that they have used the "not relevant" category as "I don't know" or to inform that the "not relevant" category was unclear as it in some questions can be interpreted as not a relevant challenge or not a relevant question.
The uncertainty concerning this question forced the decision to exclude the not relevant category from the results. The "not relevant" values were therefore reported as missing in SPSS.

STATE OF AI ACROSS SECTOR

When dividing the three main groups into sectors, it becomes clear that organizations in the private sector have started using AI or is in the phase of implementing to a larger extent than public ones.

Figure 7 shows the state of AI distributed across the different sectors.

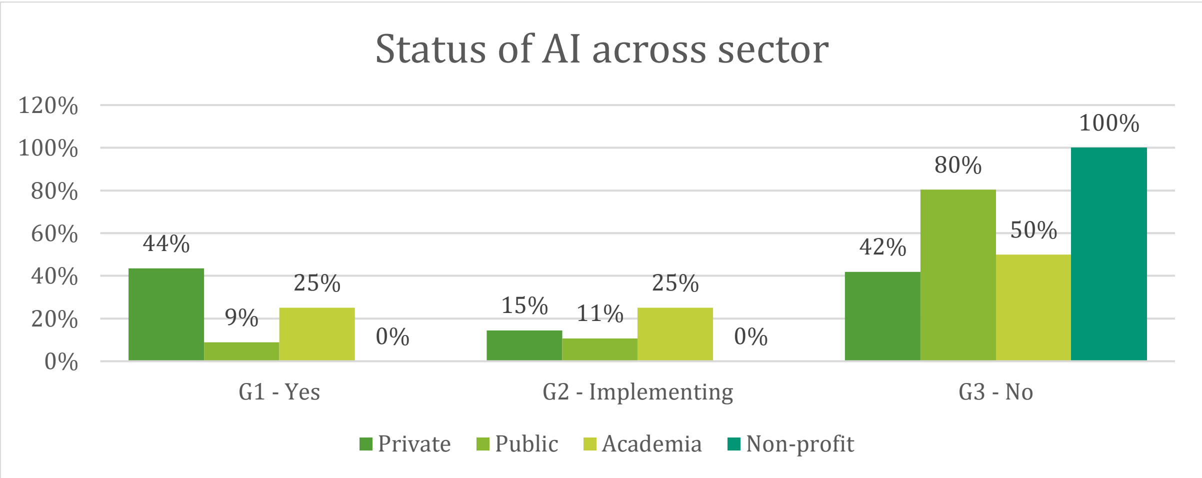


Figure 7 - Status of AI across sector

STATE OF AI ACROSS ORGANIZATION SIZE

Figure 8 shows the distribution of AI across organizations' size based on the number of employees. As the figure shows, the larger organizations with more than 100 employees are ahead on implementation and use followed by the organizations with 10-49 employees.

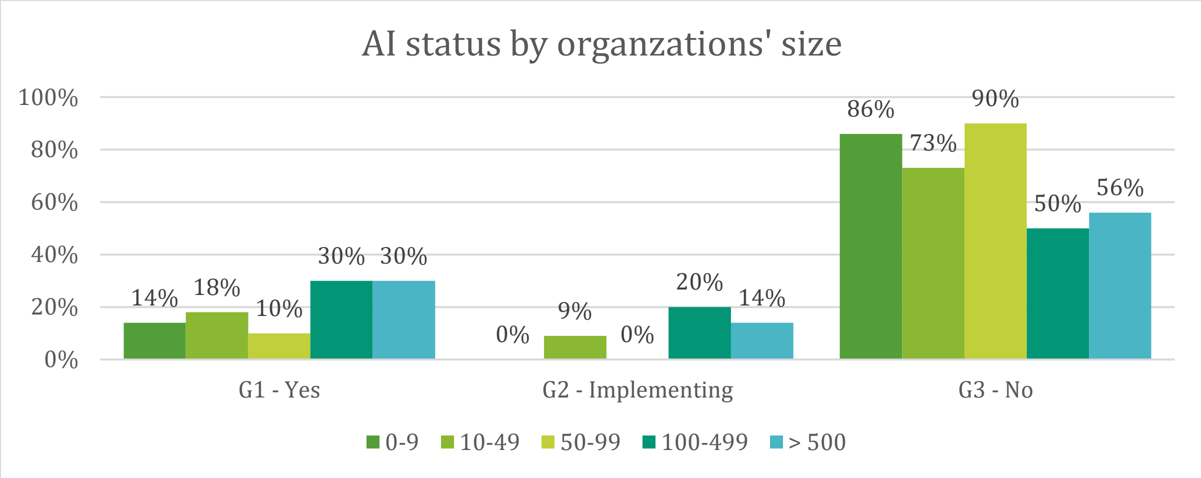


Figure 8 - Status of AI by size

TECHNOLOGY IMPLEMENTED

The respondents who answered that their organization has adopted AI or are in the process of implementing AI were also asked to report which technologies they have or are in the process of implementing. The results shown in figure 9 show that Machine Learning is by far the most popular technology and covers 94% of both Group 1 and 2. As the chart shows, many organizations implement more than one type of technology.

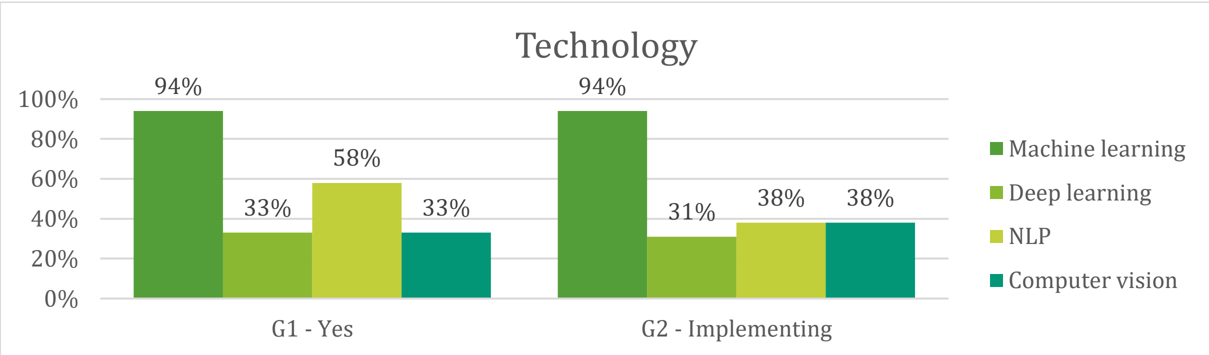


Figure 9 - Distribution of technology

4.2.1 RESULTS: GROUP 1

Group 1 consists of the respondents who reported that their organizations have adopted AI. Results from the survey show that the majority of respondents in this group belongs to the private sector and to organizations with more than 100 employees.

Table 8 shows the complete demographic overview of respondents in Group 1.

Table 7 – Group 1 - Demographic data

Dimension	Sample (N)	Frequency (%)
Total no. of respondents	**33**	
Sector		
Private	27	81.8%
Public	5	15.2%
Academia	1	3.0%
Non-profit	-	0.0%
Industry		
Healthcare	2	6.1%
Merchandizing	2	6.1%
Bank & Insurance	9	27.3%
Production Industry	7	21.2%
Education/Research	1	3.0%
Construction	2	6.1%
Public administration	5	15.2%
Transportation	2	6.1%
Culture and services	1	3.0%
ICT	11	33%
Hotel and restaurant	-	0.0%
Other	5	15.2%
Size (no. of employees)		
0-9	1	3.0%
10-49	2	6.1%
50-99	1	3.0%
100-499	9	27.3%
>500	20	60.6%

TOP CHALLENGES AND FACTORS OF IMPORTANCE

When looking into the results from Group 1, we find that there are nine factors that has had an impact on adoption of AI that has been reported by more than 50% of the respondents.
Satisfying requirements set by GDPR comes out on top with 78.8% of the respondents in group 1 rating it as an important or very important factor.

The second most important factors have been internal security and the lack of resources with the right expertise with 66.7%, closely followed by being able to explain the decision-making process and ensure ethical governance with 66.7%.

Table 8 - Group 1 - Impacting factors

Ranking	Significant factors for adoption	N	%

1	To be able to satisfy the requirements of the GDPR / Privacy legislation	26	78.8%
2	To be able to satisfy internal security requirements (human error, data manipulation and the like)	22	66.7%
2	Lack of resources with the right expertise	22	66.7%
3	Explain the technology decision-making process (algorithms)	20	60.6%
3	Being able to ensure ethical AI governance in a satisfactory way	20	60.6%
4	Lack of expertise and knowledge of AI in general	19	57.6%
5	To be able to satisfy external security requirements (hacking and the like)	18	54.5%
5	We have a large amount of data that was difficult to handle during implementation of AI	18	54.5%
5	Lack of expertise and knowledge of AI at the managerial level	18	51.5%

Table 10 shows the mean and standard deviation for the questions answered by Group 1.
The numbers in the table show that standard deviation is the lowest for the question about homogeneous data – 0.830, employee redundancy – 0.853 and general lack of expertise and knowledge in the organization – 0.877, none of which were on the list of top rated challenges.
GDPR, which is the number one factor reported has a standard deviation of 1.120.

Table 9 - Group 1 - Descriptive statistics - Mean and Standard deviation

Descriptive Statistics			
	N	Mean	Std. Deviation
A clear national commitment to AI through a national strategy	31	2.645	1.582
Clear public conditions for AI governance	30	2.933	1.437
Public financing / grants for AI projects	29	2.862	1.457
We have a large amount of data that was difficult to handle during implementation of AI	33	3.545	1.063
Limited amount of data for our purposes made it difficult to fully benefit from AI	32	2.781	1.237
A lot of unstructured data made data processing difficult	33	3.333	1.109
We had challenges accessing relevant data from other systems and parts of the organization	31	3.290	1.071
It was difficult to combine data from different sources (such as social media and internal systems)	27	3.148	1.027
We struggled with data integrity and had a lot of incomplete data, duplicates and the like.	27	3.407	1.118
We had a lot of homogeneous data (equal to data / overweight of one type of data)	29	2.759	0.830
It was difficult to find AI technology ("off-the-shelf") that suited us	30	3.033	1.217
To be able to satisfy external security requirements (hacking etc.)	31	3.613	1.520
To be able to satisfy internal security requirements (human error, data manipulation etc.)	32	3.813	1.378
Explain the technology decision-making process (algorithms)	33	3.606	1.088
To be able to satisfy the requirements of the GDPR / Personal Data Act	32	4.188	1.120
Being able to ensure ethical governance of AI in a satisfactory manner	31	3.645	1.355
Necessary process changes	30	3.233	1.135
Necessary organizational changes	31	2.871	1.056
Negative attitudes toward AI	32	2.469	1.016
Employees have become / will become redundant	31	1.935	0.854
Lack of resources with the right expertise	32	3.969	1.031
Lack of expertise and knowledge of AI at the managerial level	32	3.688	1.120
Lack of expertise and knowledge of AI in general	32	3.563	0.878
Difficult to upskill existing employees	32	3.094	1.118

4.2.2 *RESULTS: GROUP 2*

Out of the total respondents, 13% said that their organizations are in the process of implementing artificial intelligence.

As group 1, most of Group 2 belongs to the private sector, but public sector is represented by almost 40% in the group.
Most of the respondents also belong to the large companies with more than 100 employees, like Group 1.

Table 11 shows the demographic data of Group 2.

Table 10 – Group 2 - Demographic data

Dimension	Sample (N)	Frequency (%)
Total number of respondents	**16**	
Sector		
Private	9	56.3%
Public	6	37.5%
Academia	1	6.3%
Non-profit	-	0.0%
Industry		
Healthcare	4	25.0%
Merchandizing	1	6.3%
Bank & Insurance	3	18.8%
Production Industry	1	6.3%
Education/Research	5	31.3%
Construction	4	25.0%
Public administration	7	43.8%
Transportation	2	12.5%
Culture and services	4	25.0%
ICT	4	25.0%
Hotel and restaurant	-	0.0%
Other	4	25.0%
Size (no. of employees)		
0-9	0	0.0%
10-49	1	6.3%
50-99	-	0.0%
100-499	6	37.5%
>500	9	56.3%

TOP CHALLENGES AND FACTORS OF IMPORTANCE

There are six factors that have been important for the adoption of AI in group 2.

Much like Group 1, internal security requirements and GDPR ranks the highest. However, in group 2 the two have switched places, with internal security requirements ranked as number one.
External security comes in third, which is two places higher than in group 1, together with lack of resources with the right expertise which was ranked as number two by group 1.

Table 12 shows the challenges that were reported as most important and challenging by more than 50% of the respondents in group 2.

Table 11 - Group 2 - Impacting factors

Ranking	Significant factors for adoption	N	%
1	To be able to satisfy internal security requirements (human error, data manipulation and the like)	12	75.0%
2	To be able to satisfy the requirements of the GDPR / Personal Data Act	11	68.7%
3	To be able to satisfy external security requirements (hacking and the like)	10	62.5%
3	Lack of resources with the right expertise	10	62.5%
4	It was difficult to find AI technology ("off-the-shelf") that suited us	9	56.3%
5	Being able to ensure ethical AI governance in a satisfactory way	9	56.3%

The standard deviation for group 2 proves to be the lowest - 0.640 - on the question regarding employee redundancy, much like in group 1.
This question was also ranked the least important one of them all (mean 1.5).
It is interesting to see that the two challenges that were ranked as the third important factors have a difference in the standard deviation of 0,255, with a standard deviation of 1.320 for external security and 1.065 for lack of resources with the right expertise.

Table 13 shows the full overview of mean and standard deviation for group 2.

Table 12 – Group 2 - Descriptive Statistics - Mean and Standard Deviation

Descriptive Statistics			
	N	Mean	Std. Deviation

Missing / unclear national investment in the field in the form of national strategy for AI	15	2.067	0.961
Clear public conditions for AI governance	14	2.357	1.216
Public financing / grants for AI projects	13	2.462	1.266
We have a large amount of data that was difficult to handle during implementation of AI	16	3.313	0.873
Limited amount of data for our purposes made it difficult to fully benefit from AI	15	2.200	0.775
A lot of unstructured data made data processing difficult	15	3.200	0.941
We had challenges accessing relevant data from other systems and parts of the organization	15	2.933	1.100
It was difficult to combine data from different sources (such as social media and internal systems)	12	3.333	1.073
We struggled with data integrity and had a lot of incomplete data, duplicates and the like.	14	3.214	0.893
We had a lot of homogeneous data (equal to data / overweight of one type of data)	15	2.800	0.862
It was difficult to find AI technology ("off-the-shelf") that suited us	15	3.600	1.242
To be able to satisfy external security requirements (hacking etc.)	15	3.800	1.320
To be able to satisfy internal security requirements (human error, data manipulation etc.)	16	3.938	0.998
Explain the technology decision-making process (algorithms)	16	3.375	1.258
To be able to satisfy the requirements of the GDPR / Personal Data Act	15	4.133	1.187
Being able to ensure ethical governance of AI in a satisfactory manner	14	3.786	1.251
Necessary process changes	16	2.938	1.124
Necessary organizational changes	16	2.563	1.209
Negative attitudes toward AI	16	1.875	0.719
Employees have become / will become redundant	15	1.467	0.640
Lack of resources with the right expertise	16	3.750	1.065
Lack of expertise and knowledge of AI at the managerial level	16	3.125	1.310
Lack of expertise and knowledge of AI in general	16	2.938	1.181
Difficult to upskill existing employees	16	3.188	0.911

4.2.3 RESULTS: GROUP 3

The last main group of respondents is the group of people who said that their organization has not implemented AI.
As mentioned earlier, the "NO" group is divided into four subgroups

3A - Evaluating
3B - Likely
3C – Unlikely
3D - Not adopting

The majority of respondents in group 3 belongs to the public sector and is also the majority in all the subgroups.

Subgroup 3D consist of only one respondent, although this is most likely not a representative amount for the part of the population who has decided to not adopt AI, it has still been included as it is considered interesting information for the study.

Table 14 below shows the distribution of respondents in the different dimensions across the four subgroups.

Table 13 – Group 3 - Demographics across subgroups

Dimension	Evaluating	Likely	Unlikely	Not impl.	Sample (N)	Frequency total (%)
Total number of respondents	**33**	**12**	**28**	**1**	**74**	
Sector						
Private	13	4	9	-	26	35.1%
Public	18	8	18	1	45	60.8%
Academia	2	-	-	-	2	2.7%
Non-profit	-	-	1	-	1	1.4%
Industry						
Healthcare	2	5	3	-	10	13.5%
Merchandizing	1	3	2	-	6	8.1%
Bank & Insurance	-	-	1	-	1	1.4%
Production Industry	2	1	1	-	4	5.4%
Education/Research	3	2	1	-	6	8.1%
Construction	1	2	2	-	5	6.8%
Public administration	17	5	11	1	34	45.9%
Transportation	-	-	2	-	2	2.7%
Culture and services	3	3	2	-	8	10.8%
ICT	11	3	1	1	16	21.6%
Hotel and restaurant	-	-	-	-	-	0.0%
Other	2	3	4	-	9	12.2%
Size (no. of employees)						
0-9	1	-	5	-	6	8.1%
10-49	3	1	4	-	8	10.8%
50-99	1	2	6	-	9	12.2%
100-499	9	3	2	1	15	20.3%
>500	19	6	11	-	36	48.6%

RESULTS: SUBGROUP 3A

Subgroup 3A are the respondents who are in the process of evaluating AI adoption. The group is divided into the public and private sector with the majority belonging to organizations with more than 500 employees.

Table 15 shows the factors reported by more than 50% of the respondents to pose as challenges that can potentially impact adoption of AI.

The main challenges these organizations consider are the availability of financial resources to invest in AI, access to resources with the right expertise and knowledge at management level are ranked as the top two factors that can impact a potential adoption of AI. With access to resources being mentioned by 84.8% of the respondents. Public financing and the need to upskill employees are mentioned in third place.

It is interesting that this group has no less than three knowledge-related questions in their top three challenges.

Table 14 – Group 3A - Top factors of significance

Ranking	Significant factors for adoption	N	%
1	Access to resources with the right expertise	28	84.8%
2	Expertise and knowledge of AI at management level	24	72.7%
3	Public financing / grants for AI projects	23	69.7%
3	The need for upskilling of employees	23	69.7%
4	Clear public conditions for AI governance	22	66.7%
5	Ability to explain the algorithms in AI	20	60.6%
6	A clear national commitment to AI through a national strategy	18	54.5%
7	Privacy Protection Requirements (GDPR)	18	54.5%
8	Data integrity - poor quality, duplicates	17	51.5%

Subgroup 3A has three knowledge related challenges mentioned in their top three challenges. When looking into the standard deviation, we see that access resources with the right competence and expertise and knowledge on a management level has relatively low standard deviations of 0.827 and 0.936.
GDPR was ranked in the top 3 in both group 1 and 2, but only reaches 7th place in group 3A and has a standard deviation of 1.220.

Table 16 shows the mean and standard deviation of all potential challenges mentioned in the questionnaire.

Table 15 – Group 3A - Descriptive statistics - Mean and Standard deviation

Descriptive Statistics			
	N	Mean	Std. Deviation
A clear national commitment to AI through a national strategy	32	3.375	1.129
Clear public conditions for AI governance	33	3.818	1.158
Public financing / grants for AI projects	33	3.879	1.111
We have too much data	31	1.774	0.884
We have too little data	31	2.871	1.335
We have a lot of unstructured data	32	3.156	1.370
Sharing data across the organization	32	2.875	1.264
Data integration (data from multiple sources such as social media and the like)	32	3.281	1.114
Data integrity - poor quality, duplicates	33	3.303	1.185
Too much data bias / homogeneous data (equal to data)	33	2.636	0.994
Available technology ("shelf goods") is not relevant to us	32	2.813	1.330
Requirements for security against external threats (hacker attacks and the like)	33	3.152	1.149
Requirements for security against internal threats (human error, data manipulation and the like)	33	3.091	1.234
Ability to explain the algorithms in AI	32	3.594	1.132
Privacy Protection Requirements (GDPR)	33	3.636	1.220
Requirements for ethical AI governance	33	3.545	1.121
The requirement for process changes	33	2.939	1.116
The requirement for organizational changes	33	3.121	1.083
Negative attitudes towards AI	33	2.818	1.014
Impact on employees and their duties	33	3.061	0.899
Access to resources with the right expertise	33	4.394	0.827
Expertise and knowledge of AI at management level	33	4.242	0.936
Expertise and knowledge of AI in general	33	4.000	0.829
The need for skills enhancement among employees	33	3.697	1.045

RESULTS: SUBGROUP 3B

The “likely” group consisted of only 12 respondents, who were asked what factors could impact a potential AI investment.
The results show the factors that were of high importance or that could potentially impact a future decision to adopt in a negative manner.

Like subgroup 3A, this group also ranks knowledge related challenges as their top challenges, but they are the first group to mention national and public factors as having an impact and puts these in second place with 75% of the respondents claiming that these are factors that can impact adoption,

Table 16 - Group 3B - Impacting factors

Ranking	Significant factors for potential adoption	N	%
1	Access to resources with the right expertise	10	83.3%
1	Expertise and knowledge of AI in general	10	83.3%
2	A clear national commitment to AI through a national strategy	9	75.0%
2	Clear public conditions for AI governance	9	75.0%
2	Public financing / grants for AI projects	9	75.0%
2	We have a lot of unstructured data	9	75.0%
3	Expertise and knowledge of AI at management level	8	66.7%
3	Sharing data across the organization	7	58.3%
3	Privacy Protection Requirements (GDPR)	7	58.3%
3	Requirements for ethical AI governance	7	58.3%
3	The requirement for process changes	7	58.3%

In subgroup 3B it is interesting to see that the standard deviation is relatively low on most of the questions asked.
Access to the right resources, which was the no. 1 most important challenge mentioned shows a standard deviation of 0.778, while public funding was ranked as no. 2 with a standard deviation of 0,669.

Table 18 shows the mean and standard deviation for the entire group 3B.

Table 17 – Group 3B – Descriptive statistics – Mean and Standard deviation

Descriptive Statistics			
	N	Mean	Std. Deviation
A clear national commitment to AI through a national strategy	12	3.917	1.084
Clear public conditions for AI governance	12	4.083	0.996
Public financing / grants for AI projects	12	3.917	0.669
We have too much data	12	2.167	0.937
We have too little data	12	2.917	0.900
We have a lot of unstructured data	12	4.000	0.953
Sharing data across the organization	11	3.455	1.128
Data integration (data from multiple sources such as social media and the like)	12	3.333	1.231
Data integrity – poor quality, duplicates	11	3.545	1.293

Too much data bias / homogeneous data (equal to data)	9	3.333	0.707
Available technology ("shelf goods") is not relevant to us	9	2.667	0.866
Requirements for security against external threats (hacker attacks and the like)	12	3.417	1.084
Requirements for security against internal threats (human error, data manipulation and the like)	12	3.500	1.000
Ability to explain the algorithms in AI	12	2.833	0.718
Privacy Protection Requirements (GDPR)	12	3.833	1.030
Requirements for ethical AI governance	12	3.667	1.231
The requirement for process changes	12	3.583	0.515
The requirement for organizational changes	12	3.333	0.985
Negative attitudes towards AI	12	3.417	0.669
Impact on employees and their duties	12	3.167	0.718
Access to resources with the right expertise	12	4.333	0.778
Expertise and knowledge of AI at management level	12	4.250	0.965
Expertise and knowledge of AI in general	12	4.167	0.718
The need for skills enhancement among employees	12	3.750	0.866

RESULTS: SUBGROUP 3C

Subgroup 3C are the ones who have not yet evaluated AI and considers it unlikely that they will adopt AI. The group consist of 28 respondents.
This group was asked different questions than the other groups, because an assumption was made that this group has made a highlevel and unofficial evaluation which has concluded in the decision that AI is most likely not relevant for them.

The group was asked a total of six questions that covers the main areas from the literature on a high level.
Questions regarding data, governance and privacy were left out as they were considered to be a bit more detailed.
However, the questions asked provides a good overview of the challenges that these organizations consider as challenges which will keep them from adopting AI.

Table 19 shows that similar to all the other groups, the lack of resources and knowledge are ranked as the major challenges that cause the organizations to not adopt AI. Considering that this group are the ones who say that AI adoption is unlikely, only 25% say that they don't see any benefit of AI for their organization.

Table 18 – Group 3C – Impacting factors

Ranking	Significant factors for decision	N	%
1	We do not have the resources (technology and humans) to use AI	18	64.3%

2	We have little knowledge about AI and what it can do for us	17	60.7%
3	We have little knowledge of AI at the management level in our organization	16	57.1%
4	We do not have the financial means to invest in AI	12	42.9%
5	We do not know what AI will require from us and it is therefore not relevant to use it	10	35.7%
6	We see no benefit from using AI in our organization	7	25.0%

Table 20 show the descriptive statistics for subgroup 3C.

The lowest standard deviation is found in the question about knowledge on a managerial level, while the highest is found in the number one challenge mentioned by the group.
With a standard deviation of 1.445, it shows that even though this challenge has been ranked as the most significant one, the extent of the challenge is varying.

Table 19 – Subgroup 3C – Descriptive statistics – Mean and Standard deviation

Descriptive Statistics			
	N	Mean	Std. Deviation
We do not have the resources (technology and humans) to use AI	24	3.500	1.445
We have little knowledge about AI and what it can do for us	25	3.160	1.028
We have little knowledge of AI at the management level in our organization	28	3.893	0.916
We do not have the financial means to invest in AI	26	3.808	1.132
We do not know what AI will require from us and it is therefore not relevant to use it	25	4.040	1.020
We see no benefit from using AI in our organization	25	3.360	1.036

RESULTS: SUBGROUP 3D

Subgroup 3D consists of only one respondent.
Although this cannot be claimed to be representable for the population, it is still very interesting.

Being asked the same questions as groups 1, 2, 3A and 3B, this respondent gave “not important” or “to a very little extent” to every question except the four listed in table 21.

The two challenges ranked as no, 1 were given the answer “very important” or “to a very big extent” and the ones ranked as no. 2 were given “important” or “to a big extent”.

Table 20 – Group 3D – Impacting factors

Rating	Significant factors for not adopting AI
1	We have a lot of data that makes introducing AI difficult
	To be able to satisfy the requirements of the GDPR / Personal Data Act
2	Available technology (“off-the-shelf”) does not fit our purpose and our organization
	The cost of AI is higher than the possible benefits we can gain from it

4.2.4 SUMMARY OF GROUPS 1, 2, 3A AND 3B

As groups 1, 2, 3A and 3B were asked the same questions and are the groups that are most representable, the results from these groups were combined to see which factors are considered to be most challenging or have the highest impact on adoption of AI overall.

These groups combined make up approximately 76,5% of the total respondents in the survey.

Table 20 shows the 9 factors that have been mentioned to be challenging to very challenging or important to very important for the organizations in regard to adopting AI.

Lack of resources and satisfying the requirements to GDPR are the top two challenges found when comparing the results.
This aligns with the results from group 1, who said that these were the two most important ones.
Expertise and knowledge of AI in general and on management level are mentioned as the third and fourth challenge.

Table 21 – Factors of significance Groups 1, 2, 3A and 3B

Ranking	Factors of significance	N	%
1	Lack of resources with the right expertise	70	74.5%
2	To be able to satisfy the requirements of the GDPR / privacy legislation	62	65.9%
3	Lack of expertise and knowledge of AI in general	60	63.8%

4	Lack of expertise and knowledge of AI at the managerial level	55	58.5%
5	To be able to satisfy internal security requirements (human error, data manipulation and the like)	53	56.4%
6	Being able to ensure ethical AI governance in a satisfactory way	51	54.3%
7	Explain the technology decision-making process (algorithms)	49	52.1%
8	Public financing / grants for AI projects	48	21.1%
9	Difficult to upskill existing employees	47	50,0%

When viewing the descriptive statistics for these groups combined and comparing to table 22, the lowest standard deviation is found in lack of resources with right expertise (0.978) and knowledge in general (0.958)
The highest standard deviation is found in the question regarding public funding with a standard deviation of 1.390.

Table 22 - Group 1, 2, 3A & 3B - Descriptive statistics - Mean and standard deviation

Descriptive Statistics

	N	Mean	Std. Deviation
A clear national commitment to AI through a national strategy	90	2.978	1.390
Clear public conditions for AI governance	89	3.326	1.372
Public financing / grants for AI projects	87	3.333	1.335
We have a large amount of data that was difficult to handle during implementation of AI	92	2.728	1.241
Limited amount of data for our purposes made it difficult to fully benefit from AI	90	2.733	1.178
A lot of unstructured data made data processing difficult	92	3.337	1.179
We had challenges accessing relevant data from other systems and parts of the organization	89	3.101	1.158
It was difficult to combine data from different sources (such as social media and internal systems)	83	3.253	1.080
We struggled with data integrity and had a lot of incomplete data, duplicates and the like.	85	3.353	1.120
We had a lot of homogeneous data (equal to data / overweight of one type of data)	86	2.779	0.900
It was difficult to find AI technology ("off-the-shelf") that suited us	86	3.012	1.251
To be able to satisfy external security requirements (hacking etc.)	91	3.451	1.310
To be able to satisfy internal security requirements (human error, data manipulation etc.)	93	3.538	1.256
Explain the technology decision-making process (algorithms)	93	3.462	1.109

To be able to satisfy the requirements of the GDPR / Personal Data Act	92	3.935	1.165
Being able to ensure ethical management of AI in a satisfactory manner	90	3.633	1.222
Necessary process changes	91	3.121	1.073
Necessary organizational changes	92	2.967	1.094
Negative attitudes toward AI	93	2.613	1.022
Employees have become / will become redundant	91	2.429	1.056
Lack of resources with the right expertise	93	4.129	0.958
Lack of expertise and knowledge of AI at the managerial level	93	3.860	1.138
Lack of expertise and knowledge of AI in general	93	3.688	0.978
Difficult to upskill existing employees	93	3.409	1.055

4.2.5 RESULTS FROM OPEN QUESTIONS

In the survey the respondents were asked to provide information about other challenging factors that were not mentioned in the questions but that they considered to be important.

The information has been grouped by content
What is interesting is that all the challenges mentioned in the open question can be linked back to the literature except the challenge of motivation.

Table 23 - Results - Open questions

Category	Challenges and factors that can impact adoption
Technology and suppliers	• The large technology suppliers such as Google, AWS and Microsoft are a major driving force for AI. These suppliers deliver products where AI is part of the "package" and thus control some of the development in AI adoption. • An immature market and immature technologies reduce the will to invest in AI. For example; Available chatbots are of such poor quality that people do not want to invest. • Some processes are already automated by the use of other technologies, which makes it difficult to combine with AI • Old systems limit the possibilities to implement AI as it is difficult to integrate
GDPR and legal challenges	• GDPR is a barrier for AI and the Norwegian governing organizations (for example Datatilsynet) are too slow in supplying guidelines and regulations as to how organizations should govern and use AI • Norwegian laws and regulations are not updated to handle AI

Motivation	• What the competitors are doing is important for investing in these kinds of technologies • The development in AI adoption is promoted by the needs of our customers
Competence	• Knowing what we can use AI for and how much use it is to us is important. • Lack of competence in procurement • Lack of understanding of user needs • Lack of ability to define use cases / what can we use it for? • Potential partner's competence. Finding the right partners with sufficient competence is important. • Little information in society in general about using these technologies to automate parts of processes or using them to assist humans and not replace them. In other countries the discussions are not about what we should use AI for, but *how* and *why* we should use it • The Norwegian government, suppliers and users believe that AI is an IT capability and have forgotten about the "ecosystem" necessary to succeed with humans first and technology as an enabler. Not enough knowledge about what this is and how we can achieve it. • The technology is expensive, are we big enough?
Strategy	• Data governance is fundamental to adoption of AI. Meaning strategy, architecture, ownership of data and good processes for governance and quality assurance of data. • Ownership within the organization

5 DISCUSSION

This chapter discusses the findings from the study and suggest topics for further research through the discussion.

A lot of research has been done on the topic of Robotic Process Automation (RPA) in Norway, but as far as the author could find, there was no research on the use of Artificial intelligence.
Two reports were found that have been published by Microsoft and EVRY, which both show that Norway and Norwegian organizations are not using AI. The survey from Microsoft showed that Norway in fact is far behind the other Nordic and some of the European countries in terms of using AI.

The lack of research on Norwegian context leads to the research question this study aims to answer:

"What challenges can impact Norwegian organizations' adoption of Artificial Intelligence?"

The study is an exploratory study in the sense that we do not know much about this topic and because there is limited to no research on the topic in a Norwegian context.

There are two objectives of this study; 1) To get an overview of challenges that can impact the adoption of AI in Norwegian organizations and 2) Suggest areas for further research and investigation to help close the gap that exists in the literature.

A literature review formed the theoretical foundation which was used to create the questionnaire for data collection. The literature included in the review presents challenges experienced in regard to AI in other parts of the world. As this study is of an exploratory and descriptive nature, the results do not prove or disprove any hypotheses but to see whether or not these challenges also apply to a Norwegian context.

The literature revealed quite a lot of potential challenges that organizations can experience. Several factors such as time constraints and risk of losing respondents during the survey due to too many questions in the questionnaire, forced the author to include only challenges that based on the coverage in the literature and also the author's knowledge of Norwegian organizations from an IT consultancy perspective were perceived to be the main challenges.

5.1 FINDINGS AND IMPLICATIONS FOR FURTHER RESEARCH

The majority of the respondents (76.4%) have either started using AI or are implementing AI or it may be an option for them to adopt.
The remaining respondents reported that they are unlikely to adopt artificial intelligence, but one organization reported that they have decided to not adopt AI.

The literature review uncovered many different challenges that organizations might experience in regard to AI and adoption of it and that can potentially have an impact on adoption in the organizations that have not yet adopted AI.

The challenges include technological challenges such as security and explainability of algorithms, organizational challenges such as change related challenges and challenges concerning lack of knowledge of AI and finally societal challenges such as AI governance and privacy/GDPR challenges.

5.1.1 TECHNOLOGICAL CHALLENGES

Both security, and transparency and explainability which were considered technological challenges in the literature, were highlighted in the survey.
Transparency and explainability has been put into context under societal challenges in chapter 5.1.3.
Suggestions for further research is presented by bullet points.

As for security challenges it is interesting to see that the main challenge concerns the requirements for internal security to protect against human errors, data manipulation etc. Because the study does not provide any further insight into what the respondent puts into this statement, the following research questions arise:

- Does internal security concern satisfying the GDPR regulation?
- Do Norwegian organizations consider external security threats to be unlikely to happen?

5.1.2 ORGANIZATIONAL CHALLENGES

There are two organizational challenges that stand out in the study; A change related challenge which concerns the impact AI has on employees and their tasks, and knowledge related challenges.
These challenges are discussed and further suggestions for research are presented by bullet points in the text.

IMPACT ON EMPLOYEES AND TASKS

An interesting finding is that the impact of AI on employees and making employees redundant has been ranked as one of the least challenging factors.
The literature review shows that artificial intelligence does have an impact on employees, so the question is why this is not an issue for the respondents? A lot of research finds that implementing technologies such as AI that automate parts of, or entire processes will make employees redundant. If the low ranking of this challenge means that people do not become redundant, then we have two new topics of interest:

- What do the organizations do with the employees when some or all of their tasks have been taken over by AI?
- What do Norwegian organizations use AI for? And what can they use AI for?

KNOWLEDGE

The respondents were asked four questions regarding knowledge, which concerned access to resources with the right competence, knowledge on a management level in their organization and knowledge in the organization in general and also the need to upskill existing employees. Upskilling and educating employees were the lowest ranked out of the four knowledge factors. However, all these factors are highlighted as an issue by the respondents.

Lack of resources with the right competence has been rated as the top challenge by all respondents combined. The challenge is covered in the literature and has many different aspects. The "right competence" does not just concern having the technological skills and knowledge, but there is also the aspect of having domain knowledge necessary to understand the area the AI should be implemented in.
Knowing which resources an organization needs require the organization to know what they want to achieve. Lack of knowledge on a management level was mentioned as the second most important knowledge-based challenge. Not knowing what AI is and what it can do is of course a challenge for adopting AI but knowing what you are trying to achieve is a requirement for finding the right technology and resources for the job. This in turn indicates that organizations must have clearly defined goals for what they want to achieve and strategies for how to achieve these goals to succeed in adoption of AI.

- Is the use of AI a part of the strategy for organizations to achieve their goals, or is it merely a tool?

The literature also mentions that the rapid development in technology means that there is a limited amount of resources with the expertise needed to handle AI, which again can have the possibility of driving the cost of hiring these resources up as they are in high demand.

- Is the lack of resources with the right AI competence in organizations a question of limited amount of people with the right skillsets and competence or is it a question of cost?

The lack of knowledge on a management level was mentioned also ranked as a top challenge.
The literature says that lack of knowledge on a management level can cause organizations to either invest in the wrong type of technology, trying to use AI for the wrong things or to just opt out of AI entirely.

- What kind of basic knowledge should managers have to be able to make good decisions in regard to AI?

If you put lack of knowledge in combination with the hype that surrounds it, you have an entirely new issue. Some of the respondents in the survey answered in the open

question that they were looking to what competitors are doing and what their customers want and expect.
Not knowing enough about AI and what it can and cannot do, can possibly cause organizations to be carried away by the hype.

- Does the perceived pressure that follows the hype "force" organizations to invest in AI without knowing what it can really do?

5.1.3 SOCIETAL CHALLENGES

Of societal challenges, there main challenge mentioned was the requirements to satisfy GDPR. This challenge also involve governance issues which are further discussed in the section below and suggestions for research are presented by bullet points in the text.

GDPR AND PRIVACY

GDPR and privacy was ranked as the second most challenging aspect of AI adoption. The core of artificial intelligence is data processing and the more data available, the better the AI can become. GDPR was introduced in the summer of 2018 and sets entirely new requirements for the collection, storage, use and protection of data.
Although one of the principles of privacy has always been to collect as little data as possible, GDPR sets new rules for what the collected data can be used for. And a breach of the GDPR regulations can have enormous consequences for an organization.

- Has GDPR put an extra damper on the adoption of AI in Norwegian organizations?

In the survey the respondents were asked whether the requirement to explain the decision-making process in the AI was a challenge. The respondents ranked this as the 7th most challenging factor.
What makes this interesting is that the ability to explain decision-making processes is a direct requirement in GDPR under Article 22 - *Automated individual decision-making, including profiling* (Intersoft Consulting, 2018). The low ranking of the explainability of decision-making s interesting because of the connection to GDPR, but also because the public sector is strongly represented in the sample and this is a sector which collects and stores a lot of personal data.
There may of course be different explanations to this, but it does raise the question:

- Is the full scope of GDPR properly explained and understood in Norwegian organizations?

One of the respondents added that the Norwegian governing authorities such as Datatilsynet have not provided any guidelines or defined governing principles for GDPR.

- Does the lack of Norwegian governing regulations for GDPR impact the adoption of AI ?

5.1.4 DEFINITION OF AI

A question that arises from the literature, concerns the definition of AI. Sun & Medaglia (2019) argues that there is no official and agreed upon definition of artificial intelligence. This raises the following questions;

- Do Norwegian organization understand what Artificial Intelligence is, or it the term too undefined and "futuristic"?
- Does confusion of terms mean that a lot of organizations use artificial intelligence without knowing that the technology they have belongs to the AI-suite?

5.1.5 OTHER SUGGESTIONS FOR FURTHER RESEARCH

Due to the time constraint on this study, only basic descriptive results are presented by ranking (how many respondents have answered the same) and through calculating the mean and standard deviation to see where the respondents agree or disagree the most.

However, there are multiple dimensions that the data can be analyzed against, and through independent t-tests and other statistical analysis it is possible to group the respondents and compare groups by:

- Sector: Public and private sector are the two major groups of respondents in the survey. It would be interesting to see what challenges these two sectors consider to be the most relevant. Are they the same? Is the public sector more bound and inhibited by challenges related to public standards and governance?
- Size of organization: Would also be interesting to see if the size of organization has an impact on the results.
  As one respondent commented "Are we too small for AI?"

5.2 IMPLICATIONS FOR PRACTICE

The results from the survey and the literature review shows that there are especially two areas of implications for practice to enable adoption of AI.

The findings show that legal concerns such as GDPR and governance are important for adoption. As the Norwegian Government is the leading governing institution in Norway, the Norwegian government needs to put artificial intelligence on their agenda. As of December 19th, 2019, the Norwegian government's Strategy for Artificial Intelligence (Regjeringen.no, 2019) has yet to be made official.
The strategy will help govern other aspects of AI and will lead the way for Norwegian organizations to follow.

Knowledge has been the topmost discussed and rated issue in this study.
To increase the adoption of AI in Norwegian organizations, it is important that knowledge regarding AI becomes more widespread.
First of all there needs to be more research on the topic of artificial intelligence on an

organizational and national level in Norway and not just from a technological perspective. Second, the organizations that do have knowledge about AI should help spread this knowledge through for example training courses, guest lectures at universities and contribution in media.
More widespread general knowledge about AI will most likely reduce the skepticism concerning AI and help increase the adoption and thus generate more work for the suppliers.

5.3 LIMITATIONS AND DISCUSSION OF RESEARCH PROCESS.

As there is little to no research on challenges of adoption of AI in Norwegian organizations, an exploratory research design was used, with purposive and snowball sampling as the chosen sampling methods and a questionnaire was used for data collection. In this chapter the limitations of the study is addressed.

LIMITATIONS OF SAMPLING METHOD

Snowball sampling is a relatively new sampling method and although it is helpful and has been appropriate for this study, there are some limitations to it.

One of the challenges with snowball sampling is that it is not possible to control the spread of the survey if it is anonymous and this also means that there is no was of controlling that the survey was spread to people who are in the target audience.
While one of the main benefits of snowball sampling is that it can help detect groups of respondents that is not obvious, there is the risk of getting respondents that are not relevant.
This risk was mitigated by writing a description of the types of respondents that were the target group, without specifying role titles etc. and by the fact that the people who refer to other people usually have some idea of whether or not the person they refer to is relevant for the survey. Another limitation in regard to sampling is that the survey may stop spreading, and it did. It was important to not just rely on the survey spreading organically, but also continue looking for relevant respondents by purposive sampling and thus continue the spread.

QUESTIONNAIRE CONSTRUCT

When the survey was completed and the analysis of the results started, it became clear that the using “not relevant” as an alternative answer in parts of the survey caused confusion. Adding another category such as “I don’t know” would perhaps have been beneficial for the study. However, allowing for an “I don’t know” category may cause the respondent to get lazy and use this alternative instead of evaluation the other alternatives properly.
Due to the unclear meaning of the ambiguous meaning of the “not relevant” category, the values reported in this category were left out of the results and reported as missing in SPSS.

When analyzing the results it also became clear that some of the questions used in the survey did not really measure anything or at least not the right thing.
One question was " To what extent have the following either inhibited or promoted your focus on AI? Attitudes to innovation in the organization"
This question does not say anything about whether the attitudes are positive or negative attitudes toward innovation, and thus it does not measure anything except that attitudes has had some impact – but we don't know what kind.

The development of the questionnaire was difficult, and a secondary study based on this study would be beneficial to make further adjustments to the questionnaire and possibly get more accurate results.

6 REFERENCES

Bartoletti, I. (2019). AI in healthcare: Ethical and privacy challenges. *Artificial Intelligence in Medicine. AIME 2019. Lecture Notes in Computer Science. 11526*, pp. 7-10. Springer, Cham.

Crouse, T., & Lowe, P. A. (2018). Snowball Sampling. *The SAGE Encyclopedia of Educational Research,*. Thousand Oaks: SAGE Publications, Inc.

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. *Harvard Business Review*, 108-116.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, 63-71.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., . . . Williams, M. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*.

Ernst & Young LLP. (2019). *Artificial Intelligence in Europe.* EY LLP Limited.

Gabbatt, A. (2011, feb 17). *IBM computer Watson wins Jeopardy clash*. Retrieved Aug 13, 2019, from The Guardian: https://www.theguardian.com/technology/2011/feb/17/ibm-computer-watson-wins-jeopardy

Government Offices of Sweden. (2018). *National Approach to Artificial Intelligence.* Ministry of Enterprise and Innovation.

Gripsrud, G., Olsson, U., & Silkoset, R. (2010). *Metode og Dataanalyse: Beslutningssøtte for bedrifter ved bruk av JMP* (2 ed.). Høyskoleforlaget.

Guan, J. (2019, June). Artificial Intelligence in Healthcare and Medicine: Promises, Ethical Challenges and Governance. *Chinese Medical Science Journal, 34*, 76-83.

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present and Future of Artificial Intelligence. *California Management Review, 61(4)*, 5-14.

Holzinger, A., Kieseberg, P., Weippl, E., & Tjoa, A. M. (2018). Current Advances, Trends and Challenges of Machine Learning and Knowledge Extraction: From Machine

Learning to Explainable AI. *Machine Learning and Knowledge Extraction. CD-MAKE 2018. Lecture Notes in Computer Science. 11015.* Springer, Cham.

Iliashenko, O., Bikkulova, Z., & Dubgorn, A. (2019). Opportunities and challenges of Artificial Intelligence in Healthcare. *E3S Web of Conferences*, *110.*

Intersoft Consulting. (2018). *General Data Protection Regulation GDPR*. Retrieved December 19, 2019, from Art. 22 GDPR Automated individual decision-making, including profiling: https://gdpr-info.eu/art-22-gdpr/

Johnson, T. P. (2005, July 15). Snowball Sampling: Introduction. *Encyclopedia of Biostatistics*. John Wiley & Sons, Ltd.

Kaplan, A., & Haenlein, M. (2019, January - February). Siri, Siri ,in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15-25.

Kitchenham, B., & Charters, S. (2007). *Guidelines for performing Systematic Literature Reviews in Software Engineering.*

Loucks, J., Hupfer, S., Jarvis, D., & Murphy, T. (2019, May 01). Future in the balance? How countries are pursuing an AI advantage. *Deloitte Insight*. Retrieved August 25, 2019, from Future in the balance? How countries are pursuing an AI advantage: https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/ai-investment-by-country.html

Marr, B. (2019, June 3). 5 Amazing Examples Of Natural Language Processing (NLP) In Practice. *Forbes.com*. Forbes.com. Retrieved September 21, 2019, from https://www.forbes.com/sites/bernardmarr/2019/06/03/5-amazing-examples-of-natural-language-processing-nlp-in-practice/#63516b861b30

NESH • The National Committee for Research Ethics in the Social Sciences and the Humanities. (2016). *Guidelines for Research Ethics in the Social Sciences, Humanities, Law and Theology.* Oslo: The Norwegian National Research Ethics Committees .

NyAnalyse. (2019). *Digitalisering av kommune-Norge.* EVRY.

Oates, B. J. (2006). *Researching Information Systems and Computing.* London: Sage.

Pavaloiu, A. (2016). The Impact of Artificial Intelligence on Global Trends. *Journal of Multidiciplinary Developments*, 21-37.

Perc, M., Ozer, M., & Hojnik, J. (2019). Social and juristic challenges of artificial intelligence. *Palgrave Communications*. Retrieved from https://www.nature.com/articles/s41599-019-0278-x

Raaijmakers, S. (2019). Artificial Intelligence for Law Enforcement: Challenges and Opportunities. *Cybercrime and Forensics*.

Regjeringen.no. (2019). *Strategi for Kunstig Intelligens*. Retrieved December 19, 2019, from Regjeringen.no: https://www.regjeringen.no/no/tema/statlig-forvaltning/ikt-politikk/KI-strategi/id2639883/

Sadeghi, A.-R. (2017). AI Industrial Complex: The Challenge of AI Ethics. *IEEE Security & Privacy*.

Schlögl, S., Postulka, C., Bernsteiner, R., & Ploder, C. (2019). Artificial intelligence tool penetration in business: Adoption, challenges and fears. *Knowledge Management in Organizations. KMO 2019. Communications in Computer and Information Science. 2017*, pp. 259-270. Springer, Cham.

Shaw, J., Rudzicz, F., Jamieson, T., & Goldfarb, A. (2019). Artificial Intelligence and the Implementation Challenge. *JOURNAL OF MEDICAL INTERNET RESEARCH*.

Statistisk Sentralbyrå. (2019, January 30). *Establishments*. Retrieved November 2019, from Statistisk Sentralbyrå: https://www.ssb.no/en/virksomheter-foretak-og-regnskap/statistikker/bedrifter

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly, 36*, 368-383.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review, 61*, 15-42.

Tarafdar, M., Beath, C. M., & Ross, J. W. (2017). Enterprise Cognitive Computing Applications: Opportunity and Challenges. *IT professional, 19*, 21-27.

The Danish Government. (2019). *National Strategy for Artificial Intelligence.* The Danish Government, Ministry of Finance and Ministry of Industry, Business and Financial Affairs.

Thesmar, D., Sraer, D., Pinheiro, L., Dadson, N., Veliche, R., & Greenberg, P. (2019). Combining the Power of Artificial Intelligence with the Richness of Healthcare Claims Data: Opportunities and Challenges. *PharmacoEconomics*, 745 - 752.

Wang, F., & Preininger, A. (2019). AI in Health: State of the Art, Challenges, and Future Directions. *IMIA Yearbook of Medical Informatics*.

Webster, J., & Watson, R. T. (2002). Analyzing The Past To Prepare For The Future; Writing A Literature Review. *MIS Quarterly Vol. 26 No. 2*, xiii-xxiii.

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial Intelligence and the Public Sector—Applications and Challenges. *International Journal of Public Administration*, 596-615.

Yu, K.-H., & Kohane, I. S. (2019). Framing the challenges of artificial intelligence in medicine. *BMJ Quality and Safety*, 238 - 241.

7 APPENDIX

7.1 APPENDIX A – QUESTIONS AND SOURCES

Question	Source
How important has the following been to your adoption of AI? *Not important / Very little important / Somewhat important / Important / Very important / Not relevant*	
A clear national commitment to AI through a national strategy	Introduction – Lack of Norwegian government AI strategy
Clear public conditions for AI governance	Sun & Medaglia, 2019 Duan et al., 2019 Wirtz et al., 2019 Dwivedi et al., 2019
Public financing / grants for AI projects	Shaw et. al 2019
To what extent are the statements below valid for your organization? To a very small extent / To a small extent / To some extent / To a big extent / To a very big extent / Not relevant	
We have a large amount of data that was difficult to handle during implementation of AI	Schlögl et al. 2019
Limited amount of data for our purposes made it difficult to fully benefit from AI	Wang & Preininger 2019 Sun & Medaglia 2019 Tambe et al. 2019 Dwivedi et al. 2019
A lot of unstructured data made data processing difficult	Sun & Medaglia 2019 Dwivedi et al. 2019
We had challenges accessing relevant data from other systems and parts of the organization	Davenport & Ronanki 2018 Dwivedi et al. 2019 Holzinger et al. 2018
It was difficult to combine data from different sources (such as social media and internal systems)	Tambe et al. 2019 Tarafdar et al. 2017
We struggled with data integrity and had a lot of incomplete data, duplicates and the like.	Sun & Medaglia 2019 Dwivedi et al. 2019

	Yu & Kohane 2019 Tarafdar et al. 2017 Wirtz et al., 2019
We had a lot of homogeneous data (equal to data / overweight of data of one type)	Yu & Kohane 2019 Thesmar et al., 2019 Dwivedi et al. 2019 Shaw et. al 2019 Tambe et al. 2019
It was difficult to find AI technology ("off-the-shelf") that suited us	Wirtz et al., 2019 Wang & Preininger 2019 Raaijmakers, 2019 Sun & Medaglia 2019 Tarafdar et al. 2017

How important has the following been to your adoption of AI?

Not important	*Very little important*	*Somewhat important*	*Important*	*Very important*	*Not relevant*

To be able to satisfy external security requirements (hacking and the like)	Tambe et al. 2019
To be able to satisfy internal security requirements (human error, data manipulation and the like)	Pavaloiu, 2016 Holzinger et al. 2018 Shaw et. al 2019 Iliashenko et al. 2019 Wirtz et al., 2019 Wang & Preininger 2019 Perc, 2019 Dwivedi et al., 2019
Explain the technology decision-making process (algorithms)	Holzinger et al. 2018 Shaw et. al 2019 Wang & Preininger, 2019 Dwivedi et al., 2019

	Raaijmakers, 2019 Sun & Medaglia 2019 Yu & Kohane 2019 Thesmar et al., 2019 Duan et al., 2019 Sadeghi, 2017 Davenport & Ronanki 2018 Tambe et al. 2019
To be able to satisfy the requirements of the GDPR / Personal Data Act	Holzinger et al. 2018 Shaw et. al 2019 Iliashenko et al. 2019 Wirtz et al., 2019 Perc, 2019 Dwivedi et al. 2019 Sun & Medaglia 2019 Tambe et al. 2019 Schlögl et al. 2019 Bartoletti, 2019
Being able to ensure ethical AI governance in a satisfactory manner	Wirtz et al., 2019 Thesmar et al., 2019 Dwivedi et al. 2019 Guan, 2019

To what extent has the following made AI investment challenging?

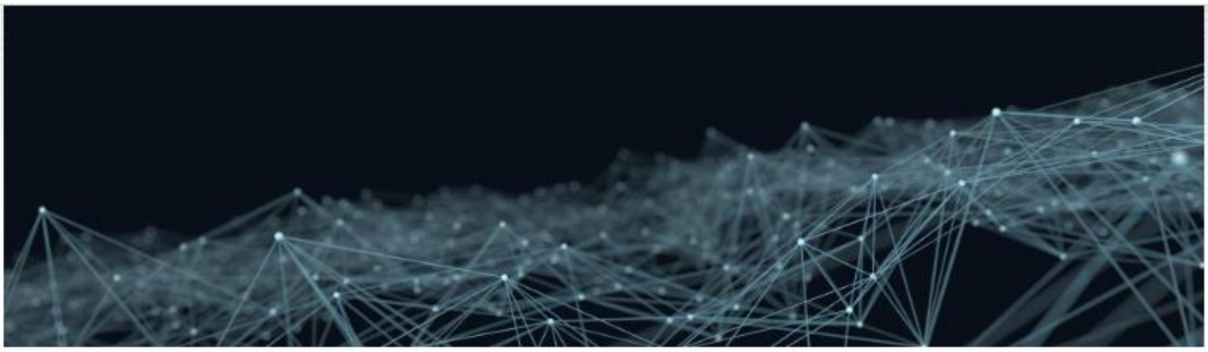
To a very small extent	To a small extent	To some extent	To a big extent	To a very big extent	Not relevant

Necessary process changes	Schlögl et al. 2019 Dwivedi et al. 2019 Yu & Kohane 2019
Necessary organizational changes	Schlögl et al. 2019

	Dwivedi et al. 2019 Yu & Kohane 2019
Negative attitudes towards AI	Schlögl et al. 2019 Dwivedi et al. 2019 Sun & Medaglia 2019 Duan et al., 2019
Employees have become / will become redundant	Schlögl et al. 2019 Dwivedi et al. 2019 Pavaloiu, 2016 Wirtz et al., 2019
Lack of resources with the right expertise	Tarafdar et al. 2017 Davenport & Ronanki, 2018 Dwivedi et al. 2019 Sun & Medaglia 2019 Wirtz et al., 2019 Raaijmakers, 2019
Lack of expertise and knowledge of AI at the managerial level	Davenport & Ronanki, 2018 Dwivedi et al. 2019 Duan et al., 2019 Schlögl et al. 2019 Iliashenko et al. 2019
Lack of expertise and knowledge of AI in general	Davenport & Ronanki, 2018 Dwivedi et al. 2019 Raaijmakers, 2019 Pavaloiu, 2016 Tarafdar et al. 2017 Duan et al., 2019
Difficult to upskill existing employees	Davenport & Ronanki, 2018 Dwivedi et al. 2019

	Raaijmakers, 2019 Pavaloiu, 2016

7.2 APPENDIX B – QUESTIONNAIRE



16%

Studie av kunstig intelligens i norske organisasjoner

I forbindelse med masteroppgave i Informasjonssystemer ved Universitetet i Agder gjennomfører jeg en studie som ser på mulige årsaker til at norske virksomheter og organisasjoner velger å ta i bruk eller ikke ta i bruk kunstig intelligens (AI).
Undersøkelsen tar kun noen få minutter og jeg håper du vil svare så oppriktig som mulig på spørsmålene.
Studien er helt anonym og din sikkerhet og rett til privatliv er ivaretatt gjennom GDPR-lovgivningen.

Definisjon av kunstig intelligens - Kalt AI i undersøkelsen:
Kunstig intelligens defineres som teknologi som utfører oppgaver som krever menneskelige kognitive egenskaper.
I hovedsak finnes det fire typer kunstig intelligens som organisasjoner benytter seg av i dag, det er maskinlæring (ML), dyp læring (deep learning), språkteknologi (NLP) og datasyn (computer vision).
Kunstig intelligens er ikke det samme som Robotisert Prosess Automatisering (RPA).

I min organisasjon har vi tatt i bruk kunstig intelligens

(1) ❑ Ja

(2) ❑ Nei

(3) ❑ Er i gang med implementering

Hvor står din organisasjon i forhold til satsing på AI?

(1) ❑ Vi er i evalueringsfase

(2) ❑ Vi har ikke gjort noen vurdering på AI i vår organisasjon

(3) ❑ Vi har bestemt at vi ikke skal satse på AI

Hva slags type(r) teknologi har dere tatt eller skal dere ta i bruk i deres organisasjon?

(Flere valg er mulig)

(1) ❑ Maskinlæring (machine learning)

(2) ❑ Dyp læring (deep learning)

(3) ❑ Språkteknologi (Natural language processing)

(4) ❑ Data syn (Computer vision)

I hvilken grad er det aktuelt å ta i bruk AI i din organisasjon på nåværende tidspunkt?

(1) ❑ I svært liten grad

(2) ❑ I liten grad

(3) ❑ I noen grad

(4) ❑ I stor grad

(5) ❑ I svært stor grad

(6) ❑ Ikke relevant

1a. Hvor viktig har følgende vært for deres satsing på AI?

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
En tydelig nasjonal satsning på området i form av en nasjonal strategi for AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tydelige offentlige rammebetingelser for styring (governance) av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Offentlig finansiering / tilskudd til AI prosjekter	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

1b. Hvor viktig har følgende vært for valget om å ikke satse på AI?

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
Manglende / uklar nasjonal satsning på området i form av nasjonal strategi for AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Manglende / uklare offentlige rammebetingelser for styring (governance) av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Manglende / uklar mulighet for offentlig finansiering / tilskudd til AI prosjekter	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

1c. Hvor viktig vil følgende være for en eventuell satsing på AI?

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
En tydelig nasjonal satsning på området i form av nasjonal strategi for AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tydelige offentlige rammebetingelser for styring (governance) av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mulighet for offentlig finansiering / tilskudd til AI prosjekter	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

1d. Hvor viktig vil følgende være for en eventuell satsing på AI?

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
En tydelig nasjonal satsning på området i form av nasjonal strategi for AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tydelige offentlige rammebetingelser for styring (governance) av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mulighet for offentlig finansiering / tilskudd til AI prosjekter	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

1e. I hvilken grad stemmer påstandene under for din organisasjon?

	Stemmer svært dårlig	Stemmer dårlig	Stemmer noe	Stemmer godt	Stemmer svært godt	Ikke relevant
Vi har ikke de økonomiske midlene til å satse på AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi ser ingen fordeler ved å benytte AI i vår organisasjon	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har lite kunnskap om AI og hva det kan gjøre for oss	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har lite kunnskap om AI på ledernivå i vår organisasjon	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har ikke ressurser (teknologi og mennesker) til å ta i bruk AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi vet ikke hva AI vil kreve av oss og det er derfor ikke aktuelt å ta i bruk	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

2a. I hvilken grad stemmer påstandene under for din organisasjon?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Vi har svært mye data som var vanskelig å håndtere ved innføring av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Begrenset mengde data til vårt formål gjorde det vanskelig å få fullt utbytte av vårt AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mye ustrukturert data gjorde dataprosesseringen vanskelig	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi hadde utfordringer med å få tilgang på relevant data fra andre systemer og deler av organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Det var vanskelig å kombinere data fra forskjellige kilder (som f.eks sosiale medier og interne systemer)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi slet med dataintegriteten og hadde mye ufullstendig data, duplikater o.l.	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi hadde mye homogen data (lik data / overvekt av data av en type)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Det var vanskelig å finne AI teknologi ("hyllevare") som passet oss	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

2b. I hvilken grad er følgende påstander relevante for deres valg om å ikke satse på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Vi har svært mye data som gjør en innføring av AI vanskelig	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har begrenset med data og får derfor ikke noe særlig utbytte av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har mye ustrukturert data som gjør dataprosesseringen svært vanskelig	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Det er vanskelig å dele data på tvers av systemer og organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Det er vanskelig å kombinere data fra forskjellige kilder (f.eks	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
sosiale medier og interne systemer)						
Vi har dårlig dataintegritet - mye ufullstendig data, duplikater o.l.	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
For mye homogen data (lik data/overvekt av en type data)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tilgjengelig teknologi ("hyllevare") passer ikke til vårt formål og vår organisasjon	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

2c. I hvilken grad kan følgende hindre en eventuell satsing på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Vi har for mye data	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har for lite data	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har mye ustrukturert data	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Deling av data på tvers av organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Dataintegrasjon (data fra flere kilder som sosiale medier o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Dataintegritet - dårlig kvalitet, duplikater	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
For mye datapartiskhet / homogen data (lik data)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tilgjengelig teknologi ("hyllevare") er ikke relevant for oss	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

2d. I hvilken grad kan følgende ha en negativ påvirkning på en potensiell satsing på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Vi har for mye data	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har for lite data	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vi har mye ustrukturert data	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Deling av data på tvers av organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Dataintegrasjon (data fra flere kilder som sosiale medier o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Dataintegritet - dårlig kvalitet, duplikater	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
For mye datapartiskhet / homogen data	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Tilgjengelig teknologi ("hyllevare") er ikke relevant for oss	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

3a. Hvor viktig har følgende vært for deres satsing på AI?

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
Å kunne tilfredsstille krav til ekstern sikkerhet (hacking o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å kunne tilfredsstille krav til intern sikkerhet (menneskelige feil, datamanipulering o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å kunne forklare teknologiens beslutningsprosess (algoritmer)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
Å kunne tilfredsstille krav til GDPR / personopplysningsloven	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å kunne sikre etisk styring av AI på en tilfredsstillende måte	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

3b. I hvilken grad har følgende bidratt til valget om å ikke satse på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Å kunne tilfredsstille krav til ekstern sikkerhet (hacking o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å kunne tilfredsstille krav til intern sikkerhet (menneskelige feil, datamanipulering o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å kunne forklare teknologiens beslutningsprosess (algoritmer)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å kunne tilfredsstille krav til GDPR / personopplysningsloven	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Å kunne sikre etisk styring av AI på en tilfredsstillende måte	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

3c. I hvilken grad kan følgende hindre en eventuell satsing på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Krav til sikkerhet mot trusler utenfra (hackerangrep o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Krav til sikkerhet mot trusler internt (menneskelige feil, datamanipulering o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Evne til å forklare algoritmene i AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Krav til sikring av personvern (GDPR)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Krav til etisk styring av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

3d. I hvilken grad kan følgende ha negativ påvirkning på en potensiell satsing på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Krav til sikkerhet mot trusler utenfra (hackerangrep o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Krav til sikkerhet mot trusler internt (menneskelige feil, datamanipulering o.l.)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Evne til å forklare algoritmene i AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Krav til sikring av personvern (GDPR)	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Krav til etisk styring av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

4a. I hvilken grad har følgende gjort satsing på AI utfordrende?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Nødvendige prosessendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Nødvendige organisasjonsendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Negative holdninger til AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Ansatte har blitt/vil bli overflødige	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mangel på ressurser med rett kompetanse	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mangel på kompetanse og kunnskap om AI på ledernivå	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Mangel på kompetanse og kunnskap om AI generelt	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vanskelig å heve kompetanse på AI hos ansatte	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

4b. I hvilken grad har følgende bidratt til valget om å ikke satse på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
AI krever prosessendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
AI krever organisasjonsendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Negative holdninger til AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Vanskelig å heve kompetanse på AI hos ansatte	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
AI kan gjøre ansatte overflødige	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mangel på ressurser med rett kompetanse	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mangel på kompetanse og kunnskap om AI på ledernivå	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mangel på kompetanse og kunnskap om AI generelt	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

4c. I hvilken grad kan følgende hindre en eventuell satsing på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Kravet til prosessendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Kravet til organisasjonsendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Negative holdninger til AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Påvirkning på ansatte og deres arbeidsoppgaver	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tilgang på ressurser med rett kompetanse	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Kompetanse og kunnskap om AI på ledernivå	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Kompetanse og kunnskap om AI generelt	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Behovet for kompetanseheving blant de ansatte	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

4d. I hvilken grad kan følgende ha negativ påvirkning på en potensiell satsing på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Kravet til prosessendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Kravet til organisasjonsendringer	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Negative holdninger til AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Påvirkning på ansatte og deres arbeidsoppgaver	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tilgang på ressurser med rett kompetanse	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
God kompetanse og kunnskap om AI på ledernivå	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
God kompetanse og kunnskap om AI generelt	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Behovet for kompetanseheving blant de ansatte	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

5a. I hvilken grad har følgende enten hemmet eller fremmet deres satsing på AI?

	Hemmet mye	Hemmet noe	Hverken hemmet eller fremmet	Fremmet noe	Fremmet mye	Ikke relevant
Mulige konkurransefordeler ved bruk av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	Hemmet mye	Hemmet noe	Hverken hemmet eller fremmet	Fremmet noe	Fremmet mye	Ikke relevant
Tilgjengelighet på økonomiske midler til å satse	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Ønsket om å møte markedets forventninger om bruk av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Holdninger til innovasjon i organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

5b. I hvilken grad har følgende bidratt til valget om å ikke satse på AI?

	I svært liten grad	I liten grad	I noen grad	I stor grad	I svært stor grad	Ikke relevant
Holdninger til innovasjon i organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mangel på tydelige konkurransefordeler	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Mangel på økonomiske investeringsmidler	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
AI koster mer enn det smaker	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
AI passer ikke til vår organisasjon	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

5c. Hvor viktig vil følgende være for en potensiell satsing på AI?

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
Holdninger til innovasjon i organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Potensielle konkurransefordeler	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Etablering av gode retningslinjer for regulering og styring av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Tilgjengelige økonomiske midler for satsing	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å tilfredsstille markedets forvetninger om å bruke AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

5d. Hvor viktig vil følgende være for en potensiell satsing på AI?

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
Holdninger til innovasjon i organisasjonen	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Potensielle konkurransefordeler	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Etablering av gode retningslinjer for regulering og styring av AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

	Helt uviktig	Lite viktig	Noe viktig	Viktig	Svært viktig	Ikke relevant
Tilgjengelige økonomiske midler for satsing	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑
Å tilfredsstille markedets forvetninger om å bruke AI	(2) ❑	(3) ❑	(4) ❑	(5) ❑	(6) ❑	(1) ❑

6. Finnes det andre elementer som har hatt betydning som ikke allerede er nevnt?

____

Noen få opplysninger om deg og din organisasjon

I hvilken sektor tilhører din organisasjon?

(Flere valg er mulig)

(1) ❑ Privat

(2) ❑ Offentlig

(3) ❑ Akademia

(4) ❑ Frivillig organisasjon

Hvilken bransje tilhører din organisasjon?

(Flere valg er mulig)

(1) ❑ Helse

(2) ❑ Varehandel

(3) ❑ Bank / forsikring

(4) ❑ Industri

(5) ❑ Undervisning

(6) ❑ Bygg og anlegg

(7) ❑ Offentlig administrasjon

(8) ❑ Transport

(9) ❑ Kultur og tjenester

(10) ❑ IKT

(11) ❑ Overnatting og servering

(12) ❑ Annet ______

Hva er din rolle/tittel i organisasjonen?

______

Hvor mange ansatte er det i din organisasjon?

(1) ❑ 0-9

(2) ❑ 10 - 49

(3) ❑ 50 - 99

(4) ❑ 100 - 499

(5) ❑ Over 500

Undersøkelsen er nå avsluttet.

Tusen takk for ditt bidrag!
Del gjerne undersøkelsen med andre: Spørreundersøkelse

Dersom du har noen spørsmål angående undersøkelsen, ta gjerne kontakt på epost