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Failure in AI Projects:

What organizational conditions and how will managements' knowledge, organization and involvement contribute to AI project failure

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This thesis is worth 30 study points

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Finally, I have come to the end of this master’s thesis which marks the end of a master's degree in economics and management with specialization in industrial economics at the University of Southeast-Norway at Kongsberg.

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Abstract

Artificial Intelligence (AI) has become a widely used term in the business world in recent times and is one of the most groundbreaking technologies being developed today. In recent years, companies have favored to see the benefits and opportunities of using AI to improve their business processes. This master thesis will take a closer look at the problems with AI projects failing. A literature review that was done prior to the master's thesis showed that there is little research on the phenomenon and that there is a need for further research into the reasons behind why so many AI projects are failing. This study will have a look at how managers' knowledge and involvement in AI projects affect the success rate, how companies' organization and organizational conditions will contribute to the failure of AI projects. This is a qualitative study where in-depth interviews have been conducted by a selection of informants with a background in Data Science, consulting, and research. The approach is exploratory where the purpose was to uncover both known and unknown reasons why AI projects fail. The results from the study show many of the same findings that have been made in previous studies. The main findings from this study are 1) lack of knowledge among managers, 2) poor handling of the data and 3) poor planning and organization of AI projects. The findings show that there is a need for more knowledge about the AI technology and the areas of user applications among managers in Norwegian companies. Managers have unrealistic expectations of their own data and what AI can do for their business. There is also a lack of how the business needs should be communicated to the project team when the management lacks technology understanding, and the team does not understand what needs the problem should meet for the business or the customer. Managers lack knowledge of how much resources and preparation that must be done in advance before the project can start. The same applies in the operational phase where managers do not know that they must have extra resources for monitoring and maintenance in the aftermath of implementation. An AI project is an exploratory process where there is a need for an acceptance for failing and that it contributes to learning and improvement of processes. AI projects will also need more AI-friendly methodologies that support the interdisciplinarity and complexity of an AI project rather than the sequential methods most commonly used today.

1. Introduction

1.1 Background

We are living in a time where major changes are taking place in the business world where digitalization and the use of IT tools have become a part of everyday life. The prevalence of digitalization in business means that it will be necessary for companies to keep up with new developments in technology to avoid being outcompeted by companies that have come further with digitalization. The workplace is becoming more and more digital where you need to use digital tools for your work, which will require more knowledge about technology.

In recent years, there has been more and more talk about Artificial Intelligence (AI) and the opportunities it brings with it for more efficiency in the work tasks. Some are skeptical while others see what great benefits the company can have from benefiting from AI in its operational activities. It may seem that AI has come to stay in the future and that companies are dependent on keeping up with the AI trends to increase profitability and efficiency in line with their competing companies that are using AI.

Along with the growth of AI projects in companies it has also become known that they have a higher rate of failure compared to other projects. Many leaders and investors are reluctant to invest in AI projects due to the high risk of wasting money associated with the failure rate found in AI projects (TechProResearch, 2020). AI projects are often highly expensive in combination with a great risk in which there are many pitfalls, and you will not get the outcome you had planned (Mendels, 2019). Many of the reasons for this are a lack of AI knowledge since there are few people who have managed to gain great experience and expertise on AI projects (Tauli, 2019). There are also pitfalls in the processing of data for use in AI. There is a need for more knowledge about cleaning the data before use and how to avoid bias in the data set.

One of the challenges in connection with the failures of AI projects is that there is poor communication and collaboration between the engineers and the management (Basefarm

Digital Ability Report, 2018). The engineers lack an understanding of the business's interests and perspective, understanding of the customer needs and other stakeholders. This makes them fail to meet the company's interests and strategic goals. The management, on the other hand, lacks enough knowledge about technology and AI to be able to see what benefit they can get from AI and what opportunities there are.

1.2 The Objectives and Research Questions

When I started thinking about suggestions for topics for my master’s thesis, I knew I wanted to write about something in innovation and technology. Innovation and technology are very interesting topics because it covers many new subject areas and says something about how the future business world will be. In the beginning, I wanted to carry out a study on companies' ability to innovate, but gradually the problem was narrowed down to AI projects that fails. Artificial intelligence is here to stay and is a technology that we economists will also encounter in our working life. More and more companies are using AI technology to automate their services and tasks, but most do not reach their goals with their started AI plans (Bayem, 2019). I thought it was an interesting and highly relevant topic that I would investigate further and learn more about. This is also an important topic to study because so little research has been done in the area before. The problem of many AI projects failing shows that there is a need for more knowledge and research on how organizations can succeed with AI and what organizational conditions need a change to facilitate AI. This made me even more interested in investigating more deeply about why AI projects fail and what organizational barriers stand in the way today.

Prior to the work on the master's thesis, a literature review was carried out on why AI projects fail and what pitfalls exist. Based on the existing literature and previous research in this area, I wanted to go ahead with examining AI projects in Norway with the intention of finding out what underlying factors may be causing AI projects to fail. This is also a topic on which there is little previous research, and it is constantly being developed, which makes it particularly interesting to study more closely.

It was also desirable to look further into whether there is a lack of knowledge among the management in organizations that is one of the main reasons why AI projects fail, or whether there are other factors behind it. Previous research finds that the main reasons for failure in AI projects are the lack of trust in the project team's skills and poor communication between the management and the project team. The goal of this study is to go deeper into the issues and investigate the underlying factors that cause project failure. I want to find out why management doesn't have confidence in the project team of AI projects and why AI projects that have closer communication with the management are more successful. (TechProResearch, 2019)

The purpose of this master's thesis is to explore projects in artificial intelligence to find out what factors can contribute to the failure of most AI projects. The survey will be limited to AI projects in Norway, specifically in the Oslo area. Through in-depth interviews with practitioners who work with and have experience with AI projects, I want to gain a deeper insight into how AI projects in Norway will be carried out and then find strengths and weaknesses. I am interested in finding out what can explain the high failure rate of AI projects and whether it is equally prevalent in Norwegian companies. It will therefore be exciting for me to investigate factors such as companies' knowledge, attitudes, expertise and culture, and how these can affect the success of the AI projects. The reason I want to carry out this study is that this is a problem that can be solved or improved with more knowledge and understanding of the reasons why AI projects fail. The scope of this study will be limited to the organizational areas and will not go into the technical aspects of which I do not have enough expertise. There will be a focus on the interaction between the management and the project team and how the projects are handled. This inquiry will be able to make a contribution to the research through qualitative interviews that will delve into the problems. The previous surveys conducted by others are largely quantitative surveys that do not say anything about the participants' own thoughts and interpretations of why AI projects fail. The results of this master's thesis may contribute to more knowledge among companies and managers about how to meet and plan their AI projects in order to succeed.

The research questions in this thesis should be able to provide answers to the factors among managers and organizations that are contributing to AI projects failing, and how to strengthen or change these factors.

The research questions for this master's thesis are as follows:

1. *How will managements' knowledge and involvement in AI projects contribute to failure in AI projects?*

2. *How will corporates organization of AI projects contribute to project failure?*

3. *What organizational conditions contribute to failure in AI projects?*

1.3 Thesis Structure

The theoretical foundation for the master's thesis will begin with Chapter 2.1, which provides a theoretical review of the technology around artificial intelligence, AI projects and the use of artificial intelligence in the business sector. The purpose is to give the reader an understanding of artificial intelligence, applications and what AI projects entail. In chapter 2.2 there will be a review of data-driven project management with various project methods used in AI projects and the coordination of the teams in AI projects. This sub-chapter will contribute to a better understanding of how data-driven projects, including AI projects differ from other projects. The sub-chapter will contain the project team and which project methods are most beneficial to use in AI projects to give the reader insight into the processes surrounding implementation. The last sub-chapter 2.3 deals with the most common organizational barriers to AI projects not being completed or getting started. This sub-chapter will contribute to insight into the most common pitfalls of AI projects and what conditions should be present to succeed.

Chapter 3 represents a method in which the methodological choices for the study are reviewed and justified. The implementation of data collection and data analysis will also be described.

Chapter 4 contains the analysis of the data collected where selected statements from the informants are presented and where the information is interpreted.

In Chapter 5, the results that emerged in the analysis of the data will be presented and discussed considering existing literature in this area.

Chapter 6 will contain the conclusions of the research questions and what the findings will contribute to research. Limitations of the study and suggestions for further work will be presented.

2. Artificial Intelligence in Projects

2.1 Introduction to Artificial Intelligence

Artificial Intelligence (AI) has become a widely used term in the business world in recent times and is one of the most groundbreaking technologies being developed today. Most people have or will at some point encounter this phenomenon, either privately or in the workplace. Although the use of the term has increased mostly in recent years, it has been around for years. It was during a seminar at Dartmouth College in 1956 that one could hear about Artificial Intelligence for the first time (Valmot, 2014). Since then, the concept has evolved from only been used for games and simple calculation, to be able to solve complex tasks and imitate human intelligence.

In order to assess whether a machine is intelligent or not, it must pass the so-called Turing test named after the computer scientist Alan Turing (Tauli, 2019). The test involves that a human and a machine should play a game against each other where a control person has to guess who is human and which is the machine. If the control person is unable to recognize which one is a machine, it means that the machine is intelligent. Chess robots developed with AI for example, will be invincible because the machine can learn to solve the most complex tasks in an incredibly short time. A chessboard has $10^{\wedge 120}$ different outcomes before the game begins (Kasparov, 2010).

The technology still has a long way to go in the development before it can imitate human characteristics and emotional life but can function as a good alternative to tasks that involve large data sets where there is no need for human assessment (Bjørkeng, 2018). AI will in many ways do a better job than humans in that it will make fewer mistakes, more accurate decisions and will be more trustworthy than humans in some tasks. In other words, AI will be able to adapt many of people's work tasks, which will lead to many employees becoming excessive. AI can be used in self-driving cars, planes, and boats. It will automate storage workers, production workers and eventually also surgeons with the use of robots. There are many people who are skeptical of artificial intelligence and imaging frightening scenarios where robots take over the world or start living their own lives, but this is far from the AI technology that exists today. Humans still have control over what tasks an AI tool should be performing and it will not be able to take over the control of humans. We differentiate between weak AI and strong AI where weak AI is where the technology has come today (Tauli, 2019). Strong AI is the type of AI we think of developing in the future, also called Artificial General Intelligence (AGI) that will be able to solve advanced tasks far beyond our comprehension. For example, there may be developments of machines that have human characteristics such as morality, creativity and even consciousness. It's not certain if we'll ever get that far with AI and in that case, it could be decades away.

2.1.1 Big Data and GDPR

Developing AI will require huge amounts of digital data collected in large datasets. (Bjørkeng, 2018) This is what we call Big Data owned mostly by companies or organizations (Datatilsynet, 2013). The datasets can contain millions of data and for this, a lot of resources will be required for storing, and handling of the data. First, it will require computers with great power to process the huge amounts of data and storage capacity (Niebel, T., Rasel, F., & Viete, S. , 2018) . Big Data contains all the information recorded through sensors, everyone's behavior on the internet, money transactions, photos, gps-positions and text documents. Hence, it is not an easy job for companies to structure, analyze, clean, and look for patterns in information from these amounts of data. With the help of artificial intelligence, we now have the ability to quickly separate out information and recognize patterns in the data. This can be a good use for companies to be able to predict trends based on historical data and see connections the human brain cannot see (Datatilsynet, 2013).

The use of Big Data will also impose strict privacy requirements when handling and storing datasets that contain personal information from private individuals. The European Union (EU) has developed a regulatory framework around the handling of personal data through the General Data Protection Regulation (GDPR) (EU, 2021). All companies in the EU must comply with the regulations regulated under the GDPR when dealing with large data sets from consumers or patients. The regulations also include companies outside the EU that handle data from private individuals living within the EU. This is to protect private individuals from their personal information being stored and used by others without their consent. For example, most things you do on the internet from searches and clicks will be stored and handled by companies, when you give your consent to allow “Cookies”. There are many opinions about the limitations GDPR sets for the development of AI in Europe and that the regulations are too strict to be able to develop better AI (Castro, D. & Chivot, E., 2019). Especially in medicine that has great potential to be able to use AI to diagnose and recognize, for example, cancer, cardiovascular diseases and Covid 19 (Watts, M. & Hatzel, J., 2021). The strict regulations around patient records and the fact that few people will give their consent for companies to handle their personal information therefore put an end to their development.

2.1.2 Machine Learning

AI technology works in this way by inserting input data into the form of a data set into the machine that will be able to quickly recognize patterns in the data set and predict an outcome using advanced statistical calculations (Bjørkeng, 2018). This process requires that a specific output or result is given which the machine must be trained to be able to distinguish from the data set and then learn to recognize. The data set should contain a high number of historical data in order to have a good enough data label for the training. The machine learns by trial and wrong decisions and that each wrong step the machine will be able to increase its accuracy by reducing the number of possible error decisions. It is as if the machine learns through its own experiences and will avoid making decisions that do not lead to the expected outcome. The process is what we call machine learning and can take place over several hours of training.

When training a machine to perform a task, an algorithm must be placed. An algorithm is a set of rules in a programming language that the machine must follow in order to get the output we want (Hovde &Grønmo, 2020). It can be compared to the arithmetic rules in mathematics. The machine then must follow the algorithm determined by the programmers in order to arrive at the desired output. The output will contain a specific criteria such as an image of an apple. An easy way to explain the decision-making process is to imagine a tree, where each branch represents several choices with different outcomes. This is called a decision tree where the machine weights each branch with different values or arguments and makes the decision that the weighs heaviest . These branches with choices that we find between input and output are called neural networks and they have similarities with the neural networks in the brain when we make decisions (Bjørkeng, 2018). A decision made by a machine can be explained for example through a data set with many different images (Sander, Beslutningstre, 2019). The machine will give each image the value 0 or 1. The value 1 means that the image is of an apple and the value 0 means that the image contains something other than an apple. The process is a bit more advanced than that, where each image is divided into pixels where the machine uses advanced statistical methods to calculate how likely it is that each individual pixel will represent part of an apple. For this type of learning, the term guided learning is used where output is given and where people can monitor the decisions the machine makes and adjust the weighting if necessary.

The type of machine learning when there is no given output has the concept of non-supervised learning. Unsupervised learning is a type of learning where the goal is for the machine to make decisions based on input data where the output is unknown. While in supervised learning there is only one decision tree, in non-supervised learning there will be an enormous number of decision trees that are weighted in parallel. This is what is called deep learning where the weighting algorithm is kept hidden from us. Challenges associated with this type of learning are that one does not get to know how the machine arrives at the decision and on what basis. This could lead to skepticism and opposition from being able to be used in court decisions, employment, and processing of trials. On the other hand, it works great in face recognition or motion recognition.

2.1.3 Creation of the AI model

When implementing AI in the company, you can use existing AI tools and platforms, or you can choose to develop your own software (Tauli, 2019). You should get acquainted with what IT equipment is in the company and what opportunities you have with the existing IT structure. As said before, it is very expensive to replace all the IT in the company. Using existing AI tools is the simplest and most affordable option and there are numerous AI tools that are so-called open source (Ismail, 2020). Open source is an AI framework that is a pre-programmed machine learning tool that makes it easy for developers to enter datasets, train the machine and adjust parameters along the way.

Furthermore, one should think about which programming language one wants to use. Python is the most widely used programming language in AI because it is one of the easiest languages to learn, but one can also use C++, C#, and Java even though they are more advanced to use (Tauli, 2019). In recent years, an even more efficient AI tool called AutoML which stands for Automated Machine Learning has emerged. The idea behind the tool is that companies that do not have enough expertise in machine learning should be able to create simple AI models. Table 1 on the next page shows the results of the improvement after the implemented AutoML in the company Lenovo Brazil. Although the results show a clear improvement, these results will unfortunately not apply to everyone. Lenovo Brazil had the advantage of having a computer scientist with expertise in machine learning. The expert had a better understanding of the nuances of machine learning and could adjust for biases and optimize learning. If you don't have a professional data scientist to perform the task, the results can be very different and may even be aggravated compared to without the use of AI.

Table 1

Tasks	Before	After
Model creation	4 weeks	3 days
Production models	2 days	5 minutes
Accuracy of predictions	<80%	87.5%

The effect of AutoML (Tauli, 2019)

In order to assess whether the AI model has been a success, it will be useful to select KPIs that measure how well the model works (Tauli, 2019). This can be for example customer satisfaction, number of errors, accuracy, or speed. There will always be room for improvement and the AI model will need adjustments if the accuracy goes down or the decisions are not good enough.

2.1.4 Changing Business World

In recent years, companies have favored to see the benefits and opportunities of using AI. This will increase the competitive forces in the market by companies saving a lot of time and resources, increasing efficiency and improving products and services. There will be large cost savings to be made that will give a better profit for the company. AI can be used for prediction by being able to predict when machines and fixed assets need maintenance, sales analysis, and customer analyzes. (Tauli, 2019) It will contribute to increased safety and shorter downtime. You will receive an alert that the machine or plant needs maintenance or replacement before an accident occurs or becomes out of date. Prediction of sales and customer behavior will help the company to anticipate when the customer usually repurchases a product and be better able to adapt production or purchasing to demand.

Amazon has had great success in changing their business model using this type of prediction (Agrawal, A., Gans, J., & Goldfarb, A., 2018). Instead of the customer ordering and Amazon delivering, the item is already shipped before the customer makes their order.

This will be able to help reduce the storage costs, obsolescence, and delivery times for the customer. There are also great opportunities for using AI in finance. The machine can detect and reduce errors as well as detect suspicious transactions and events. Other possibilities are decision-making AI where the machine makes decisions based on historical data and by predicting which decision will be able to give the best outcome. AI is also a useful tool for digitalization of project management, and it is said that in a few years, 80% of project-related work tasks will be taken over by AI (Costello, 2019). These involve tasks in planning, budgeting, monitoring, and measuring the progress of the project.

What makes it easy for a company to use AI is that you don't need programmers to program a completely new software. The software for using AI has already been programmed to be used to train the computer to find special patterns in data sets. It is also possible to create your own in-house models instead of buying software from outside (Tauli, 2019). The most common uses for AI today include the use of chat bots, where the machine learns to recognize words and concepts from customers to be able to offer customer service in the same way as human customer service representatives (Tauli, 2019). Chat bots will over time learn the language and become more and more accurate in what the customer's needs are. This tool only works for simple frequently asked questions from customers and will not be able to completely replace the customer service representative.
Artificial intelligence is also often used in marketing channels such as online stores, where the machine learns to recognize each customer's shopping pattern and interests based on data, they leave behind by looking at products, web searches and activity on social media. The machine will then be able to display customized advertising and suggestions for products that it believes the customer will be interested in (Bjørkeng, 2018). This type of marketing will be able to increase sales by marketing directly to those who are interested in buying the product. Other uses for AI technology are face recognition, diagnostics by seeing patterns in X-rays or medical records.

Tesla has implemented AI in its cars that can recognize the owner who walks towards the car and opportunities to start the car with a voice control (Bjørkeng, 2018). Tesla's cars are equipped with sensors that constantly collect user data about the user's driving behavior and behavior in traffic. In this way, the cars learn to recognize movements and objects in traffic, such as whether it is a human being crossing the road or whether it is a pole. This collection of data will be useful for machine learning if it will be safe enough for more use of self-driving cars in the future. It is not only in cars where this self-driving technology is developed, but also in shipping, submarines, and aircrafts. The challenge with this is how much we can rely on technology and whether we will have enough confidence to risk our lives and safety.

What is important to think about before starting to implement AI in the company, is to check that the data is clean and that it does not contain errors or bias (Tauli, 2019). Then you should clean the data set for any discrepancies. It is also an advantage that you have randomized the data because if they are sorted by a system, the machine will see a pattern in the data and learn on the wrong conditions.

2.2 Data-Driven Project Management

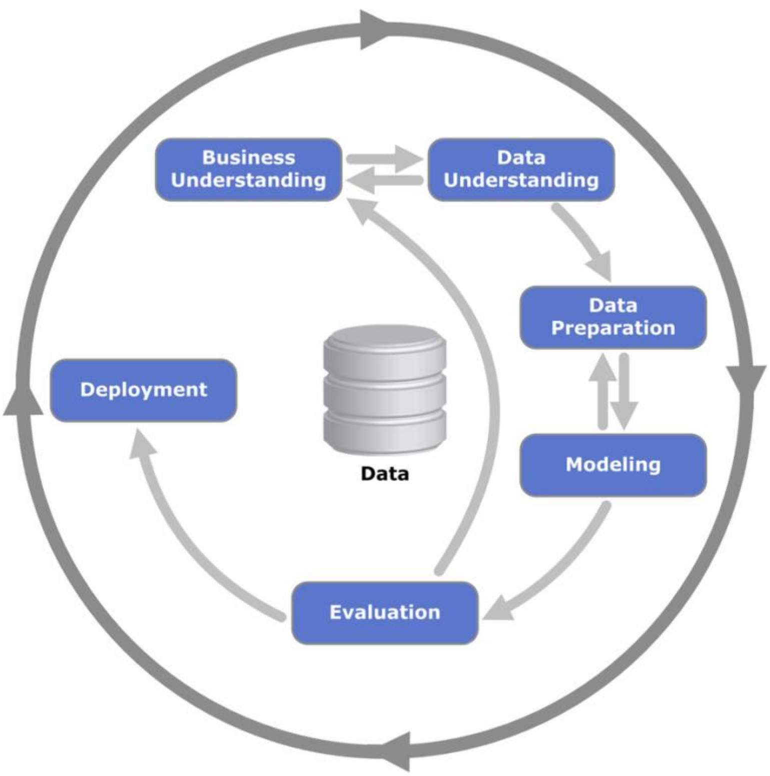
Project management differs from traditional management in that it is a temporary process, while management is an ongoing process (Murray-Webster, 2019). Project management is becoming more and more data-driven and there is a need for new and updated knowledge in project management, as AI will become an integral part of project management in the future. (Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Jonsdottir, H., 2021) Using the traditional methods that have been used in the software industry is often development-based and has more focus on the organizational structure (Walch, 2020). These methods will challenge AI projects by having AI projects focus more on the data material and training of data that is a continuous process, even after the project is completed. AI projects depend on the quality of the data and how it is collected. Traditional software projects focus more on programming. Project management of an AI project will differ from other projects in that it is more open and not a set plan to be followed (Govindarajan, 2014). It is common to have a more experimental approach to the project where one tests and improves along the way. Therefore, there are no absolute requirements for how the final product will become. The gap in competence and communication between the project teams and management may result in the AI product not meeting business goals and the user's needs. There is a lot of uncertainty surrounding an AI project because of the requirements for data quality and competence. It is important that the AI project is integrated with the business strategy to achieve the desired outcome (Najdawi, A. & Shaheen, A., 2021).

2.2.1 Methodology in AI Projects

AI projects need a different approach and methodology than traditional software projects. (Walch, 2020) Agile methods are the approach that has emerged in recent years and is becoming more and more popular in innovative companies. In the traditional approaches, the project is performed step-by-step where each step can take months or years before it is finished and can begin on the next step. An agile approach to the project makes it possible to divide into smaller processes where one works iteratively and faster can deliver a product that works out to the user. The project team will be able to make quick changes than stick to a strict plan. The agile approach is based on spending less time on processes that delay the development of the product such as traditional project planning with documenting, contracts and sticking to the plan (Beck, K., et al., 2001). There will be more time to develop the product and get it out to the user. The method focuses on and sees the value of better interaction between the developers, business side and customer, continuously improving and delivering new products.

There is a need for a methodology that considers that the AI project is more computerized and has a different life cycle (Walch, 2020). It must be considered that the work on the data material is the largest part of the project and that there are several steps to be taken in the field of handling data from planning until the data is fully structured and cleaned. AI projects therefore need a more specific methodology that addresses the different phases found only in AI projects. CRISP-DM (Cross Industry Standard Process for Data Mining) is the best known and used methodology in AI and machine learning (Bouvet, 2021). The methodology was originally developed in 1996 for use in data mining. Data mining is the processing of large datasets to extract information and see patterns in the data using statistical methods (Sannsyn, 2020). CRISP-DM divides the project into six stages where one starts with planning the business goal and what the purpose of the product is. Then follow the steps through data understanding, data preparation and modeling, which deals with the work on the data material, building the model and testing the result. This plan is not a fixed plan that needs to be followed, but you can jump back and forth and adjust the model. The model will then be evaluated whether it is ready for implementation or if changes are needed. In the figure 1 below, the process in CRISP-DM is presented and as seen, the approach is an iterative and agile process without a strict multi-phase plan with documentation and requirements.

Figure 1

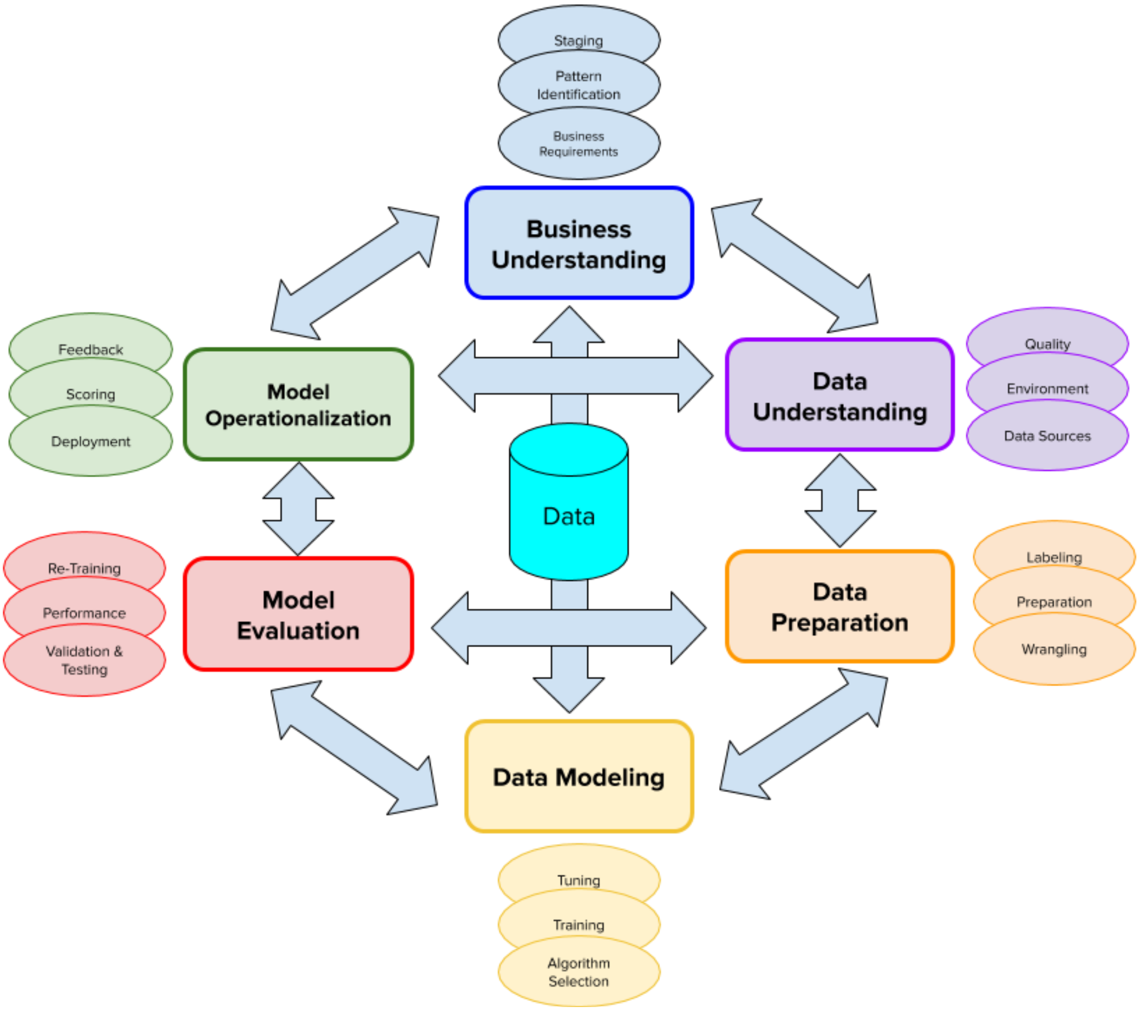


CRISP-DM Model (Bouvet, 2021) Reference: https://www.bouvet.no/ting-vi-kan/fagomrader/innsikt-data-og-analyse/cross-industry-standard-process-for-data-mining

This model also has some weaknesses in that it is better suited to smaller AI projects where the data material already exists (Bouvet, 2021) . The model is very clear and easy to understand, but if you are going to start a larger AI project where there is no data already available and that includes several different disciplines and roles, it will be more complex. In a larger AI project that includes the process of data collection, a methodology that includes data collection will be needed, which is perhaps the most critical phase of the project. It is the data collected that forms the basis for the success of the project. One must be able to collect the right data that will give the algorithm a proper basis to train on. Too little data or poor data quality can cause bias and the model will not be able to function right. The methodology of larger AI projects should also include role descriptions for each one, as the projects are often composed of several different competencies that can have different roles and responsibilities.

After working on hundreds of AI projects, Cognilytica has developed a new method tool that adapts specifically to AI projects (Cognilytica, 2020). They gained enough knowledge and experience to see which methods were best suited for AI projects. The methodology is based on experiences after best practice and has been named CPMAI (The Cognitive Project Management for AI). The model is presented in figure 2 in the next page and is a more data-centered extension of the CRISP-DM model. The CPMAI model is a better method to use in AI and machine learning projects because it sets the importance of data higher and possesses higher iteration that enables to change and adjust the relevant problems quickly. There is no firm approach and one can go back and forth between the different processes in the project. If the model has a low accuracy, it is possible to simply go back and adjust the data quality when cleaning data and continue training the model again without going through all the steps and processes of documentation again.

Figure 2



CPMAI Model Reference: (Cognilytica, 2020) https://www.cognilytica.com/cpmai-methodology/

The methodology not only addresses the importance of the data, it also addresses the competence, interdisciplinarity and knowledge development that is just as important in an AI project (Ram, 2020). AI touches many different disciplines that need to be included in order to get a successful result. Each of the activists in the model includes one or more types of skills that are put together to do that activity. AI projects involve machines that solve cognitive problems that make them different from traditional software projects and make it all more complex. CPMAI is as much a knowledge methodology that includes a framework for managing data, developing the model, implementation, competence, and learning. In AI projects, you are constantly learning new ways of doing things as you learn from mistakes and gain experience and knowledge. There is a technology under development and new ways of working and the methodology around it must be adapted to the project according to size and complexity.

2.2.2 The AI Project Team

In AI projects, there is not necessarily to be so many people involved in the project team. There will be no need for more than approx. 3-5 people on an AI project (Tauli, 2019). In AI projects, there is normally no need for broad interdisciplinary competence where team members from several subject areas are brought in. The teams in AI projects should consist of a software engineer, a computer engineer, a machine learning engineer, and a project manager (Mendels, 2019). The machine learning engineer can set up the AI model, the software engineer can integrate the AI model into the data systems and the data engineer can set up and connect to the company's data structure. These are usually people with expertise in data science, machine learning and business. In most AI projects, team members are not expected to have a PhD in AI if there are no new innovations to be invented. AI projects are usually simple tasks where you use existing AI technology for existing applications where you will only be required to have an education in software engineering. A project manager in an AI project should have both technological and business expertise because he must communicate with both the developers and their superiors in the management and the rest of the stakeholders. The project manager should have both the product perspective, the customer perspective, and the business perspective as one should be able to satisfy the requirements and achieve the goals in all areas. It is important that everyone in the team understands what the goal of the project is and that everyone is equally motivated and that they are passionate about achieving success. These are important qualities for the team to be able to take with them further to achieve further success in future AI projects. The team members should have a great interest in AI which means that they stay in future projects and develop their competence and gain expertise in the field. It is also important that team members are creative and can think outside the box when finding new solutions and opportunities in AI. It is important that they are willing to take on risks since AI projects are experimental. People who do not have this quality will be able to complicate the progress of the project and create conflicts within the team. The team members will also be able to have incentives in that they will have a more attractive portfolio by having several successful AI projects behind them. If their portfolio shows poor results, it could ruin the opportunities to participate in AI projects in the future. One should not have too high expectations for the team members' competence either because few people have managed to become experts in AI projects. The company should think of the selection of the team as an investment for the future and have a focus on building up their competence through training and education. Then the company will be able to increase knowledge about AI projects that will be a valuable resource to have with you in the future.

2.3 Organizational Barriers to AI Projects

There are also some disadvantages to implementing AI in your business. AI projects often have a higher risk of failure due to budget overruns, major delays, and human errors (Bjørkeng, 2018). The projects are also very expensive for the company. On the bright side, the AI project will generate high earnings if you look a few years ahead. AI projects are more complex and advanced than other projects and will have a higher risk of failure. As many as 85% of all AI projects experience that their project fails and there are many reasons for this (Rayome, 2019). One mistake that many people make is that they exceed the scalability of the AI system which leads to an unnecessary amount of time and cost being excited (Abramov, 2019). If you are going to start planning for an AI project, first the company should be able to withstand large budget overruns and be realistic when setting a date for when the project will be completed. AI projects take time and should not be done at too short time. It is recommended to work according to an iterative life cycle for the best possible control and quality assurance before the finished product is delivered to the project owner. It is important not to set too high goals or have too high expectations for the project (Tauli, 2019). Think of the project as a child learning to walk. Along the way, the AI projects will give the company new experiences and new lessons where they can constantly improve in the implementation of AI projects. One should have in mind that the project will last for 6-12 months if it is going to lead to success. You may want to have several projects that could increase the likelihood that one of the projects will be a success.

When the company is planning for an AI project, it will be important to be prepared that it will most likely go over budget and there will be delays. When you are going to carry out an AI project, you should not be in a hurry to finish it by the deadline. It will be time consuming and there will be more pitfalls than with less complex projects. Errors or changes may occur along the way that lead the project back to the start and the process will be repeated. The process in AI projects is usually iterative, which means that it is not completed until you have received repeatedly feedback and testing, where you go back and optimize the AI model again (Abramov, 2019). Each step in the process must be approved before proceeding to the next step. Here it is important to use the time it takes to be able to have the most successful outcome of the project. The first versions of an AI model will often contain bugs and poor customizations (Tauli, 2019). Then it will be important to let consumers test the product to detect errors or improve user-friendliness.

2.3.1 Data Management

Before you start implementing AI, you should think about what kind of data system and data infrastructure the company already has. If the company's data systems are old, it will be more expensive to implement AI. Implementing AI will require newer machines and a high-capacity data infrastructure. You may want to hire consultants in advance of the project who can assist with giving advice and ideas about what opportunities that exists within AI. When starting the planning of an AI project, one should think about whether there is any historical data in the company or something that can be measured, registered, or assessed. Think about which of the employees' daily work tasks can be replaced by AI tools. In AI, it's easy to focus on all the possibilities that technology offers because there's so much exciting to do. Then you will often forget the business perspective and take the focus away from whether the technology will really satisfy the stakeholders. Much of the technology may sound exciting, but not all solutions the customer wants or needs. For example, many customers have bad experiences with the use of chat bots and do not experience that it meets their needs, as they do not get the help they need or the good service.

Managing data is probably the most critical success factor for what the product will be like (Agrawal, A., Gans, J., & Goldfarb, A., 2018). First of all, it must be examined whether you have data, whether it is good enough and what it can be used for. It will also be important to think about how you intend to collect the data. Data can be extracted internally within the company or obtained from the outside. There are many forms of data that can range from text, images, sound, and gestures. Data is probably the most important resource for AI success. Lack of data, inadequate data or incorrect data will mean that the final product will not be able to produce the results it was intended to be able to provide. It will then be important to ensure that the data you have is large enough to give the most reliable and desirable result.

One of the more common weaknesses of the data material is that there is too little data (Roh, Y. & Whang, S. E., 2019). A chat robot will need huge amounts of data to be trained to recognize the different variations in our language. As the chatbot makes more and more calls like training data, it will get better and better at recognizing what the customer is asking for and returning the right answers. The more data, the better the results. This is comparable to using a sample of only students for a study that will examine the population's divorce rate. Few students are married or through a divorce, and the data will therefore not be representative of the rest of the population. Too little data material will cause bias in the results in the same way as when a machine makes misjudgments because the existing data material is not representative of the big picture (Bjørkeng, 2018). In order to predict as accurately as possible, there must be enough data to bring out all variations in order for the machine to recognize the relevant patterns in the data material.

The data must then be structured and cleaned of data that is not relevant or errors that may cause unnecessary bias. Data management is primarily about all the work around the data that includes collection, cleaning, analysis, visualization and featured engineering (Roh, Y. & Whang, S. E., 2019). This can be a tedious, routine and very time-consuming task and is the part of the AI project you spend most of your time on. If it later turns out that the final product does not give good enough results, there will also be a need to go back and clean out data again as part of the adjustment of the algorithm. Another important thing to consider is that you have people who have domain knowledge in the area where to use AI, which will help you know how to collect data and what data for the machine to solve this task. Clearing and structuring data will be necessary in order to achieve an accuracy of 85-90% (Nimdzi Insights and Pactera EDGE, 2019).

There are three forms of data for the use of AI (Agrawal, A., Gans, J., & Goldfarb, A., 2018). Training data, input data and feedback data. Training data is the type of data we use to train an algorithm for prediction machines, where the data is no longer needed when the algorithm is fully trained. An example of that is when training a machine to learn chess. The algorithm will get training data in the form of chess rules and the number of routes on the game board that we provide countless many combinations (Bjørkeng, 2018). There will be no need for new data once you have trained a machine to be able to predict all possible future results in chess.

Input data is the type of data in which the algorithm continuously needs new data to adapt changes in possible outcomes, such as by predicting customer preferences in order to direct marketing to those that the algorithm expects to be interested in the product. Customers' preferences constantly change according to trends and their needs throughout all phases of life, and then the algorithm will get input data from the customer's clicks and search for products (Bjørkeng, 2018).

Feedback data is the type of data where the algorithm needs new data to adapt to changes in the environment over time (Agrawal, Gans, & Goldfarb, 2020). For example, an autonomous vehicle will need to adapt to changes in its surroundings, such as new roads and sudden ploughing edges. Another example of that is facial recognition on the mobile phone. The sensors in the mobile phone collect facial data for the first time, and in this way the algorithm will recognize the patterns in the face shape in seconds. Once the algorithm has learned to recognize your face, it needs feedback data to be able to adapt changes in your face over time. It can be aging, weight change, sunglasses, makeup, and various facial expressions. Each time you open the mobile phone, the sensors will get a new image that will eventually provide a large data base in order to recognize different variations.

Another challenge when implementing AI is that bias can occur from the dataset, which will lead to a lower accuracy in order to get the right outcome. These can be adjusted manually by removing certain data or criteria during machine learning to get an almost correct outcome (Bjørkeng, 2018). A dataset of historical data collected by humans will be based on the same human judgments with human errors, attitudes and incentives. In this way, decisions made through AI tools will contain human bias and may not necessarily provide better decisions than humans in all applications. This will apply to diagnostics that have previously been made by doctors' assessments or court decisions that have previously been made by judges. The machine will then learn to assess and judge people according to historical attitudes and subjective opinions.

The use of machine learning to predict possible outcomes is as much about judgment (Agrawal, A., Gans, J., & Goldfarb, A., 2018). The machine is trained to predict data based on human judgment, and using deep learning we don't even know what judgment is based on. In order to make the outcome more accurate and avoid bias, people with enough knowledge will be needed to assess whether the machine has shown good judgment in its predictions. For example, when used in legal decisions, a judge will be needed to assess whether the machine has drawn the right decisions, and in predicting customer sales, someone inside the company will be needed who has insight into the company's trends in sales and inventory.

A report from Dimensional Research showed that 80% of companies engaged in AI and machine learning have projects that have stopped (Bayem, 2019). The report also shows that 96% of respondents have experienced those projects have failed due to poor quality in the data set, data labeling and building model confidence. The CEO and co-founder of Alegion says that the biggest obstacle that stands in the way of the AI project being implemented is the low quality of the data set and too little data base. This indicates that the project team or management has too little knowledge about data cleaning and how machine learning takes place. A recent study of the most common causes of AI projects failing also identified low data quality and lack of access to data as a common cause (Ermakova T., et al., 2021).

Chat bots need a huge amount of data in order to function optimally from a customer perspective and usually have too little data material at the start (Agrawal, A., Gans, J., & Goldfarb, A., 2018). The algorithm will then have to train itself over time and one just must accept that it will not meet the customer's queries accurately enough at the start. The positive thing is that the chatbot will become more and more intelligent as it gets trained on new input datafrom customers.

Many AI projects fail because of bugs or errors occur in connection with programming (Yampolskiy, 2019). This may be due to urgency with the implementation of the project, team members who have knowledge gaps or are inaccurate. A project can also fail due to conflicts between the engineers or project manager or other human errors. When errors are detected during the testing of the AI model, routines should be put in place to find the cause of the error, so that one can avoid making the same error next time.

It is rarely the problems that arise in the start-up phase that are the least costly phase to detect errors in (Kerzner, 2014). It is in connection with the testing and after the implementation that the errors are most often discovered, which will be costly for the company when the project team must go back and start the process again to correct the error. Much of the reason for this is because the actual implementation and the operational phase is poorly planned. Reasons for this may be that the project team does not have enough experience with implementation because there are few who have gained enough experience in this field. Another reason may be that the project manager or top management has not communicated well enough how the implementation is to be carried out. For many years it has been believed that project management is the reason why many software projects fail, when it turns out that it is the project management practice used that is the reason (Kerzner, 2014).

2.3.2 Lack of Knowledge

One of the main reasons AI projects fail is that there is a lack of knowledge about AI and machine learning among managers (Nimdzi Insights and Pactera EDGE, 2019). Managers do not have the expertise to discover new business opportunities with AI, which can put an obstacle to the development of AI for many companies. They can also have such high expectations for an AI project that they don't know what to expect and what can go wrong. They often have higher expectations of the job a machine is supposed to perform than a human being should. Despite the fact that a machine has only had a couple of years to train. The report from Nimdzi Insights and Pactera EDGE (2019) also points out that there is too little focus on business goals . Managers see a business opportunity in the data they are sitting on, but forget to design a problem description that the data can be used to solve. The product should be useful to the customer, but not all data the managers hold is usable for this purpose. One must be able to integrate the user's needs and the business objectives with the problem one is trying to solve. Some managers may get a great idea of what to solve using this data, but it will not solve a need or create financial gains. The AI project should focus on solving a real problem.

In the future, it will be a prerequisite for operating profitably and efficiently and thus achieving a loading competitive advantage, managers must have knowledge of how to utilize AI in the most efficient way for the company (Ismail, 2020). More and more companies are integrating AI into their operational activities. Therefore, it will be important for the management to have a good knowledge of what opportunities they can have for the use of AI and how to use it in the most effective way. Many managers only have expertise in accounting, finance and business areas. This will make it difficult for management to see opportunities and to be able to communicate well enough with the data engineers (Basefarm Digital Ability Report, 2018). Managers who lack knowledge about AI can be in possession of good datasets without knowing how to utilize them effectively with AI. There are large costs of implementing AI that can lead managers in small and medium-sized companies to downgrade the use of AI and will face increased competition in the market. Small and medium-sized businesses are more vulnerable to embarking on a failing project and may be reluctant to invest in a risky and long-term project such as AI projects. It is difficult for managers to bring AI knowledge into the company, as there is a shortage of expertise in AI. There will be a tough competition for the best candidates who will end up in companies like Google or IBM. In the future, there will be increased demands that managers must have interdisciplinary expertise in computer science, people, and business. (Romero Gázquez, J. L., et al., 2021)

A survey called "Artificial Intelligence in Europe" conducted by EY (Ernst & Young) on behalf of Microsoft showed that the willingness to invest in AI in Norway lags far behind other countries in the Nordic countries and the rest of Europe (Lein-Mathisen, 2019). Over a period of 10 years, 5 major investments in AI were made in Norway worth a total of NOK 250 million. In comparison, 21 and 73 major investments were made in Denmark and Sweden over the same 10 years, with a total value of NOK 2.2 and NOK 2.7 billion.

In a 2018 survey of companies' capabilities for digitization, it was found that small companies are faster at offering digital functions in the market (Basefarm Digital Ability Report, 2018). This may be related to the fact that according to the survey, larger companies have more investments in innovation and make larger digital transformations that will take longer to complete. It was further revealed that many large companies fail with their AI projects because of the management they do not have knowledge of what potential lies in the data they already have. This problem is exacerbated when data engineers do not have enough knowledge about customer needs and the business-related considerations that need to be considered.

A survey showed that 84% of companies started up with AI because they think it will give them a competitive advantage (Nimdzi Insights and Pactera EDGE, 2019). The leaders had an opinion that AI will be their great rescue and their ultimate key tool for the future. This means that some managers may be willing to invest in anything if it involves AI. In another survey of 3,000 managers worldwide, 59% responded that they already have an AI strategy and 70% responded that they know how to create value out of AI (Ransbotham, S. , et al., 2020). This may indicate that many managers may overestimate their own knowledge of AI, or have misconceptions about what AI might do for the company. It also appears when 85%

responded that AI will give their business a lasting competitive advantage. AI is a new technology where there has been a lot of hype around how fantastic this is for business and what opportunities it will provide for the business. There are many factors that must then be present in order to succeed in terms of data infrastructure, data, resources and knowledge. Even among managers with these factors present, only 20% had succeeded in getting financial gains out of AI. It will be a prerequisite for being successful that managers have knowledge of the possibilities of AI for companies to gain a loading competitive advantage in the future.

A survey conducted by Pactera Technologies showed that 85% of all AI projects fail and do not get what they had planned to do (Rayome, 2019). As many as 77% of respondents thought that the reason why the AI projects fail is that the top management is unable to see the value of the technology and does not see the opportunities it will give them. Due to the lack of knowledge among top management, it will also be challenging to get investors to invest in AI projects. Everyone replied that their company is interested in using AI-based language software. It is a program that can learn to understand the content of written documents such as contracts, judgments, and other case processing. Only 23% answered that they already used such a program. These shows that there are still some organizations that are skeptical about adopting new technologies. It is also important to keep in mind that this will also apply to customers who also do not have enough knowledge to be able to show new technologies that trust.

Tech Pro Research conducted a study of how companies manage their AI projects, and they found that organizations see the value in AI and machine learning, but that they have a hard time trusting that developers have enough expertise to have a successful outcome (TechProResearch, 2019). This indicates that there is not only a lack of competence in the management or that they do not see the value in AI that is the problem, but that they do not have confidence in the people who will carry out the implementation. This may be due to previous experiences that most projects involving AI and machine learning fail, and the fact that there are few people in the world who have long experience with AI. This is a subject area that is new to most people and entails a great risk that the project does not go as it should. Managers and investors will therefore have a careful approach to their AI projects.

Management or investors want profit and do not see the value in taking the risk of a loss-making project as most AI projects are.

2.3.3 Human Capital

Although artificial intelligence is an area that has grown more and more in recent years, there is still a shortage of professional AI experts in Norway. This means that this competence is difficult to acquire in the company and that there is fierce competition for the best candidates. Therefore, it will be more challenging for small and medium-sized businesses to be able to succeed with their AI projects. (Basefarm Digital Ability Report, 2018)

The expertise companies need to develop AI is currently highly sought after and inadequate in Norway. (Jørgenrud, 2017) Within AI there is a need for labor that has knowledge of the use of statistical models, programming languages, robotics and computer science. There is currently no special study program specializing in artificial intelligence, but several studies have courses that are included in the topic. This is not enough when there is a growing demand that seems to be becoming very important for the future of business operations (Romero Gázquez, J. L., et al., 2021) . There will not only be a need for knowledge about AI, but also the demand for interdisciplinary expertise is increasing. There will be a need for data knowledge in all disciplines as they are digitized. For AI to produce the best possible results, there will also be a need for developers to have knowledge of what they are going to develop the model for. For example, if a model for detection of different atoms or bird species is to be developed, developers who have this domain knowledge will be needed. What companies can do to deal with the problem is to develop and increase competence within the company (PwC, 2021) . There is also an opportunity to outsource the AI projects by making use of competent teams internationally (Nimdzi, 2019).

Something else that raises concerns is whether the automation of the use of AI will cause the enterprise and people to lose competence and skills (Agrawal, A., Gans, J., & Goldfarb, A., 2018). For example, look at automation of accounting or driving. Over a couple of decades, we will be able to risk this knowledge disappearing and being forgotten. Then we will not be able to detect errors in the accounts or be able to drive a manual car if necessary. The same can happen with the knowledge in medicine, if doctors no longer have the knowledge to be able to diagnose from X-rays or heart monitors anymore.

2.3.4 Poor Communication

In the future, when AI will largely be integrated into the company's operational activities, it will be important for data engineers and the management to communicate and share their perspectives to succeed in their AI projects. Then it should be possible to arrange for the management and the computer engineers to share their knowledge and experiences with each other for increased interdisciplinary knowledge in the company. Expertise in business and technology will merge in the future as the business world becomes more and more digital. In companies where the data engineers and management do not understand each other's field of expertise, it will be difficult to plan and set common goals for the project (Basefarm Digital Ability Report, 2018). The project will spend an unnecessary amount of time in the start-up phase, and it will be difficult to get to the next phase when they are unable to make a concrete plan for the implementation of the project. This problem is most common in small businesses.

Tech Pro Research repeated a similar study in 2020 and already saw that something had changed (TechProResearch, 2020). What was seen was that decentralization one saw before where there were C-level managers the project manager reported to have changed in that it is now middle managers and top management who get involved and to whom the project manager reports. This can increase the pressure on the project manager and team members because one will not disappoint the management. At the same time, the survey showed that this has led to closer communication between management and developers, where there has been more collaboration between the business area and technology. This development can be positive for the failure rate in AI projects when the management will gain better insight into technology and the engineers will gain better insight into business and the strategic goals for the company.

Interdisciplinarity will become more and more important as companies become more digital and high-tech. Those who develop the AI tools should not only know the technical and make statistical models (Nimdzi Insights and Pactera EDGE, 2019). They should also have knowledge of marketing and be able to sell the product further. Then there will be a need for knowledge about developing a business model, market plan, financial planning, the user's needs, and expectations of the quality.

A recent study showed that one of the most common reasons for AI projects failing is a lack of business understanding and understanding of the user's needs (Ermakova T., et al., 2021). It shows that there is a need for closer communication between management and developers so that developers can understand the business goal of the product and what needs it should meet, and management can get a more realistic perspective on the time-lapse and what to expect. In addition to understanding what is possible with AI and the importance of good data.

A study conducted by MIT Sloan Management Review in collaboration with BCG (Boston Consulting Group) shows that only 10% of companies manage to achieve financial benefits from the implementation of AI (Ransbotham, S. , et al., 2020). According to BCG, it is a prerequisite for success that the business strategy is integrated into the development of AI and that there is close cooperation between the engineers, economists, and project owner according to the design of the AI model (BCG, 2021). BCG's study showed that 10% of the AI project is about algorithms, 20% about technology and 70% about business application. This shows the importance of an interdisciplinary approach to AI projects and developing the model from a business perspective.

2.3.5 Cultural Aspects

The company's culture has a lot to do with how ai and technological initiatives will succeed. Companies that have a long tradition of their way of working will have a higher propensity to make major organizational changes in structure and work processes. The manager has a great responsibility for what the company's innovation ability will be like, as the manager has a great influence on the culture of the enterprise (Maher, L., Plsek, P., & Bevan, H., 2009). It is the manager's manner that determines what corporate culture will be like. Innovation requires leaders who are open to renewing and adapting to technological developments. Leaders who want to keep the traditions they have had for generations and are not willing to change will risk being outperformed by competitors who facilitate an innovative culture. An innovative culture is characterized by being open to testing new things and having an acceptance that it is allowed to try and fail. Failure will contribute to learning and improvement. One must be willing to make changes to the organizational structure and work processes in order to adapt to new ways of working as a result of technological developments. In recent years, the culture of innovative companies has become more team-based, increased interdisciplinarity and gained flatter organizational structure. An innovative culture will enable employees to have more freedom to make their own decisions and have confidence in the decisions they make. The road to the goals to be achieved is more open. Innovative managers do not give instructions on how to achieve the goals, but what needs to be achieved, and then it is up to the teams to achieve that goal in the best possible way.

A study conducted by EY on behalf of Microsoft showed that the companies with the greatest technological maturity responded that they were highly emotionally intelligent (Lein-Mathisen, 2019). This may be due to the fact that managers with high emotional intelligence may be more open to making changes and want to enable employees to have more freedom to make decisions and test out new ideas. These managers have a better understanding of what motivates and what it takes to increase enthusiasm among employees. They may also have a better understanding of the customer's needs that increase their chances of success with the final product. The study also showed that the human and cultural aspects of innovation and AI are often underestimated. When everything becomes digital and automated, we are left with the people who have been given time to think more creatively in addition to automation making it possible to change the way we work with more flexibility, learning and interdisciplinarity.

A survey of software companies in Europe conducted by Microsoft showed that companies with an innovative culture had employees who wanted to stay in the company, while employees of companies that had a more traditional culture were more open to changing jobs (Dagens Perspektiv, 2019). Managers of companies with an innovative culture were more concerned with giving employees the freedom to be innovative than traditional managers who are more concerned with keeping productivity up. The survey also showed that time was a waste of time, part of the reason companies' innovation ability was held back. It takes a lot of time for unproductive meetings and emails that could instead be spent on giving employees more time to stay focused, stay focused and get the job done. The study showed that employees who were given more time to work concentrated had increased well-being in the workplace.

A study conducted by MIT Sloan Management Review in collaboration with BCG shows that only 10% of companies manage to achieve financial benefits from the implementation of AI (Ransbotham, S. , et al., 2020). The study also showed that what was special about these companies was that they transformed the entire enterprise through organizational learning. That is, the whole organization learns to adapt to new environments in technological development, and that in the long term people will become smarter and more efficient by learning from the job the machines do. These companies don't change processes in the company to adapt to AI, they learn from AI how processes should change. We humans will learn the machines and humans will learn from machines. The machines help us make decisions, while we help the machine assess the decisions and then teach the machine to make better decisions. In this way, both humans and machines will learn from each other and get better. By adapting all processes in the company with a focus on AI learning, the organization became adaptable to be able to quickly cope with major technological innovations and be at the forefront of new opportunities. The companies that succeeded with AI had organizational learning as their main strategy in favor of the purely technical bit.

Spotify has found its own way of organizing itself called "Spotify Engineering Culture" (Kniberg, H. & Ivarsson, A., 2012). Here they have further developed agile working methods and Scrums and taken it a step further. They have several cross-functional teams called "Squads" that are composed of people who together have the expertise needed to develop a complete product. Each team has a specific product area within which they develop products, helping each team become experts on their product. For example, a team is only responsible for the development of the app, a team is responsible for the music player, one for the playlists, one for the albums, one for the radio, one for the design, etc. Spotify's offices are also designed in a way that facilitates collaboration and creativity. In addition to office space, they get a lounge area and their own huddle room. The walls of the office landscape are covered with whiteboards that allow employees to work wherever they want and with whomever they want. The Squads have no project manager in their teams, but each Squad has a product owner and all the product owners of each Squad meet to align the development of Spotify and make sure that the entirety of the product is taken care of. The Squads are then given the freedom to do what they want with the support of an agile coach, which gives them ownership of the work they do. The Spotify model will help increase transparency in the organization where one can take part in what the other teams are working on that allows for increased learning and innovation (Cruth, 2021). The model facilitates an experimental approach where there is room to try and fail, and test out new ideas. This leads to a higher level of engagement from the employees where the entire organization is trust-based.

3. Methodology

In this chapter, there will be a review of the choice of method and the execution of the study. This study lies within the concept of social sciences that deals with all phenomena from our reality and everyday life (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). Social science studies want to know something about a phenomenon or humans and study their reality based on interactions, experiences and interpretations. When conducting a study using scientific research methods, one must think about which method one wants to use. There is an option between two types of different scientific research methods. It is the choice to make use of qualitative or quantitative methods (Grønmo, Forskningsmetode - samfunnsvitenskap, 2021) . When choosing a research method, it is important to choose the method that is most appropriate according to the problem or phenomenon one wants to find out something about, and which method will best be able to shed light on the research question and provide answers or evidence for a hypothesis or theory. In some cases, it will be appropriate to combine both methods in a study. This is called method triangulation. The research methods form a framework for how a research question can be answered with a systematic, reliable, and ethical approach. The difference between quantitative and qualitative methods lies in the empirical investigations and the methodological procedure.

In quantitative methodology, the data collection will consist of quantified data in the form of values from surveys, documents or statistics (Grønmo, Forskningsmetode - samfunnsvitenskap, 2021) . The number of informants will be large and the more informants, the higher the validity the survey will have. It will be important that the selection of informants is representative of the group to be investigated. For example, a survey that will look at different opinions in the population must be able to have a sample of all ages from all over the country. The data material is analyzed using statistical methods such as regression analysis, correlation and use of tables.

When using qualitative methods, the data material will be more fluid and not concrete and quantified as with quantitative methodology. In qualitative methodology, it is common to include in-depth interviews and observations (Grønmo, kvalitativ metode, 2020) . The data collection may consist of written material, audio recordings, images, art or notes from observation. The number of informants will be fewer because a qualitative survey will be more time-consuming and contain a greater degree of information. When deciding on the number of informants, it may be a good rule to end data collection when you no longer receive new information. When examining a narrow topic with a qualitative method, the informants will usually provide much of the same information where 5-15 interviewees will be enough. The data is analyzed through coding where statements and observations are categorized into different themes or code words, in order to see patterns in the data. The findings of the empirical surveys based on qualitative data can go on how the researcher perceives and interprets what is said or observed. The findings will also be influenced by how the information is collected, what questions the researcher asks about, in what setting the participants are observed in, and the extent to which the researcher is involved in the observations. Researchers' attitudes and their own performances may influence how the findings are presented.

Researchers will largely be bound by their own ontological perspective, which means that the research is based on and concluded on their own assumptions about what social reality will be like (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). I also had my own assumptions and expectations of what the real world looked like before I started my master's thesis. I had my assumptions that AI projects fail because management and the project team will not be able to communicate the applications, the technical, the business and the customer's needs to each other. I gained these perceptions without having any insight into AI projects or work experience with AI and therefore had no prerequisites for having these assumptions. Through the empirical data, I gained more insight into the organizational and practical aspects of the AI projects where I could discover that there are other reasons why AI projects fail without letting me be influenced by my own preconceptions.

3.1 Research Design

The research questions in this master's thesis were to investigate the reasons why many AI projects fail and whether this is based on management's lack of knowledge and involvement, the developers' lack of business understanding or whether there may be other factors. There is little research in this area and there were several gaps in existing literature on the topic. A qualitative method or triangulation of the two methods could be used to shed light on the research questions, but I chose to use the qualitative method. The reason I chose a qualitative method was that I wanted to capture information that can't be obtained using surveys with fixed questions. I wanted to delve into the research questions in order to capture any other causes or root causes of AI projects failing, and gain a broad perspective on the phenomenon. The purpose of this survey is to be able to describe a cross-section from the business community of practitioners' perspectives and experiences with AI projects in Norway , and to uncover any weaknesses in its implementation. The approach will therefore be exploratory as it is not a concrete discovery I would like to find, but possibly the discovery of new theory. Previous investigations of AI projects originated in the US and may not be representative of Norwegian AI projects. Therefore, the use of in-depth interviews with practitioners will be able to give a picture of how the situation is in Norway. It must be pointed out that this will only be a cross-sectional examination of the phenomenon that will not be able to produce results that say anything about the future, but a snapshot of reality today (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). This study will then show a cross-section of the situation surrounding AI projects in Norway in the period February to April 2021.

Furthermore, the study will have a so-called case design. A case design is characterized by the fact that there are one or more devices to be studied (Wæhle, E., Dahlum, S., & Grønmo, S., 2020). In this study we have a comparative case design where the same information will be collected from several practitioners who have in common that they work on AI projects. A case design makes it possible to go into depth on each individual practitioner or informant where it is the practitioner's experiences and experience of AI projects and the factors around which are the phenomenon being investigated. Their experiences can then be compared to see if there is great variation or if they share the same experiences and experiences. In this case, there are AI projects in Norway to be studied, where we have a phenomenon to be investigated in several entities or enterprises. Therefore, according to the two-dimensional model of design strategies for case studies, it will be a multi-case design with an analytical unit (Yin, 2018). The analysis unit to be studied are practitioners in AI projects and there will be practitioners from several companies and industries as in a multi case design. The case to be studied will be the practitioners' experiences with AI projects in companies in Norway and then it will be appropriate to study more practitioners from several companies. Then one will be able to compare and see differences and similarities between the practitioners' experiences and perceptions through a so-called cross-case analysis (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). In a cross-case analysis, one will be able to look for commonalities in the data material within specific topics being investigated.

3.2 Research Approach

When choosing an approach for the study, one will usually distinguish between inductive and deductive design (Sander, Induktiv og deduktiv studier, 2020) . An inductive implementation will be based on coming up with new theory from the empirical data and will be more exploratory where one wants to find new knowledge about something on which there is little study already. The research question in inductive surveys will be shaped as "why" and "how" a phenomenon occurs. When using a deductive approach, one assumes the theory that already exists in the field with a desire to test or deny previous theories. One often goes back to the theory and compares with the findings of the empirical data to see if the hypothesis is correct. The research design for this study will be an inductively exploding design. The study may then, if possible, contribute to developing new theory based on experiences with real-world AI projects. Inductive investigations try to predict something about the future. The findings from the data collection may therefore reflect how the situation around AI projects in Norway will continue to be in the future.

An exploratory approach to the surveys is defined as sited by Sander, *exploratory study to provide insight and understanding on an obscure issue* (Sander, Eksplorerende design, 2021).

The problem in this study is somewhat unclear as it has not been decided what kind of factors or causal relationships that may provide answers to the research questions. The reason for this is that one has little or no insight into how the status is in Norway in terms of AI projects that fail. There is little literature or research on the problem in Norway where quantitative surveys have so far only been carried out. It is an open research question where answers are needed as to what underlying factors may be behind AI projects that are failing, and whether the us surveys are representative of AI projects in Norway. The approach will be exploratory as information is requested about the practitioners' experiences with AI projects in Norway, which will be able to provide new information I do not have knowledge of before the study. An exploratory design may provide the study with new insights and an increased understanding of the topic of the study. The phenomenon to be investigated is continuously evolving where knowledge and methods for the implementation of AI projects are constantly increasing and improving. The design makes it possible to gain new insight along the way and will be able to discover new phenomena that should be researched in more detail. In this way, an exploratory design will be like a pre-study for further research in an area where more insight and knowledge is needed. AI projects and AI initiatives in Norway are a new area of knowledge where more insight is needed on how to implement it in the best possible way to prevent developments from stagnating or projects from failing. There is a need for more knowledge about which development methods, organizational structures and which competencies will best adapt to technological developments.

3.3 Literature Review

Prior to the start of their master's thesis, preparations were made through a pre-project. The pre-project was based on the fact that many AI projects fail and I was interested in in depth investigating existing literature in this area. The preliminary study was carried out as a literature review with the intention of finding gaps in the research that I could explore further in my master's thesis. Some of the findings from the literature study are represented in the thesis theory chapter apart from recent studies published after the pre-study was submitted.

When conducting a literature study, it is important that researchers or students find updated information about the phenomenon to be studied (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). This is because research is a cumulative process where new theories are constantly published and new discoveries are made. The main perspective or hypothesis of the preliminary study was to investigate whether a lack of knowledge among management could be the reason why most AI projects fail. There was little previous research on the topics of management's technology knowledge and why AI projects fail. The literature I found was mainly studies conducted by technology companies and consulting firms using multiple surveys sent out to a large number of companies in the US and Europe. The findings I made in the literature suggested that AI projects that fail could be related to little communication between management and the project team, or that managers had little confidence in AI projects and therefore refused to invest in AI. After delving into the literature in this area and gaining more insight into the topic, it aroused my interest to delve deeper into the topic of the master's thesis to find any other reasons why AI projects fail. In an AI project, there are many different roles and processes to be merged and coordinated for the implementation and quality to be beneficial or successful. Therefore, there may probably be several factors that can contribute to an AI project's failure.

3.4 Data Collection

The data collected for a qualitative study is usually collected in the form of interviews and observations (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). The purpose of data collection is to be able to collect information from different settings in the hope of being able to document a phenomenon from reality. In quantitative studies, data will be collected from far more objects than through qualitative studies where it usually goes more in-depth on each individual object. In qualitative studies, data will be documented in writing or by audio recordings or images, while interviewing or observing individuals or groups of people.

When choosing a sample for who will participate in the study, it will be important to consider the research questions and which individuals will best be able to give a good picture of the reality surrounding the phenomenon to be investigated. Qualitative interviews are the most commonly used method for collecting data. This is probably because you get the opportunity to go into depth in a conversation with the informant and be able to document the informant's experiences, attitudes, and reflections.

In this study, it would be most appropriate to make a selection of individuals who have a lot of experience and who work hands-on the AI projects. These will have experience from both working with developers and management. When gathering the information I am looking for, it will be most beneficial to use in-depth interviews with the use of a semi-structured interview guide. This will provide as much information as possible about the AI projects and the participants' perspectives. Since this master's thesis is a very time-limited study that has a duration of 4 months, it will be limited how many participants to include in the sample. Much of the time spent on qualitative studies lies in the transcription where everything from interviews and observation is written down through notes or from audio recordings. A good rule for the number of participants in the sample will be to conduct interviews until new information is no longer provided. In a master's thesis that spans 4 months, a number of 5-10 participants will be enough.

When collecting data, it will be important that the researcher or student has prior knowledge of the topic to be researched (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). If one does not have knowledge of the topic in advance, there may be phenomena that are overlooked and too much emphasis may be placed on things that are not as relevant to the study. I am no Data Scientist and have no experience with AI projects myself. The knowledge I have as an economist about AI projects is easy-to-read books and literature on AI and the literature from the pre-study. There can therefore be many things about the process around AI projects that I have overlooked because I do not know about the phenomenon or not considered relevant to AI projects. For example, I want too little insight to be able to investigate the technicalities of statistical models and model training. This will mean that any weaknesses in the development of the AI models will be excluded from the study and the focus will be more on the organizational that I am influenced by as an economist.

3.4.1 Selection of Informants

When selecting informants for qualitative studies, it will be important to have a sample that can provide rich descriptions and information that can provide answers to the problem (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). In qualitative surveys, one has a clear measure of what information one wants to collect and will therefore not make any random selection of informants. One wants a selection of informants who will be most relevant to the problem and who can give us the most interesting information. The selection strategy chosen in this study is what we call a strategic selection of informants whose purpose is to obtain informants who can provide us with as much relevant information as possible (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016).

During the preparations for the selection of informants I started to think about who and where there might be people who can provide information that can contribute answers to the research questions. There was a need for informants who have experience with and work on AI projects on a daily basis, because they are the ones who can best provide the information I am looking for. I started by contacting companies that develop AI solutions for other businesses, hoping to recruit developers. This proved difficult as they could not find time for an interview and that I found that it would not be appropriate as they did not implement AI in the enterprise themselves or participated in AI projects, but developed AI models for other companies. It would therefore not be relevant to interview these when I was looking for information from companies that have experience with AI projects or have adopted AI. I then found that it was most appropriate to recruit consultants and Data Scientists who work on AI projects or help other companies with their AI projects. These then had experience with AI projects from many different companies in several industries and could therefore provide broad information about their experiences on a general basis about the companies in Norway. These will have experience with both AI success companies and those companies that do not have what it takes. A wide range of in-depth interviews from practitioners who hold different backgrounds and experiences will be able to give a holistic picture of AI projects in Norway. It may also help to increase complexity and contribute to more in-depth knowledge of the phenomenon I want to investigate. Since these informants have participated in AI projects in several companies, they want a better overview of the companies' strengths and weaknesses and what is most common in AI projects around communication, management, competence and integration. I also recruited a couple of researchers in AI and project management, but saw that it was Data Scientist and consultants who had relevant and interesting information for the research questions. Nevertheless, it was interesting to also hear researchers' experiences and thoughts that come from a slightly different perspective. One of the informants in this thesis I have included from the in-depth interviews from when I wrote my bachelor's thesis because this informant's statements were very relevant to this survey even though the bachelor's thesis had a different topic within AI. Table 2 below shows an overview of the informants included in the study.

Table 2

Name	Business	Position	Date	Time
I01	Bank	Data Scientist	13.02.2019	19:58
I02	Consulting	Director of Data & Analytics	23.02.2021	19:44
I03	University	Scientist	04.03.2021	09:39
I04	Consulting	Senior Consultant	08.03.2021	42:58
I05	Consulting	Data Scientist	12.03.2021	56:23
I06	Consulting	Senior Data Scientist	19.04.2021	01:06:23
I07	Software	Scientist	20.04.2021	35:32

Informants

The size of the sample I had envisioned that would be 8-10 informants, but found out after I had 7 informants that the informants had pretty much the same experiences and gave the same information. Several informants would then necessarily not be able to contribute new information to the thesis. It is a good rule to have enough informants for the problem to be addressed or when new information is no longer collected (Kruzel, 1999; Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). Since this is a master's thesis that takes place during a limited period of four months, there would also not have been enough time to recruit more informants due to the work on transcription and coding after the interviews. The recruitment of the informants took place via an e-mail request that was sent directly to the informant or to the company in which the informant worked.

3.4.2 The Interview Guide

The interview guide was written as a structured interview divided by topic, but the order and questions I asked the informant were adapted to the information I received along the way (*See Attachment 1)*. When I designed the interview guide, I thought about having as open questions as possible in order to get the informant to speak freely and to be able to capture information I have not asked that may be relevant to the study. The questions about their experiences with AI projects may open the possibility that the informants will be able to share different experiences and reflections. The questions were angled so that the informants would share their own experience of a phenomenon or situation. I often started the questions with "Do you experience that…" in order to get the informants to describe their own experiences and thoughts with the phenomenon. There were probably some yes and no questions as well, but the informants were good at sharing their experiences and thoughts about the questions anyway. The design of the interview guide is likely to be influenced by my own perceptions from the preliminary study. This means that the questions may seem a little leading to the interviewee. For example, when I ask the informants what challenges they have experienced with AI projects, I would indirectly suggest that AI projects have challenges. The questions I have chosen will also limit the information I get based on what I have chosen to focus on. This, in turn, will also affect how I screen out important information in the coding later.

3.4.3 The Interview Process

Due to the current situation with the Covid-19 pandemic and the calls not to meet physically, the interviews could not be conducted in the traditional way in physical meetings. The interviews took place in the video meeting program Zoom where participants were sent a link to the video meeting by e-mail before the meeting. Unlike the physical in-depth interviews I had during my bachelor's thesis, I would say that holding the interviews through video meetings was a big change. I got the impression that the whole situation with the interviews became more informal by the fact that all the informants had home offices in informal outfits and surroundings. Unlike the interviews from my previous bachelor's thesis where the interviews had a more formal setting with offices and access cards, and where everyone was nicely dressed. There were also some technical challenges in having video meetings when some of the informants could experience poorer access to networks that went beyond video quality and the sound quality of the interviews. There was also an informant who did not make it into the program where the video meeting was to take place.

Before the actual interview started, I always opened by asking if the participant agrees that I take audio recordings of the entire interview and that the recording should only be used in connection with transcription. This was something all the informants consented to. They were also informed that they will remain anonymous and that the information they provide will be anonymized. This will be important for the interview process that the informant knows that they are anonymous and can speak freely that will be able to get them to share information they might not share in full public view by name. I opened the interviews by asking them to tell me about their background, their role in the company and their experiences with AI projects. This gave me the opportunity to know more about their background before I ask the interview questions, and the opportunity to get to know the informant more. The informants had a varied educational background from physics, mathematics, engineers to economics. Then I could know in advance how much insight they have in business or project management. At first, I asked more general questions about how far the evolution of AI has come in Norway and whether they experience Norway ripe for AI. The purpose of giving the interview is to be able to understand and describe the phenomenon I want to know more about (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). I asked the informants the questions from the interview guide, but it varied slightly with which questions I asked each informant, because several of the questions had already been answered in previous questions, or perhaps the informant's background or experience meant that I did not find the question appropriate. The interviews were then conducted as a semi-structured interview. It was not always that I formulated the questions in the same way as was written in the interview guide, but rephrased the questions along the way and used the guide mostly as a keyword to come up with questions to ask. The informants were good at providing complementary and broad answers, and I therefore had no need to ask follow-up questions. As a final part of the interview, I asked if the informant had anything more to add and thanked for participation.

3.4.4 Research Ethics

As the author of this master's thesis, I will be subject to following some research ethics principles and legal guidelines for the handling of data (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). There are requirements that it should be my own work and that I should not use other people's research without referring to the source. It will also be required to follow up the guidelines for the Personal Data Act for the processing of data that will be regulated by the Norwegian Data Protection Authority. The principles of research ethics state that the informant shall have the right to self-determination and autonomy, the researcher has a duty to respect the informant's privacy and that the researcher has a responsibility to avoid harm.

Before collecting data, I had to apply to the Norwegian Centre for Research Data (NSD) for permission to process personal data in connection with the interviews. My data collection will be subject to a duty to report because I will store information electronically that can identify the informants. During the interviews, audio recordings were made that were processed and stored on my personal PC for the transcription and coding of the information. This data will then be deleted at the end date of the master's thesis. The audio recordings can identify the people I have interviewed by several people entering personal information such as their name, the name of the company they work in and their background. Prior to the interview, the participants were informed that their names and the company they work in will be anonymized and they have all consented to me recording audio during the interview. The consents were given both orally and in writing by e-mail. I will then be committed to the duty of confidentiality for the information that is identifiable and that I treat the data as person sensitive and that the participants will keep their anonymity. Violations of the ethical and legal obligations may entail personal consequences for the informants involved.

It will also be important for the ethical principles that I reproduce the exact information that the informants have provided from their own perceptions and experiences, and do not create false results according to their own attitudes and hypotheses. I would also like to have an ethical responsibility to the participants in the survey, that the information they provide is used for what I have informed them about and not for entirely different purposes (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). The survey in this thesis is not very personal as it may be in many other surveys in social sciences and sociology, where it goes more on the personal level in the people they investigate. In this survey, the participants will only provide information about their own interpretations and experiences with a technology in their workplace and will not be in a particularly vulnerable situation where I must tread carefully during the interviews. I want to be responsible for ensuring that the information I reproduce in my master's thesis cannot identify any of the informants and that the information is not sensitive and should not go public. I will have to consider what information can identify the informant and be careful to include specific incidents the informant talks about or information about customers and other companies that can be identified. During the interviews, I asked the informants to tell them about their educational background, previous work experience and position in the company. I will not reproduce this information in my master's thesis because this is information that is not relevant to the problem and can help identify the informants.

3.5 Data Analysis

In this chapter, the analysis of the collected data will be reviewed. When you have finished collecting data, you will prepare the data in order to perform an analysis of the collected data (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). In this process, the data collected will be analyzed and interpreted to be able to look for patterns and cohesion between the informants. In this study, audio recordings were made of the informants during in-depth interviews that were later transcribed into written documents. This was a time-consuming process that turned into a total of 48 pages of written material from the interviews. This was done in order to later categorize the information when coding the data.

3.5.1 Data Reduction and Coding

When the interviews were completed, they were entered into the computer program NVivo, which was used for coding data. I had a large amount of data from the interviews and there was a need to sort and remove information that was not relevant to the problem. The written information from the informants was categorized into nodes with themed code words. Sentences or paragraphs were then moved into the appropriate node. The nodes also had several subcategories that made it possible to categorize a sentence or paragraph into several nodes if it dealt with several themes. This was done to get an overview of the topics on which information was gathered about and how frequently the topics were mentioned during the interviews. I then had a total of 14 nodes with a total of 17 subcategories. Information that was not relevant to the problem was then omitted from the categorization. The coding tool NVivo also made it possible to compare the informants' nodes with each other pair-wise in order to see how much each one has in common with each other. It was clear that the informants who were Data Scientists provided approximately the same information and had the same experiences and attitudes. The comparisons also showed that it was those who were Data Scientists who provided the most relevant information for the study.

3.5.2 Interpretation of Data

In the analysis and interpretation of qualitative data, it will be important that it is the same researcher who has collected data that also performs analysis and interpretation of data (Silverman, 2006). This is because it is important to have the same preconceptions and attitude to the phenomenon also when interpreting the data. The analysis of the data material should be able to give the researcher an opportunity to look for patterns in the data and uncover an opinion or message from which a conclusion will later be drawn (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016).

By analyzing the data, I try to see connections and the causes behind it. In order to get an overview of what information the informants talked about the most, I ranked the code words according to how many times the topic was mentioned and how many informants talked about it. This gave me the opportunity to exclude topics that only one informant talked about and which were therefore not enough information to draw conclusions from. The coding gave me an overview of what were the most important topics about the reasons why AI projects fail that were lack of knowledge among managers and handling data. These are the biggest weaknesses the informants picked up from their experiences from several companies, which leads me to interpret the data in the direction that lack of knowledge among managers and poor data are the key factors here. This will of course also be an effect of me focusing on knowledge and competence among the management in the questions that will in a way provide the answers I was looking for. Managing data and data quality, on the other hand, was something I did not focus on in the questions and was something all the informants pointed out that often appeared as a problem in AI projects. In the analysis of the data, an interpretive reading was used where one is interested in the informant's background and statements about his experiences and perceptions of the phenomenon (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). I will then try to interpret what the informant means by his statements and the extent to which the informant's experiences and background have influenced the informant's attitudes and experience of the phenomenon.

3.5.3 Validity

The validity of the data says something about how well the data matches the real world and whether it can be said that it is representative of the phenomenon one is trying to show (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). Validity represents the validity of the data, distinguishing between conceptual validity, internal validity, or external validity.

Conceptual validity is when the data collected is the right data according to being able to provide answers to the phenomenon to which one wants answers (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). The data must be able to match the phenomenon being investigated. The empirical data in this thesis has a validity of concepts because the sample of informants and the information I received were very relevant to the research questions. The analysis of the data has taken place as neutrally as possible in that the information was encoded and then got an objective overview of what information was frequently mentioned by several, and what information was mentioned by few, and what phenomena were important. When I thoroughly reviewed the documentation, I was also able to recognize a pattern in my data.

Internal validity is about assessing the credibility of the survey (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). For the study to have internal validity, the data collected must align with what the research question wants to find answers to. The questions from the interview guide were related to the research questions, and I therefore received exactly the information I was looking for in order to answer them correctly. I would therefore say that this survey had a high degree of internal validity. The data were also processed and coded by categorized relevant statements into topics with subcategories according to which barriers contributed to AI projects failing and which topics the informants had problematic experiences with.

External validity says something about the transferability of the survey to reality (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). This study will have a high external validity because it contains data on the experiences of a large number of companies and industries in Norway, both large and small. In order to say that the study has external validity, it is also important that I look at information in the data that differs from one's own perceptions and theoretical assumptions. Presenting results and findings based only on the information that best fits in with your own perceptions will reduce the transferability of findings to reality. Therefore, it will be important that I include all informants' attitudes and interpretations of the phenomenon even if that was not what I expected from findings in advance.

3.5.4 Reliability

The reliability of the research says something about how reliable the data collected is (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). The data must be collected correctly according to the problem where the correct information has been obtained and that the data has been analyzed and interpreted correctly. It can be about how you have chosen to collect data, what sample you have, in what way you have coded and what you have considered important findings. The fact that the research results are reliable means that other researchers conducting the same study will come up with the same results. Much of the data documented will be influenced by the researcher or the student's own perception of reality and what is being observed. The data will then be interpreted based on the researcher's interests, attitudes, and experiences. There may be a risk that important details will be overlooked because one often perceives and places more emphasis on the information one expected to receive. This will especially occur with the use of observation. You often focus on the details you notice, and the rest is overlooked. 3 different researchers will then be able to come to 3 broadly different results on the same study because they have individual interpretations and perceptions of the data. As a researcher or student, it will be important to have an open attitude and a certain objectivity to the phenomenon or people to study. If the researcher angles the data towards his own attitudes and perceptions, and does not follow the scientific procedures correctly, the results will have little reliability and give the researcher personal interpretations. The information documented will also depend on the characteristics of the researcher or student. How good the researcher is at listening, noticing details and reading other people, interactions and situations will also affect what is documented. The researcher or student will also be influenced by the existing theory that will hinder being able to debunk or explore new theories. Two researchers exploring the same problem may end up with two different conclusions. Therefore, it will be important to make up your own hypotheses and test previous research, even if one has other perceptions of the phenomenon. The findings should be a result of the research and not of the researcher's own attitudes and perceptions.

The empirical data in this thesis I would think has some reliability because the committee was mostly Data Scientist consultants working on AI projects in several companies. The empirical data showed that although they did not work in the same companies, they had mostly had the same experiences and experiences with AI projects in Norway. Therefore, I would think that there is a high probability that other researchers would have made some of the same findings in a similar study with informants from other companies. Through the collection of data, I was probably a little influenced by the literature study and what insights I gained from previous research on AI projects that fail. It turns out how the questions in the interview guide are formulated and highlighted that most AI projects fail and how communication between management and developers is the cause. I don't get to know anything about phenomena I haven't asked about. We can say that the information I collect will be filtered through a filter of what questions I have designed in advance (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). There has traditionally been little contact between managers and developers, especially in the US where the previous surveys originated. Therefore, the responses from the informants that there is little contact between management and the developers will have little correlation with AI projects failing here. It is more relevant if the AI projects that succeed have closer contact with management. Then there may also be other causes such as the increased likelihood that these companies have a higher capacity for innovation by having a modern flat organization where agile methodologies are well integrated. Another thing that will affect the reliability of the master's thesis is that the data only represent a cross-section of the phenomenon from spring 2021. This is a technology and field of expertise that is constantly in development, and it is quite fast. In 2-3 years, perhaps a researcher conducting the same study will make completely different discoveries. In essence, I would say that this thesis has high reliability because new published studies from 2021 have come up with the same result (Ermakova T., et al., 2021).

3.5.5 Generalization

This study is based on across-case analysis where I have compared the experiences and perceptions of several informants to a phenomenon. A cross-case analysis will help increase the study's transferability to the real world (Johannesen, A., Tufte, P. A., & Christoffersen, L., 2016). The experiences and perceptions that the informants had in common will increase the generalizability of the survey because it shows that this is a common perception and experience in the environment. It also gives reason to believe with great probability that if I had examined several informants they would also have the same experiences and perceptions. I must point out that the informants had experience as consultants who were hired for different companies in several industries. They have experience from both small and large enterprises, in both the construction industry, the energy industry, banks and the health sector. They then have enough basis to be able to talk about managers and projects from many settings. That, I would say, gives the survey a high generalizability. Nevertheless, I would be cautious about generalizing the findings of the survey to the rest of the business community at this time. This is because more research will be needed in the field that can confirm or deny my findings. This is also only a cross-section of the phenomenon that can change every year as it is constantly evolving. There would also be a need to investigate a larger proportion of practitioners and companies in the business sector in order to give the study an even higher validity and reliability. One could say that the study involves some degree of inductive generalization as there is little existing theory in this area. The empirical data from this study have no statistical generalization, but it can also have a theoretical generalization. Seven practitioners were selected where those with a background as Data Scientists had many similarities in their experiences and experiences with AI projects. These Data Scientists were consultants from various consulting firms and had experience with AI projects in many companies in Norway with whom they had assignments. This will give reason to believe that their similarities in experiences and experiences in different companies in Norway may be theoretically generalizable as these are phenomena that together occur in very many companies. There are currently no studies in Norway that can deny this.

4. Analysis and Results

In this chapter, the results of the in-depth interviews will be presented and how I interpret the information collected. The sub-chapters represent the most important topics and associated findings from the analysis.

4.1 Definitions

There are many different concepts that remain in everything that deals with AI and AI projects that must be clarified before the actual analysis is to be presented. Some of the terms are Data Science and Data Scientists. Data Science is the field that combines scientific methods with the use of mathematics, statistical methods, advanced programming, analysis and processing of large datasets (IBM Cloud Education 2020). Especially in the development and modelling of AI and machine learning. Data Science has an interdisciplinary approach where one can find Data Scientists who have a background in science, economics, medicine, philosophy, and other scientific disciplines. A Data Scientists is a person who works with this field and who is an expert in AI and machine learning in addition to having to have knowledge of the business and have a holistic perspective on the AI project. A Data Scientists can be an employee of a company's Data Science department or work as a consultant and help other companies in the field of Data Science.

There is also a need for a conceptual clarification around the fact that the informants can use both the concept of artificial intelligence and machine learning. Artificial intelligence is the general term used to describe the very technology of a computer being able to mimic the human brain to be able to make decisions based on large datasets using statistical methods to recognize a pattern in the data (Microsoft Azure 2021). Machine learning is the term used to describe the technology by training an algorithm to get better and better at recognizing patterns based on experiences.

The informants use terms such as "model" and "solution". An AI model that the informants refer to as the model is a computer program that is fully trained by a dataset. It is this finished model that will be implemented into the companies' own systems and make decisions based on the data it has trained on. If a type of real-life data is used that is constantly changing, one must be able to maintain the model by providing the continuous input data to train on. (Chooch, 2020)

The methodologies discussed are Proof of Concept, Waterfalls and Decision Gate. Proof of Concept (POC) is a method of being able to prove that the idea is feasible before starting to invest fully in the project. The method aims to uncover gaps or weaknesses in the project and prove that it will lead to success and earnings. It's a test project that you run before you start the real project. (Malsam, 2019)

The Waterfall method is a methodology in system development where the project undergoes several phases in turn, where the next phase cannot be started until the preliminary phase is completed and approved. This method isn't as suitable for AI projects because it makes it difficult to go back and change things. (Javatpoint, 2018)

Decision Gate is a method that is based on the waterfall method and is about the same approach. The project will be divided into gates and every time you finish a phase or street, a decision will be made from the project manager on whether to proceed to the next street or whether improvements must be made first. (Mulder, 2018)

When you talk about an AI project failing, it is meant in this task that it deals with projects that do not get started, do not work for what it should or that are never realized.

4.2 Lack of Knowledge

Most of the informants who participated in the survey pointed out that there is a lack of knowledge about AI and the applications among managers in Norwegian companies. Most people found that Norway haven't gotten very far with AI either because it's difficult to get the right expertise, but that we have the potential to go far. At the same time, there are some who are far ahead with their AI projects. There were divided opinions among the informants about how far the development of AI has come in Norway and whether we are further ahead or further behind than other countries. Several of the informants mention Kolonial as a company that has come to terms with its AI projects and succeeding. They believe this is because Kolonial is a relatively new and small company that can easily adopt new technology and restructuring. I07 says that there is a large breadth of variation and says *"It is not so crazy what Norwegian business leaders and public organizations have taken in AI. At least there's something on their road map.".* The informant also explains that they have become aware of it and that they have some awareness workshops where the purpose is to link business to a technological opportunity space. I06 says that "*I see more and more that in the big organizations, more and more people have started it. Not everyone is there that they're done building teams, everything around data architecture, building everything that's ready, but you kind of start a little bit in different places, and you try to stitch it together."* Several of the informants have seen that the larger companies have started ai more. This will probably have something to do with the fact that the larger companies have the resources to reorganize and develop their own AI development departments. They will probably also be easier to attract the most competent and experienced Data Scientists. I05 explains that "*You're still at a pretty immature stage in AI/ML in terms of project planning and things like that. I guess you're still taking and trying to learn and figuring out how to try to estimate projects in an ok way, even if there's a lot of uncertainty in that.".* There is probably still little experience around the planning and implementation of AI projects and which routines and methods are most appropriate to use. Since there is a lot of exploration with trial and error in AI projects, it will be more difficult to estimate how long it will take, how much resources and how much costs will be. The informants generally find that most companies are willing to implement AI in their company and that many people talk about it and are curious. They also find it easy to sell a consultancy assignment within AI to the companies. Managers are often motivated by hearing about the companies that have succeeded with AI and will try to do the same.

I01 says that *"Finding out how the strategy of using data and AI is related to the business processes is closely related to the competence of the organization."* The informant also explains that there are far too few managers who understand what AI is and how it can be used to support their business. The absence of expertise about what AI can do and what business processes can be used in will be a significant weakness among managers when planning strategies for digitizing work processes. When they lack expertise in their applications, they will overlook potential business opportunities, and they may be in possession of good data for which they do not know what can be used. The managers also had too high expectations of what AI should be able to do for their business. Executives often only have basic knowledge of AI such as facial recognition on mobile and preference algorithms in Netflix, but they know little about the uses in their company. Such as how to achieve better customer contact, predict customer churn and that sort of thing. I06 tells of a customer who wanted a model that would predict customer churn "*The only thing the model is trained to do is give a probability that a customer is going to terminate the customer relationship. Then the customer sits for some reason and also thinks that he will know why.".* This shows that there is a lack of knowledge about how AI works and that the results are based on statistical methods calculated from historical data and patterns in the datasets. It's on probability calculations. It would not be possible to calculate the customers' thoughts and needs behind the choices they make, but the customer believed that the model would provide answers to this. I06 says that it will be a challenge to communicate statistics to non-statisticians.

The informants were able to tell that there were several managers who think it is just hiring or hiring *one* Data Scientist and that this person alone should be able to solve all problems and achieve great things with AI. This, in turn, seems to be a misconception among managers and Norwegian companies about how to succeed with AI. I02 points out that among leaders who do not succeed in AI, it is often about understanding what is actually required for technology to contribute to efficiency in their company.

The informant goes onto say that «*It is another challenge that one has some unrealistic expectations of what AI can do and that it is about not understanding what it is*».

IO4 states "They have seen that people automate this and this, but then they do not have that expertise themselves. They often don't have the right expertise in their company, that they realize that in order for us to come and automate with AI, we have to do this and this step first." It seems to be an experience that several of the informants have made themselves, and several point out that they would like to see that there was more expertise about AI and applications among managers. Managers do not know how to facilitate AI and what preparations they must make before bringing in a consultant. They believe that a Data Scientist can do the whole job when it is the company that needs to have all its resources ready for Data Scientist to do its job. There are several conditions that must be present in order to start an AI project, such as good data or a way to retrieve data. I05 says that *"When we come in, we have to take a reality orientation, both in terms of data and what is possible, and how much resources it will take." .* The informants also point out that there is considerable variation among managers. Some stay up to date and are good at AI and have knowledge of how to succeed, while others are far behind. I02 says that "*One is never fully taught, but that's the way it is with everything else as well. In other words, there is a development in cardiology in medicine, for example, and if you are not part of it, you will never become a good cardiologist. So, it's a bit the same.".* As AI is implemented into the companies, it will affect many different disciplines. This will require managers and employees to stay up to date on AI and their applications and how they can use AI as a support for their jobs. I04 points out that "*To put it briefly, it is purpose, data quality, data infrastructure and resources of the customer. It's often the problems that come up then.".*

AI has long been a hype among managers and many people think that this is something they have to implement, but they lack the prerequisites for getting to the finish line with the projects. I04 points out the importance of having a purpose. One must have a purpose as to why one should implement AI and what problem it should be able to solve. Many managers think that they just must have AI because everyone else has it, but then they don't have a clear purpose for what to use it for. Instead of having a problem to solve using AI, managers often start the wrong way with the idea that they should have AI first, also figuring out what to use AI for afterwards. This seems to be a widespread problem among leaders' attitude to AI as a hype they must have. The leaders lack a clear definition of what problem they want to solve with AI. I04 says that this is the first challenge that arises, that the problem description becomes too vague.

4.2.1 Human Capital

According to the informants' experiences, few companies have internal expertise that know AI. It is usually the large companies that have this expertise internally, while the small and medium-sized enterprises do not have internal resources or expertise. Most of the informants found Norway need more technologists and that those with expertise in AI and machine learning are difficult to obtain. According to the informants, those who are good at AI are very sought after. I02 says that *"Over time in Norway, I think we must continue to invest in educating technologists. We must continue to educate those who can operate and create the software itself, do the coding and develop the product. It's one thing, but also educating more people who master everything else around, who will make arrangements for us to actually be able to implement AI.".* There is a need for so many different roles during an AI project, and one can imagine that the need for expertise in AI and machine learning will continue to increase in the future, and perhaps in several disciplines as well. The informants report that there are few people in Norway who have a high level of expertise in AI today and that it is often people with a science background who are brought in for positions such as Data Scientists. This is because there are currently no opportunities to be able to take a master's degree in AI or machine learning for example, but this is something that should have existed considering the demand for this type of expertise in the future. There are a lot of statisticians, physicists and mathematicians working with AI, but the informants find that it is very different what competence the people in the AI projects have. They find that it is everything from a trade certificate to a PhD. I04 finds that even those with little experience can model the most incredible things if they give them time to try and get the right tools. The informants explain that the most important thing is that you know statistics and one or two programming languages, usually Python and SQL. Today, one can say that it is the employee market in Data Science. I02 points out that there are many who have the prerequisites to become a good Data Scientists. It can then be useful for companies to develop this expertise internally by acquiring skilled technologists and people with science backgrounds who have the prerequisites to become good at AI. I04 says from its former workplace that "*Instead of bringing in experienced people who have done this before, we brought in graduates with good programming and mathematics skills, and we also ran them through a number of courses when they started and let them explore it for themselves. In a way learning by doing approach, because getting to grips with people with the right skills is difficult and it's expensive.".* The informant also explains that Norway is ready for AI and that we are a digitized society where everything is in order to become good at AI, but that it is to get the right people who are difficult, and that you usually have to bring in expertise from abroad if you are going to have someone with long experience.

The informants find that companies often hire external consultants when implementing AI. According to the informants, in an AI project, data scientists, computer engineers and machine learning engineers will usually be needed. If AI is to be integrated into an app, you will also have application developers, Frontend designers, UX designers and usability. There will be a need for someone who can work with complex data collections, managing data streams and data retrieval. You also need someone with domain knowledge in the field in which to develop the model. There will also be a need for someone with ties to the company and the business who can make decisions with respect to the interests of the company. The consultants hired do not have the overview of each company as they work in many companies. It is often you have a Business Analyst or Scrum Master who is the person who keeps in touch between management and the team and who leads the project through each phase. I06 says: *"I've encountered customers who haven't thought about it at all. On that whole and how this should be used. So, they'll be surprised how big this project will be.".* Several of the informants point out that it is a problem that so many people think that only one or two people are enough to carry out an entire AI project, but you need many different roles and backgrounds. I02 says that "*It is again about us being very profiting from Norway educating more people, but not only educating those who understand the technology itself,* *but also those who understand the framework conditions around it."* . There will be a need for people who also see the whole of an AI project and what requirements are set for privacy, handling data and how the data will be used. You must have someone who understands how the AI model is built up and how it works to understand how bias in the data can contribute to discrimination against people, and how to avoid this. An AI project that does not comply with the guidelines of the Norwegian Data Protection Authority and the GDPR will not be able to be realized.

The informants find that the project teams they have worked with have mostly had the expertise needed to develop AI and that no one has been able to do what they are talking about. They also find that you have an openness that if there is something you cannot, you ask others and share their knowledge with each other. I06 says that sometimes someone with the wrong skills can be hired for a role. The informant explains that when an analyst is hired as a developer in an AI project, time must be spent training the employee because this is another field of expertise. This will probably often happen in Data Science when Data Scientists often have very different educational backgrounds that are outside of IT and computer knowledge. It may be doctors, economists, physicists, and philosophers, but with a good statistical understanding. I06 also has experience that project managers on an AI project have never encountered AI before. Then, like Data Scientists, they will help the project manager implement it. The informant also explains that one cannot expect that everyone can already know machine learning, especially those who are obtained as domain experts on a project. The informant finds that those who develop the model themselves have the expertise needed, but that AI is relatively new and therefore not many people have so much experience with it.

4.2.2 Business Understanding

I07 Says that much of the work is about connecting business understanding and technology opportunities. The informant believes that this will then go both ways. The management who possesses the business understanding has no insight into the technical, while those who are

Data Scientists do not have customer insight or knowledge of the business related. I07 says that *"Management and suppliers understand what the technical opportunity space is and what it is going to be, and that technologists understand what the business challenges are that they are trying to solve here."* Managers need knowledge about the opportunities available to make the best use of AI technology for their company. Perhaps one has, for example, a company that does production and manually checks their products for deviations, and management does not know that one can automate the process of AI that detects deviations much faster than a human. This will then be a major cost-saving opportunity that management then does not know about because they lack knowledge of the technological possibilities that exist. On the other hand, we can have Data Scientists who will develop a model where they have received a vague problem description from management, which should be able to provide decision support in relation to investments or production capacity. Then Data Scientists do not know how to get the best possible model and make new improvements, because they do not have knowledge of exactly what the model should be able to solve and what to automate. When asked if the developers of the AI projects have a business understanding, the informants answer that this is something they should have and that this is important to have to create a solution that can match reality. Developers should be familiar with who the stakeholders are and what needs they have to create a solution that meets these needs in a good way. When developing concepts, they should also have an understanding of which concepts meet the company's strategy in terms of costs, sustainability goals, ethics, image and vision. It is important that management communicates their strategic goals well enough to the developers so that they know what needs the concept should meet and what goals one wants to achieve with it. This, in turn, will go both ways where it is important that management has good insight into the technical opportunity space as they develop their strategies and plans for the future. I02 says that in AI projects, it is common to have a product owner who will be a connection between the project teams and management by having knowledge of both the technical and business aspects of the problem one is trying to solve using AI. I02 goes on to say that "*Mostly it's about Data Science, Data Engineering, product understanding and business understanding. The four are basic building blocks.".* I06 says that it varies with the role of the project, how much business understanding and insight into the company you need. The informant claims that "*Some people are not* *interested in the business aspect at all. Maybe you do the analysis because you like the mathematical challenges and that's it, and that's why you're in the game, because you want to solve something difficult. There should always be someone on the project who has a business understanding, clearly, because what you create in the end is something that should add value, but I don't think everyone on such a large team thinks about it or cares about it.".* A person who is only set to develop a code for the model and nothing else will have no need for business understanding to do this job. It is probably more at the beginning during the development of the idea and concept and in the integration and maintenance that it will be useful with business understanding to be able to meet the customer and the company's needs and interests. On the other hand, developers may want to have insight into the business they're trying to solve in order to see what changes they should make to their model and data, and what other business opportunities might emerge. I02 finds that there are Data Scientists who have very good business understanding or who come from the business area. The informant also finds that it is a challenge that they do not have enough business understanding on the technical side. Furthermore, the informant says that this can be solved by educating the developers to get a better understanding of business or to have interdisciplinary product teams where there are people from all disciplines. It seems that it is these multidisciplinary teams that are most needed in AI projects, as one needs knowledge of so many disciplines, and one can share and teach along the way in the project that contributes to more business understanding among developers and increased domain knowledge by making one's experiences with models from multiple domains. I04 also explains that at the start of the project, they often do not know the subject area to model, but that you read, talk to people and ask along the way, and in this way, they gain more knowledge about it. The informant also points out that one should not isolate each individual for each task but involve them in the strategic objectives of the project and to make them see it in a larger context. The informant believes that this will increase motivation by involving them in why they do the various tasks in the project. I05 finds that the best projects are where you have someone with insight from the business side, which allows you to go in the same direction.

4.2.3 Communication with the Project Team

In general, the informants find that there is little contact between management and the project team. They also find that many wishes there was closer contact with management. Much of the reason why there is little contact may be that the project teams have more freedom now than before and only give presentations to someone from management after each milestone to show what they have achieved along the way. In the first place, it was more common for management to manage the teams more. The informants agreed that they wish there had been closer contact between management and the project teams. I05 explains that *"It has varied slightly compared to Scrums then, where we have had daily updates with a project manager who has been involved and cared completely into the details of what one is doing at all times, or whether there have been more weekly presentations of what has been done.".* It may seem that it varies slightly how much management takes part in the process around the AI projects. The companies that have become involved in agile working methods and the use of Scrums may have a greater overview of what the project teams are doing and what they are thinking next. Several of the informants find that it depends on the manager's leader style how much contact there is between the management and the project team. Some want to be more close to and run micro management, while some have little insight into Data Science and are more concerned with how the project directly affects the business. It would also not be appropriate for a manager without the professional expertise at AI to make decisions on behalf of the team working on it. I04's own experience is that you tell management what to do and how long it will take, and then there is no more contact until the project is finished. Then they controlled everything themselves how to build things and how to structure and organize the project. This shows that the manager has confidence that the team is going to achieve something sensible and that they possess the competence to be self-propelled on this. The manager probably also has good experiences with the team and what they can achieve. The informant has the impression that most managers have confidence that professionals can carry out the project and that the results will be good and that they will receive feedback.

4.3 AI Projects

All informants in this survey had experiences with AI projects that fail. There were also different opinions about what it means to fail with an AI project. Failure does not always have to be negative. One can see failure as something positive that contributes to the learning and improvement of processes for the next project. Most people have little experience with AI projects in Norway, as it is a relatively new field in the companies. Therefore, it will still be in an exploratory phase in most companies, and hence many that fail with their projects. I01 explains that creating the model itself is the easiest and least problematic aspect of an AI project. The informants explain that it is the planning or the actual integration of the AI model that are the most critical phases in an AI project. Planning will be critical because that is when it will be decided whether to proceed with the project or whether it should be scrapped. The data shall be examined whether they have sufficient quality, and an assessment shall be made as to whether this will work. Then we will constantly get better at AI and the chances of failure will probably decrease in the future. I06 can tell that when it comes to the failure of 90% of AI projects, the informant could well relate to it based on his/her own experiences. I06 says that *"For my part, I have been in quite a few solutions that we have begun, and it has also stagnated because the organizational was not in place".* This is a reason that remains with all the informants. Managers do not know what organizational conditions need to be in place or how to solve the problems that arise, things must be postponed and there are delays because there is a lack of resources that should have been available. I04 says that companies are aware that unforeseen things can happen in all types of projects because they have experience with it, whereas in AI projects they do not have that experience and perhaps therefore react more to it when they do not know the methods and processes around them. The fact that they do not have extensive experience with AI projects will probably increase uncertainty somewhat among the companies, as they may not have enough knowledge and experience in how to solve the problems that arise. I06 can tell that many people can complete the AI project and implement a ready-made solution, but then they are unable to apply it and integrate into their routines. This will also be a way of failure, as companies may have thought they had a good idea, but then it was perhaps completely unnecessary, or they do not know how to use it. It may also seem that more people may have good data, but not succeed in the implementation and maintenance of the model. Several of the informants also report that there may often be delays because the development of AI is a relatively new field that is constantly being developed and that changes may be needed, and that new solutions may be learned during the process. The informants say that it is often a step forward and two steps back in the development of AI models. I07 points out that there may be some challenges to measuring success, "*What does it mean that an ML model is better than anything before? Benchmarking and possibly improving a model that was already there, that's a critical thing over time. If you don't have a good idea of what it means that something is good, and what it means that something is better, then you are almost out swimming.".* A model that should be able to diagnose a disease using X-rays will be quite different from a model to be used in chatbots. It will be difficult to say whether one is better than the other. Two models can be compared for diagnosing X-ray models, but it will have no purpose when they are based on the same type of data from reality and should then be able to have equal predictive ability. It is difficult to plan what you should aim for prediction when you do not know what is possible to achieve with the data you have. The aim will be to improve the model's prediction capacity as much as possible through adjustments to the model and data purification.

I02 says that *"One underestimates the complexity of what is required beyond purely technological, i.e., technology is not the problem here. The technology is aware that works, so what is demanding is to ensure that the surrounding framework conditions are in place to succeed in implementing artificial intelligence, as a model or as an improvement initiative. If those framework conditions are not in place, I think that is the main reason why these types of projects could potentially fail.".* Strict regulations in ethics, privacy and GDPR will also help to set some restrictions on the development of AI that cause the project to fail. I01 has an example from a bank where they had created an AI model that could predict whether the customer would pay next month or not. This then showed good results and could predict with high precision, but they were not allowed to operationalize the solution because one could not explain how the model came up with the decisions. These are problems that may arise when creating a model based on personal data that may also be discriminatory and judgmental when one does not have an objective explanation of the decisions the model makes about the future actions and behaviors of private individuals. I07 finds that it is the public agencies that have a more bureaucratic attitude to the preparations for AI projects because they are more likely to process personal data where they have to do the work of obtaining consent and more risk in connection with GDPR. I06 points to China and the US that have gone much further than Norway purely technological and started with AI long before us. This will be because the framework conditions around are different than here in Norway, where they do not have the same limitations on what they can do with AI according to GDPR and ethical issues. Several of the informants mention that the GDPR helps to delay the development of AI in Norway. This is also a good thing that there is legislation that protects our personal data and that companies cannot store and use anything.

4.3.1 Data Management

Most of the informants said that managers do not see the potential of the data they have or have too high expectations of the data they have when they cannot really be used for anything. I01 states that "*The bottleneck lies in the lack of understanding and maturity in the organization on what data to collect and how to create value out of the data collected.".* I04 says that often companies do not know where the data is, poor quality or it does not exist at all. I06 says that "*... In addition, many customers have not checked their data quality. It may be a bit of a job too, but you often think you have so much good data, lots of good data, and they start digging, and they also find out we don't really.".* The informants agreed that one of the most common problems that arise is that the company they are going to develop AI for lacks data or has poor data. Here, companies should be aware of the amount of data they actually need in order to achieve results, and that there are no major biases in the data. The informants find that many companies are unaware that this is something that should be prepared in advance, before they bring in consultants to create a model with a data base that cannot be used. Then they may also have someone internally in the company with knowledge of data to be used in machine learning, who can investigate whether the data is good enough. I06 says that it is the work of building these datasets that takes the longest time in an AI project. They spend about 80% of the time building the datasets while the remaining 20% agree to train the models. I06 goes on to say that not all managers know this beforehand that working with the data takes so long. The informant points out how important it is to have domain expertise when working with the datasets. Without that domain expertise, it will be difficult to know what to remove and whether the data quality is good enough. I05 explains that “*Some have both good routines for handling data, collecting data, they have the system in place, while others are a little more surprised when they discover it. If they've taken care of good data, it's strewn in lots of Excel files and other formats that are hard to handle.”.* Then they often must look for and structure the data before they can start the job they were set for. The informant finds that there is considerable variation between the companies, but that more people are starting to become aware of data management before the project can start. The informant also explains that some companies have a willingness to make an effort to clean and improve data quality, while some are more interested in making the best of what they have, even if you get a model that does not deliver what it should. The informant also finds that the data the company sits on did not provide as much information as they thought beforehand.

The informants also report a lack of infrastructure as a problem that often arises at the beginning. The right infrastructure is important for making your data flow work. It must be facilitated for how the data material should be collected and how the data should be able to be integrated into a model to get a good result. I04 says that companies often don't have a data infrastructure that supports an AI project. *"The data is kind of scattered in the production systems without you having a way to extract it. You have to have your own data infrastructure for it, and it needs to be built. Often the customer hasn't."* Several of the informants report that sometimes there may be a need to build the data infrastructure in advance or that additional architecture and additional solutions must be built. This will then delay much of the process when the consultants come in and the company does not have this ready in advance, nor does it know that this must be present. The informants also talk about companies that have an old computer infrastructure and old systems that can be difficult to work with.

4.3.2 The Planning of the AI Project

The planning phase is the phase the informants point to as the most critical that concerns the data and what to use it for. A concept will be developed, and a future evaluation will be carried out. It is also this phase that the projects often must go back to when problems arise along the way. The problems that arise are often that the data is not good enough or that the problem description becomes too vague and will not meet the customer's needs well enough. I05 argues that "*It almost always happens that when you talk before you start doing things, they don't have enough insight into the data and the problem, and the customer often doesn't have enough experience from machine learning projects to be able to explain the need they are looking for."* . This shows that there will be a need for people with AI expertise internally in the companies who can identify what needs they are looking for, preferably among management. Several of the informants say that it is often the management who takes the initiative to start AI projects, and then they need that expertise in advance to know exactly what they want AI to be able to do for them. The company must also plan whether to hire consultants or whether to develop the AI model internally. I06 says that "*If you are going to do everything yourself, you have to develop a new department, data science and analysis department. This means that you may have to make organizational changes, and there is also a lot of cost to hiring people. It's kind of going to be a big process then.'* This can be a challenge for companies that do not have knowledge and experience internally, to know what they need to be able to develop a new department and expertise. Then it is often easier and less expensive for companies that are beginners in AI to hire consultants for the task. I05 also finds it challenging when selling an AI project. To praise the project correctly and how long it will then. Since AI projects are often exploratory with a lot of trial and error, it will be difficult to estimate costs, time spent and resources in advance. The informant says that the planning of AI projects is still at an immature stage, where one is still trying to figure out how to plan the projects in a good way. It may therefore seem that companies find it difficult to plan and estimate the time and costs of an AI project, because they do not have much experience with it yet. There may be a lot of uncertainty associated with an AI project where companies do not know how much resources and work there will be in the end, due to insufficient knowledge of what one needs for a project. Several of the informants point out that it is important that time is set aside to explore different solutions. Then you will often get a better result in the end than if you do not have time to try out other solutions.

I06 explains that another challenge that often arises is the planning of who will do what. I06 says that *"I have encountered projects where one comes in as a consultant, and they have not previously set aside resources on their side, which should be a domain expertise for me. I'm not a medic, so if I was hypothetically put on a project where we were going to diagnose a disease, I don't have any knowledge of that domain.'.* This shows that more knowledge is needed about the planning of which resources to put together for each project. There is a need for more knowledge among managers about what resources are needed for a project and what domain knowledge is needed. There are many disciplines that Data Scientist consultants do not have knowledge of, and then they will not be able to create a good model, such as a model that will be able to predict when a car needs parts replacement. An AI project will usually be an interdisciplinary project where there is a need for people from several disciplines who need to communicate each other's needs and expertise if one is to unite the technical with the professional and finally with the rest of the organization. I06 explains that "*It is very often a challenge that you do not get domain expertise, and it takes a very long time to find out who in the company is what we consultants can talk to to understand and improve the model, and that one continuously has that access."* In other words, companies must set aside resources for consultants to have a domain expert involved in planning and developing the model. It is also important that managers know in advance that they need to before the consultants come in and start developing the model. I06 also says that this is something that is left on every project. Furthermore, the informant explains that when you come in as a consultant, there will be a lot of time spent by not knowing who to talk to about where the data is located, what the data means and how to access data. I06 claims: "*I think that's because they simply don't know they have to do it beforehand. If you're dealing with a customer like that, you have to guide them and tell them that you have to do this before we can start.".* This planning of an AI project seems to be a phase where more knowledge is needed among managers about what preparations they need to make. Consultants are costly to hire and more time spent on consultants having to start by making the preparations that the company thought were clear will make ai projects even more costly. I06 also explains that there is often a lack of a mandate to be able to make decisions during the projects. This is also a waste of time when the Data Scientist consultants working on the projects do not have a mandate to make a decision and then do not know who will make these decisions. Several of the informants also had experience that not enough money has been set aside in the budgets to do what they wish to get a good result, and then the product often becomes a bad result. Several also said that a sum of money was usually set aside for each step of the project, which then made it easier to stay within budgets.

4.3.3 Implementation

Several of the informants point out that managers underestimate how much work there is in an AI project. Not only should they facilitate the collection and disclosure of data, they must also plan for how this will be implemented and maintained. Who will do what and what expertise one needs for each step of the process. I02 says that "*Some of the challenges with AI projects, it is that they may underestimate complexity, do not have sufficient resources to be delivered on it, do not have sufficient understanding of what needs to solve, etc."* Several managers believe that once the AI model is implemented there will be no more work, but this must be continuously improved and maintained for adaptations after changes in the real world. An AI model intended to predict customer churn or customer needs will continually need customizations, as the customer's needs and interests are not constant. There was a consensus among the informants that there is little knowledge and experience in developing AI models in Norwegian companies, and that this was most often carried out by hired consultants for a limited period of time. As stated by I06 "*When it comes to a typical Norwegian company, we probably don't have as good experience in manufacturing models, which are in a way the brains of AI solutions. That's where we as consultants have to come in and try to help companies through the process that is required.".* The informants say that it seems that many managers do not know how many resources are actually required to initiate an AI project. I06 goes on to say that "*If you have the organizational in place and the computer engineering in place, then in a way it is the cherry on top that is the here analytical AI solution* *that can be put on top of everything that exists then. So it's kind of a pyramid.".* This says something about how important it is that the organizational conditions, data infrastructure and data quality are in place to be able to succeed with the AI solution. I04 also says that the company must also understand how the solution should be used and be more involved than they might have thought beforehand. Companies are unaware of how much resources they need to set aside for an AI project. I06 finds that there is often a lack of a strategy for how the solution should be implemented, and that it eventually stops or pauses. The managers will often not admit that they have then failed and say that it is only a little slow. I05 says that there are some challenges associated with its implementation. The informant finds that companies do not see the importance of implementation when they are only hired as consultants on a time-limited project, and that this should be implemented into the organization and built on from there. The informants also point out the importance that it should be the same engineers who developed the model that also further develops it in the organization. I06 explains that "*If I get hired into a company and do just the concept development and leave again, then it is quite critical as they should have me in the integration, so that I can tell those who are going to integrate the model and data stream what has been done, how I intend. Even ask why and who they can ask.".* When the model is fully developed, and the consultants have finished their assignment, further development and maintenance is often left to others who do not have insight into how the model was created.

I06 says that *"Data represents something in the real world, so if something in the real world has changed drastically, the model doesn't know about it, and then it can't predict correctly. So, you have to constantly have that continuous re-training and continuous maintenance of the process."* Several of the informants point to the challenges of getting companies to continue the AI model after it has been delivered and integrated into the company. I05 believes it is important that you have people internally in the company who can take ownership of the models afterwards and have it implemented. Once Data Scientists have fully developed and delivered the model, the company must have someone who can do the work of re-training and maintaining the AI model in the operational phase. I05 mentions that *"We have projects where we have delivered a model, and we do not know fully whether the company has been able to use it, or if it is a person who sits and runs it for himself, or at worst* *that it has only been put aside." .* When the company does not have knowledge of what preparations and resources need to be available to start an AI project, they may also not know what resources are needed after this is implemented either. Managers may seem to think that an AI project is a short-lived process where consultants come in and develop the model and that the company itself takes over after the AI model is delivered. This may be a bad idea if the company lacks resources internally that have expertise in AI. I05 also states that if an error occurs in the model after it has been delivered to the customer and the project is completed, then the customer will not be able to detect errors or correct the error. Especially then in AI models where input data and feedback data are needed, where continuous maintenance and updating of the model is needed. Larger companies that have the expertise in-house probably have a better ability to continuously improve and maintain the model during the operational phase. Another problem that often arises according to I06 is that when the model is delivered, the company is unable to implement this into its routines and actually adopt it. Then they also do not know how to use the results. I06 says that "*There is something called MLO that is Machine Learning Operations, where people work specifically with monitoring and maintenance solutions. It is demanding because it is so new, and there is no common consensus in this field on how this should be done in the best possible way."* This is probably because there are not many companies in Norway that have extensive experience with AI and maintaining an AI model over time. Then there will also be few who have put in routines and best practice for this as it is still in an exploratory phase where different methods must be tested. There are also many managers who do not consider that the operational phase must be planned and that they must have expertise internally that can monitor and maintain the model, and the costs this entails. I06 says that "*... After that, many people fall off when it comes to implementation and maintenance. Mostly because they don't realize that there are costs here and that it's a long-term commitment if someone is going to maintain the process.'* . It seems like a lot of people are reluctant to start an AI project because of the huge costs it entails, but the gains are often much higher than the costs in the long run. This may indicate that some managers do not see what opportunities they have for a future gain on their AI projects, but also that smaller companies have fewer resources and that it will be too costly to make use of and maintain at first. I06 says that implementation is a major challenge both professionally and renewing solutions and making it fit into the company's existing technical solutions. Then they also had to explain to management why they should spend money on this. It should probably be more adapted to how it should all be coordinated and what competencies are needed for each part of projects. Especially during the implementation phase where it is important to have someone with domain knowledge and someone who knows the organization's integrated systems and needs.

4.3.4 Successful AI Projects

I03 says that *"Those who succeed, many of them are in an industry that can be hi-tech and have expertise in-house or tradition for it. At least they have access to expertise. They tend to have users who are used to that kind of functionality. Perhaps even expect it in some cases. They have also been working on it for a while, tried and failed. I dare say they've introduced it step by step, not a big all-in-one.'* This could mean that those who succeed are larger companies that have the finances to be able to acquire high levels of expertise in AI and develop it in-house. With higher competence in companies, they will probably also be better at seeing the technological opportunities and how to make the best use of it to satisfy the customer's needs. They will probably also be better at being able to integrate this into their business processes, maintain and use it more efficiently. They probably also have more experience in adopting new technologies and being able to adapt to technological changes in society. They may also be better at seeing the customer's needs, such as ease of use, customizing the customer segment, and what it takes for the customer to have confidence in adopting it.

Several of the informants answer that companies that succeed with AI have an acceptance of trying and failing, and that when starting a project, management knows that you may not be able to do so. This acceptance, the informants say, is quite important for the culture. I05 believes that in order to succeed, one should be open to new ways of working and that one is also concerned with doing the tedious job around data quality. One should have a conscious relationship with the data you have and treat it in a good way. The informant says that it is important to have an attitude that one is willing to change because many traditional companies may feel that they have no reason to change and will then continue as before. I06 talks about the importance of the fact that in order to succeed with AI, there must be room to scrap the original plan and make changes to the plan along the way. Unforeseen events can occur, and you see more solutions as you get more overview. Then one should not be locked according to a set plan, but that one is prepared that one may have to change the plan along the way. According to the informant, this flexibility will be a good prerequisite for success.

4.4 Cultural Aspects

Some of the informants believed that it is the small and medium-sized enterprises that have the greatest challenges in succeeding with AI because they have too few resources and internal expertise to be able to get started. On the other hand, other informants believed that it is precisely the small companies that succeed with AI because they are not stuck in old traditions and are more dynamic and agile, who quickly adapt to changes in technology and get the products quickly available. The informants also had different opinions about how mature Norwegian companies are for AI and how far the development of AI has come in Norway. Some believed that we have come a long way compared to other countries, while some believed that we have a long way to go. They find that small businesses are more likely to become more data-driven than large organizations.

I04 explains that *"Sometimes you have a purpose, you have a sensible data structure, the data exists, but you can't model what you're going to do well enough. It happens from time to time, but you have to be open with the customer about it from the start, that this is a bit of an exploration case."* Several of the informants report that an AI project is a more experimental project where it is important that you have a culture of trying and failing as part of the process. I05 finds that most companies understand that AI projects are a type of R&D project. I02 says that “*The other side of the medal is that there must also be an acceptance that something should fail, because it contributes to learning."* . It is also important to set aside time to be able to experiment with different solutions. If the focus is to finish within the fastest possible time without room to try out different solutions, you will not end up with an equally good model, and maybe you will not make the model work at all. Many of the applications in which AI is now implemented have not been tested with AI before. No dataset is the same, and it will therefore be required to test and improve the algorithm along the way to get a good result in the end. In the AI projects, they often work iteratively where, after each step in the process, one can go back and improve the model or clean data. I04 also says that it is quite important to have a culture of trying things out and that you know that it may not work. The informant also claims that it is important that there is also a culture that the focus is not on rapid profit because it will then be difficult to run the projects. The informant says that having room for innovation is very important, because if you don't, you never get started. It can be interpreted as saying that in innovative projects such as AI projects, one should change the traditional attitudes where rapid profit and cost cutting are the focus when starting new initiatives. There should be room to spend more to achieve something good, by focusing more on idea exchanges, exploring and trying out new ideas, and increasing the freedom of project teams.

I07 says that *"I think that in general there is great respect for the fact that in the purely professional decisions that are made, the teams themselves account for to a considerable extent.".* The informant explains that things have changed from how it was 25 years ago, where managers without knowledge of technology should mean something and make decisions in projects, they had no preconditions for thinking about. The project teams probably have more responsibility and freedom to make their own decisions now than they were before. It has become a trend to be innovative and adaptable and be able to adapt quickly. It has also become more popular with Lean philosophies and continuous improvements. I05 explains that *"If you take new startups or fairly small agile businesses where it's easier to turn around and there's less of that history around with 'that's how we've always done it'. Then it is more often easier to get it implemented, whereas in the older large enterprises there will always be more friction then.".* This seems to be something that remains in several of the informants that the older traditional companies may be a little more entrenched in their traditions, and it takes more to make organizational changes and adapt to new trends in technology and change management. They may have an old data infrastructure and there is a lot that needs to be replaced before one can implement AI in the organization. They can also show more reluctance to make major changes in their culture and their way of working. I05 further explains that when consultants come into companies that have recently started up with AI and they have their way of working, but then the consultants come in and tell them how to work and what changes they need to make. Then the informant finds that there may be some tension between those who want to work their way and those who come up with new experiences. I06 claims that the culture has a lot to do with how a company manages to implement the model into its routines and adopt it. Adopting the results of the AI model and getting them into their routines and acting based on them. If they can't do that, you'd say they've failed with AI. I02 explains that *"Within the power industry that I work a lot in, if you are going to use artificial intelligence to base all the decisions you make in maintaining infrastructure, then I think some of those who work in maintenance will frown a little on the nose and think that 'no, here we have good methods at the bottom', and have methods that have been used for many years that should instead be used."* . This is an example of a business that is bound by its traditional methods and that shows a reluctance to change its well-functioning methods.

4.5 Methodology

Several of the informants explain that AI projects have an exploratory approach where it is okay not to get it right away. The purpose is to experiment and learn from the mistakes you make. When it comes to methodologies, informants find that waterfalls are used, agile and iterative approaches in AI projects, while some have no methodologies at all. I06 finds that many small startups don't quite know what kind of methodology they have, while larger companies have a strategy and plan for implementation. The need for a development methodology is probably also greater in larger companies than in a small one with few employees. I07 finds that a lot has changed in methodologies for IT projects in general in Norway last 30 years. The informant claims that almost no one uses sequential waterfall methods where one specifies first and builds afterwards longer. The informant also explains that the projects are more informal and agile now than before, and that DevOps in particular is a big deal now. It seems that development methods in AI projects can vary widely from company to company and how experienced they are in it. Most informants find that most projects have an agile approach where you have Scrums and Sprints where you have a project manager who is in contact between management and the team. I06 says that "*Often heavy organizations have an organizational tenaciousness then, that is, everything takes a very long time.".* This is something that remains among the informants, that in the larger organizations it can be a little more challenging in terms of making changes in work methods and restructuring. The smaller companies will have an advantage in the fact that they can more easily introduce and test new methods and ways of organizing project implementation.

I04 says: *"It makes quite a sense to think when you have an AI project then, instead of what we're making to solve everything right away, you should make a little case instead. You describe the whole problem first, but you say that goal #1 is to solve this bit of the problem, and it also works. Then we solve a slightly bigger bit, and it works."* This method is often seen in development projects within both general software projects and AI projects. This is the waterfall method that seems to be the most prevalent. The method is easy to use when you can break down larger complex projects such as AI projects into several steps where each step must be completed before one can start the next one. Then you will have several smaller projects that make it easier to coordinate who will do what and what expertise is needed in each part. They will also save costs when better utilization of resources is made by dividing the project into several parts. There is no need for all resources through all parts of the project. I04 explains that if you start with the first part of the project and you can't get to that part, you can choose to scrap the project already then or if you are going to spend more time solving this part. There will be a better solution with this approach than spending a lot of costs on bringing in resources for the entire project and you can't get it right at the start. Completing the project will then offer a lot of extra costs as it will take longer to complete. By taking one step at a time, you will avoid investing too much in something you can't function. I04 says that you must tell the customer at the beginning, that we may not be able to do it. I06 explains that "*Very many people are willing to first do a Proof of Concept and see if based on their data and their data quality, they can create a model that has a good predictive ability. After that, many people fall off in terms of implementation and maintenance."* This will also be a good way to find out if you have data that will work or not before starting a project that will fail in the end. The informant explains that many people use Decision Gates as a methodology in the AI projects. The project will be divided into small "gates" where each street has a defined goal and it is well defined who will be involved each street. At the end of each street, a qualified decision will be made on whether to proceed to the next street. The project manager will then present the results and what they have done to management, who will then conduct an evaluation based on all aspects of the project. I06 says: "I think that *methodology is very good, but it can be very frustrating in terms of delays and budgeting. You may have budgeted a little too little or something has delayed the project, and then it's tough to be near the next street as well there is time pressure and hard to get through."* . This may indicate that too little budget is budgeted or insufficient time for the various parts of the project. This may probably be due to insufficient experience with AI projects and the amount of work that will be needed on each project. Some projects can be more complicated than others with a greater need for exploration or more domain experts. It will also entail extra time and costs if you discover errors or deficiencies that mean that you must go back and do things again. I06 has the impression that the use of Decision Gates is more prevalent among larger companies, and has not yet experienced small businesses that have used this.

I05 says that it is easier to get a good idea of new opportunities with AI after you start to get results, because then you get a more clarification of the opportunities that are there for further development and can run an iteration on it. If you make the model work on an area, you will also see that it will work on it and that area. In other words, new ideas and opportunities may emerge along the way as the model is improved and further developed. The informants explain that an AI project goes through several phases where one has idea development, concept development, testing, implementation, deployment, integration, and maintenance.

4.5.1 Interdisciplinarity

The informants agree that AI projects should have a high degree of interdisciplinarity. Engineers or data scientists know little about the company's business processes or the domain, and therefore there is a need for an interdisciplinary composition of the project team to develop and/or implement AI. Both the organizational and the technical aspects of an AI project must be taken into account, and different roles must then be involved in the planning at the start of the project. The engineers or data scientists are good at working with data and performing statistical models and testing of models, but they usually do not have knowledge of the domain for which they will develop an AI model. If an AI model is to be developed for an accounting program or the stock market, there will be a need for people who know this because the engineers have little knowledge of what the model should be able to perform. The informants explain that the companies often do not know that interdisciplinarity is required when integrating models and not just Data Scientists. There are many different roles that must be part of an AI project, and these must be able to communicate across disciplines. I06 explains that when developing an AI model into a subject area you do not have knowledge of it is important that you bring a domain expert with you who can teach a little about the domain for which you are going to model. This could be, for example, in medicine, geology or finance.

4.5.2 Learning and Knowledge Sharing

The informants' experience is that managers often acquire expertise in AI through conferences they have attended. Several of the informants also report that knowledge is shared during conferences or professional days where you show up and talk about what you have done. This is arranged both internally and externally. Several of the informants find that several companies have internal seminars where everyone in the company can come and see what other teams have done and how they got it done and share ideas with each other. The informants have also experienced that external people come into the company and give a speech, and that some companies spread knowledge through blogs and podcasts. I06 believes that one has a kind of social responsibility to contribute knowledge, and that one therefore takes initiatives to give lectures, courses, show up for interviews, etc. In the informant's company, they are keen to make themselves visible and help customers understand what the solutions are, what it requires and what it can give a company. I04 says: *"I don't think the threshold is very high for sharing really. Since it is such a new subject area that you lack expertise, you don't know if you can achieve a project when you start.”.* It will be difficult to replicate the same success other companies have had with AI unless you have the same prerequisites and resources required to achieve it. Therefore, there will also be no risk associated with sharing their knowledge and experiences with others. I05 tells about previous projects where knowledge was quantified by modelling things and then being able to share what you have done with several people. This allowed knowledge and experience to be disseminated through a dash-table solution that was accessible to everyone. The informants do not find that as much knowledge is shared between companies in the same industry as they are then competitors. I06 finds that you do not go into the details of confidential projects, but that you often share abstract things or algorithms and general solutions you have achieved with people you know in the industry.

5. Discussion of the Results

In this chapter there will be a review of the results from the data collection, which will then be compared with the existing literature within the topic of the master's thesis from the theory chapter. Possible answers to the research questions will be discussed considering the empirical data and previous investigations carried out within the phenomenon being investigated. The empirical data being discussed are statements from a selection of informants who work as Data Science consultants with experience from several companies and researchers in AI and project management.

5.1 AI in Norwegian Corporates

According to the empirical data, how far the development has come in the use and development of AI in Norway will be that Norway have good opportunities to get far. We have the resources in addition to being a digitized society that invests heavily in AI and there is a willingness to invest in and implement this around Norwegian companies. What places limitations on developments in Norway is that legislation such as the GDPR will make it more challenging in terms of obtaining consent and it places restrictions on the applications. This applies to all countries within the EU, and we will therefore lag behind countries such as the US and China that are not as strictly regulated.

According to the empirical evidence, when it comes to leaders' prior knowledge of AI, they will be limited. It seems that many managers may have unrealistic expectations of what AI can contribute to their company and what the model can do. Managers have little knowledge of the applications and how the technology works. This can make it challenging for managers to discover what opportunities their company has in using AI. Some people may sit on very good data they don't know they have, or that the data has the potential to become a very good AI solution. The results of the empirical data on the leaders' lack of knowledge about AI and its applications seem to match previous research from the theory. The same findings were made in this survey as in previous surveys that managers have too high expectations and do not have the competence to see business opportunities with AI. Previous research showed that managers tend to overestimate their own knowledge of AI and how much competitive advantage their projects will give the company. This can also be recognized in the informants' experiences that managers often think they have much better data than they have, or when they do not know that there is much they have to do in advance such as having a data infrastructure and a large enough data material.

When it comes to the cultural aspects of Norwegian companies, it varies greatly. The informants find that in some industries they may have stronger and more entrenched traditions than others, especially in older and larger companies. Their experience shows that smaller companies are more likely to organize and adapt to changes in technology. The majority pointed out that that acceptance to try and fail, and the fact that the leaders understand that it is an exploratory project will be very important for the culture.

5.2 AI Projects

All informants had experienced AI projects failing, but several also pointed out that it is not necessarily negative to fail because it contributes to learning, and that many people have an acceptance that it is okay to fail. Some of the informants could also relate to previous surveys that showed that 80-90% of all AI projects fail while others believed that they do not fail more than other projects. I can imagine that there are several pitfalls in AI projects considering all companies and managers who do not know in advance what resources are required both before and after the project is finished. Other projects have more experience, whereas with AI projects you often do not know in advance where it is common for problems to arise or identify errors. What the informants were able to talk about challenges that can contribute to AI projects failing were the same ones found in the literature on poor data quality or lack of data that then often recurs. The reasons for this may be that managers know too little about what data they need and how they should be collected and structured in advance. They also know little about how to access this data. Managers should gain an increased awareness of how to get good data by making it available knowing how to extract the right data.

When it comes to developing an AI model, it seems most common to hire external Data Scientists consultants to do this job, rather than develop it in-house. The informants' experience is that only a few large companies have their own Data Science department and do this internally. This is of course a very costly initiative to start with, especially if the company does not have the knowledge of what it needs to succeed. It seems to the informants' perceptions that the demand for Data Scientists consultants is currently growing. This is probably due to more and more companies becoming interested and curious about AI and showing a willingness to have this implemented in their company. The informants also found that some managers are beginning to acquire more knowledge about everything that entails in an AI project and what it takes. According to the empirical data, some managers show a lot of will at the start of an AI project, but may become more skeptical as they see how much cost there will be in the end. It is clear from the informants' experiences that many managers do not know how much work and costs AI entails after it has been implemented and will need continuous maintenance of the model. In order to do this in a good way, there will be a need to hire a Data Scientist or a Machine Learning Engineer to monitor and maintain the model during the operational phase.

5.3 Methodology in AI Projects

According to the empirical data, an AI project will be demanding to plan how long it will take and how much costs it will incur in the long term. There is a consensus that an AI project is an exploratory project with which very few people have extensive experience, and where there is much that is untested in the field. The field of artificial intelligence and machine learning is constantly evolving. There is a development in both technology and how the organizations can best adapt to more appropriate working methods in order to promote the development of AI in the best possible way. Project management is therefore an important topic in the development of AI, which we see from the empirical data that can be a complex process where many different roles will be coordinated within several phases during the project. According to several of the informants, 80% of the total time spent on the project agrees to process and structure the data material before the actual modelling. An AI project will differ from a purely software project in that a large part of the project will focus on handling and cleaning data, where data quality will be a very critical point on which the entire project will depend. In the software projects, it will be the coding itself that is the critical point and what takes the most time in the project. The final AI solution will not be better than the quality the data will have. AI projects will also differ from software projects in that the AI solution is not finished when the model is integrated and delivered to the customer. It will also be an operational phase where one must monitor and maintain the algorithm and continuously conduct re-training as reality changes. AI projects are still in an exploratory phase where there is no widespread method that is the best way to implement it. The informants, on the other hand, felt that the best projects were those where time has been set aside to explore different solutions and where there was an acceptance to try and fail. This is something that managers should consider that one should not plan for a set plan with strict deadlines, but that one has an attitude that this is an exploratory project for which one may not find a solution. It also follows from existing theory that says AI projects are more open and have no set plan. The informants find that this varies from project to project where the governing leaders are in accordance with the time horizon and budget. The empirical evidence aligns with existing literature that AI projects take an experimental approach. The empirical data show that most companies have adopted agile working methods into their companies that contribute to less bureaucracy and control the progress of the project with system requirements to be approved. Previous research from the literature showed that smaller companies were faster with new technologies, while in larger companies things took longer. This was something that the informants also experienced.

The methodologies mentioned in the empirical data as Proof of Concept bear many similarities to CRISP-DM from the literature that was the most commonly used AI methodology in the United States. It does not appear that the methods most prevalent in the United States are as well known in Norway, but it seems that we have some methods similar in terms of the iterative way of working and the different phases from planning to testing and implementation, where one evaluates whether or not to proceed with the concept. Several of the informants mentioned waterfalls and similar methods, and this method may not be the most optimal method to use in an AI project. This method puts some limitations on being able to go back and it does not consider that large parts of the project are about the work on the data that one often has to return to clean and adjust.

CPMAI is the methodology of literature that is best suited for complex AI projects where data collection and many different roles are involved. This method does not seem to have come to Norway yet. Not among the experiences the informants have made at this time. The informants say that the AI projects they have worked on have been quite complex where they have spent a lot of time structuring data that has occasionally been strewn around the systems in different formats. The informants also explained that there are many different roles that must be part of an AI project and that there may be confusion about who should do what and who to ask. Based on what the informants tell about their experiences with complex AI projects, there seems to be a need for a methodology similar to CPMAI. This method is also specifically aimed at AI projects because it includes the phase of re-training and the continuous operational phase in retrospect, where these phases can take place in pairs with data management. An AI project is exploratory where it will be necessary to be able to go back when trying and failing different solutions. Then stepwise sequential development phases will not be appropriate when an AI project should not be sequential. An AI project will need to be able to quickly make changes to the model or data at any time in the project without having to go through detours and strict set plans. There is also a need for different roles in each phase that must be available throughout the project to know who to turn to if needed. CPMAI is based on the interdisciplinarity one must have in each phase and that one shares that knowledge with each other in the different phases. This is also something the informants pointed out that is important in an AI project.

5.4 The Project Team

According to the literature on the project teams in AI projects, it was not necessary to have more than 3-5 people on an AI project, nor was interdisciplinarity or other disciplines required. This is not the impression I got after hearing the informants' experiences from several companies. It seems like there is a complex team in each phase that can have different roles. You need computer engineers to prepare the data architecture and structure the data, and you will need Data Scientists to create the model. You will also need people with domain expertise in the field to model in as well as someone from the business side. A majority of the informants claimed that AI projects are highly interdisciplinary, and that 1-2 Data Scientists are not enough, as many believe. A previous study from the literature showed that many managers find it difficult to have confidence that the project team will be able to achieve a successful outcome on the project. This is something I do not recognize from the empirical data, as the informants find that managers give them a lot of freedom to find out for themselves through trial and error, and that they present to management what they have achieved at the end of a phase. It may seem that managers have confidence in professionals who have experience with AI projects and that they will be able to carry out the project because they have done it before.

It turns out, and from the empirical evidence, that high expertise in AI is a highly sought-after resource of which there are few in Norway. This will then also place restrictions on the development of AI in Norway. Not many colleges and universities in Norway have fields of study that specifically target Data Science, AI/ML, and these types of projects. I think this is something that will come as demand increases and educational institutions see the need. Today, it seems that there are many people with science backgrounds such as physics or mathematics who end up in Data Science. Several of the informants also had this background. It is mainly expertise in statistical methods and programming for which there is a great demand in Data Science. It seems that since there is a shortage of expertise in AI in Norway, several managers have looked at the possibility by acquiring people who are well-equipped to become good at AI and develop these in-house within the company.

5.5 Business - Technology Perspective

The literature says that it is important that the AI project is integrated with the business strategy in order to achieve the desired final product. This is something that the informants feel may not be done well enough. There is little communication between managers and the project team and managers without technology expertise may not be able to communicate their strategies and business needs well enough with the developers and Data Scientists. On the other hand, there may not be a need for a developer who is only going to write a code to know what purpose that code has business-wise. Not all computer engineers have an interest in the business aspects of it all. For some, getting involved in the business purposes of the project will have an impact on motivation and the fact that the work on the model makes a greater sense when seen in a larger context. If developers know the goals and strategies of their business, it will also help them know what other AI capabilities they can try out that might work better. The theory showed a study in which a lack of business understanding and understanding of the user's needs is one of the main reasons why AI projects fail. This is something that the majority of the informants wish there was more of and that should be present. The theory states that in order to succeed, there should be close cooperation between the engineers, economists and the project owner when designing the AI model. This was because as much as 70% of the project is about business application. In other words, integrating the model into the business problem one wants to solve using interdisciplinarity with a focus on the perspective and needs of the business and users.

When you turn it around, the informants also find that managers do not have technology expertise and are not able to communicate a good definition of the problem they want to solve. The empirical evidence shows that leaders come up with vague descriptions of the problem that can be short without any more explanation. They may want a chatbot but are unable to describe what they want the chatbot to be able to perform or learn. It was also an example of managers who believe that AI will be able to give them a justification for why a customer terminates the customer relationship. Previous research from the literature also showed that managers had too little focus on the business goals that AI should solve. Empirical data could also show that it is challenging for Data Scientists to communicate and explain statistics to managers without knowledge of statistics. There were several people who had experience with managers who believe that AI is something magical that can do incredible things and had too high expectations of what AI can do. It seems that more people had experience with the projects starting with having to give managers a reality orientation about what to expect and what AI can do. This will be something that will improve as more and more managers gain experience through AI initiatives and acquire more knowledge. The informants also explain that there are many ways for companies and managers to acquire knowledge and keep up to date with AI by attending conferences and holding seminars from both internal and external Data Scientists. It may seem that many people want to share and show off what they have achieved even though they may not want to be too detailed with competitors in the industry together.

6. Conclusions

This is the final chapter of the master's thesis where I will review which conclusions I have drawn based on the results of this study. The purpose of this study was to investigate the reasons why AI projects fail and what possible causes are behind this phenomenon. This is to raise awareness of why AI projects are failing and how to reverse this trend. Are there organizational changes that are needed or is there a lack of knowledge among managers? Do the project teams and managers communicate their technological and business needs well enough when they lack knowledge of each other's field? Based on a pre-project in the form of a literature review, I was interested in finding out if AI projects fail due to a lack of involvement and knowledge among managers or whether there are other organizational factors that cause the AI projects to fail. I also wanted to investigate whether there were any weaknesses in how Norwegian companies organize their AI projects to find possible causes that could contribute to AI projects failing. Through a qualitative survey through the use of in-depth interviews of people who have good knowledge of working closely with the phenomenon around Norwegian companies, I came up with several interesting findings.

The first research question I wanted answered was how managers' knowledge and involvement in AI projects affects the project's success rate. When it comes to managers' knowledge of AI and AI projects, the results showed that most managers in Norway have insufficient knowledge of AI and its applications, as similar research has shown. In addition to their unrealistic expectations of the technology, they have too little knowledge of how to leverage the technology and their own data to create gains from it for their company. They don't have enough knowledge about their usage capabilities, or what data and resources they need to start up with AI. Most managers also do not have knowledge of how complex such a project can become or how to integrate this into their routines for adopting it. Many of the managers did not know that an AI project is a continuous process where monitoring and maintenance is needed during the operational phase. These limitations in the manager's competence may affect the success rate of the projects in that the projects have less efficiency and more time spent in that Data Scientists must do a lot of preparatory work before project start due to deficiencies in the company's data and problem description. As for the managers' involvement in AI projects, the results showed that managers are not involved in the AI projects, but they get an update on the state of the project along the way from the project manager. Between management and the developers, themselves, there is no contact. After working on this task, I would like to conclude that there is also no need for management to get involved with the project team other than for increased motivation and recognition among the developers. The weakness will lie in management's ability to communicate the business need and describe the problem AI should be able to solve in a more detailed and precise way.

The other research question I wanted answered was how companies' organization of AI projects contributes to the project's failure. The findings I concluded were that it is at the beginning of the project and the process after the AI model has been delivered that are the most obvious contributing reasons for ai projects' failures. The data is often inaccessible and unstructured where companies lack a system for collecting and handling their data. There is insufficient planning when companies believe that 1-2 Data Scientists can carry out a project on their own and that they have not put resources in advance and after the project has been delivered. Data Scientists who enter companies don't get the resources they need, such as domain expertise and they don't know who to ask or who makes decisions. The findings also show that most AI projects in Norway use so-called waterfalls and similar sequential methods that, according to the literature, will not be of use for AI projects. A methodology should be facilitated that considers that AI projects are an interdisciplinary process where there is a need to be able to make rapid adaptations across the different phases continuously, as the projects are characterized largely by data that needs to be updated and models that need to be re-trained. Based on this study, I would conclude that the lack of organization in advance and after the project, the acquisition of resources and poor organization of roles will be a contributing factor to many errors with AI projects.

The last research question I wanted answered was which organizational conditions will prevent organizations from making success with AI projects. The findings I made around this research question were the problems around managing data and having the right data infrastructure. Many companies have an older data infrastructure with old systems that makes it difficult for engineers to have to put this in place before they can start the project. This question will also apply to the lack of technology knowledge among managers and a lack of business understanding by the developers. There is little business understanding among the developers who create the AI model and they do not get involved in the strategic goals of the enterprise, which means that they create a model they do not know the purpose of and what it should be able to do for business purposes. Another organizational factor is the lack of the right human capital. Few people have an education in AI and there is a great demand for this expertise. It turns out that several companies have found a solution to this by hiring people with science backgrounds or who have good expertise in statistical methods and programming, who will have good conditions to become good Data Scientists. The cultural aspects of the AI projects in Norway show that there is a need for a culture where there is acceptance to try and fail, and that failure is part of learning. AI projects are a relatively new field where few companies know which ways to do it are the best. It is therefore an exploratory project where one should not have a set plan and strict framework, because it can prevent the development of better solutions.

In conclusion, I would say that the benefits of this study are about the same as other surveys from abroad where there is data, managers' lack of competence and lack of business perspective in the developers that are the reasons why AI projects fail. The findings, which have not been investigated in the past, include a lack of organization around resources and the various roles included in an AI project, and the use of more AI-adapted methodologies, which help to delay or cause the AI project to fail.

6.1 Contributions and Implications

The findings in this master's thesis bear similarities to previous findings from international organizations and researchers. At the same time, it is a relatively new phenomenon on which there is little existing literature. At the time of writing, only one published research article has examined the same phenomenon that was published in 2021. The remaining studies are mostly carried out by organizations and are only six months old and are based on surveys that means that they have used a different method than I have done in this master's thesis. What makes this study different from previous surveys is that it is limited to Norwegian companies and that in-depth interviews have been done that help to obtain more detailed information about the phenomenon. Norwegian companies want a corporate culture and leader style that differs from quite a few other countries that will influence what we perceive as traditional management or if there is little contact with management. The findings made in this master's thesis may provide increased insight into the weaknesses in Norwegian companies when it comes to implementing AI and AI projects. Based on the findings made, managers may become more aware that they should acquire increased knowledge about AI and how best to organize an AI project. The digitalization of companies with increased use of AI will require companies to keep up with rapid developments and adapt to changes in ways of working and the increased demands on interdisciplinarity. Both in AI projects and more technology knowledge among managers because the business of the future is digital.

6.2 Limitations

The limitations of this study will be that this is a master's thesis carried out by a student who is conducting his/her first research study without previous experience as a researcher or previous publications. The master's thesis will be written and carried out by an inexperienced student for a short period of time in the form of a 4-month semester. The short period of time and the extra pressure in the form of this being a study that is essential for the student to get their final diploma will clearly affect the content and scope of the thesis. The master's thesis results are based on a sample of 7 informants from 6 different companies who may be too few to be able to do a thorough enough investigation of the phenomenon. If this had not been a master's thesis and there had been more time, more people from several companies and industries could have been interviewed. At the same time, there were many possible informants who declined.

Another limitation may be that the issues are not concrete enough and that the phenomenon being investigated is too broad. I eventually found that there were quite a few factors that go into the phenomenon of why AI projects fail, where I could only investigate one of the factors. For example, I could limit the study and research questions to only address how Norwegian companies' leadership culture contributes to AI projects failing. What I wanted about this study was to have an exploratory approach where I would find undefined causes for which no findings have been made yet as reasons why AI projects fail. That's why I've gone out wide and had in-depth interviews with Data Scientists consultants who have gained experience from many AI projects in several companies and industries. This was done to uncover possible causes that have not been investigated before. If I had more time at my disposal, I would have liked to have had surveys in addition because then I could have collected data from a large sample that I could compare with in-depth interviews, and the findings of the study had become more reliable.

Another thing that limits the study is that when I wrote the interview guide I had virtually no insight into AI projects and there were many questions I came up with in retrospect that I should have asked the informants about in retrospect when I had gained a better insight into the phenomenon. If I could have asked more questions about the findings that emerged, I could have gathered even more information about the phenomenon I wanted to shed light on. It is also a weakness of the interviews that I have no experience in conducting qualitative interviews and that I think in retrospect that I should have asked them some questions that were not in the interview guide and conducted the interviews more as a conversation, which could potentially have uncovered more information. One last weakness of the study I want to mention is that this has been a very independent work where I have not discussed the task with anyone along the way and no influence from others. I should have made more contact with the supervisor and fellow students along the way to be able to hear other people's perspectives and whether I am on the right path through my choices and how I interpret the study.

6.3 Future Research

In light of the findings that have emerged in this master's thesis, I will explain what more research should be done that this study has not included. In order to investigate AI projects in Norway and be able to examine the background to why they fail, it may be appropriate for further studies to investigate a broader sample with a combination of both quantitative and qualitative investigations. This would make the findings more representative of the AI projects in Norway in general that provide a greater transferability to reality. It would also be interesting to have a study that is angled directly at the leaders with qualitative interviews where the leaders' own perspectives are examined. Then you will be able to find out more about the reasons why AI projects fail by hearing the managers' experiences, knowledge and what choices and thoughts behind the choices they make. The same could be done by interviewing the developers and hearing their experiences and perspectives. Developers may have a different perspective on the phenomenon and perceive things differently than Data Scientists who have a more responsible role.

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List of Tables and Figures

Attachments

Attachment 1 – Interview Guide

Interview Guide

I will investigate the reasons why many AI projects fail and the impact of management's involvement, knowledge, and trust in AI projects on the outcomes of the projects.

Before we start the interview, I would like to ask if you agree that I take an audio recording of the entire interview? It will be for transcription before analyzing the data and will be deleted afterwards.

Can you tell me about your background, your role in the company and your experience with AI projects?

1. How far has the development of AI come in Norway?
2. Is Norway ready for AI?
3. Is there enough expertise in the applications for AI in Norwegian companies? What's it going to take?
4. Are companies willing to implement AI? What's it going to take?
5. Do companies have confidence in the technology? What's it going to take?
6. Do users have confidence in the technology?
7. What is the willingness to invest in AI projects in Norway?
8. What do you think it takes for managers and investors to dare to invest more in AI?

9. What experiences do you have with AI projects?
10. What challenges have you experienced in AI projects?
11. Have you experienced AI projects fail?
12. What was the reason for this?
13. What do you think it came from?
14. What could have been done differently?
15. What challenges do you see at companies that bring in consultants for AI projects?
16. What qualities do companies have that succeed with AI?
17. Are you experiencing more delays or unforeseen incidents with AI projects compared to other projects?
18. Do AI projects stay within budget?
19. Which phase of AI projects do you see as most critical and at what stage do the most errors occur?

20. What is the expertise of the teams in AI projects?
21. Do you experience the project teams working with AI as skilled or have insufficient expertise?
22. Did the project teams have short or long experience with AI projects?
23. Are there enough people with expertise in AI and machine learning in Norway?

24. Is it difficult to acquire high expertise in AI and machine learning in Norway?
25. What methods are used in AI projects?

26. Do you find that managers have confidence that the project team knows what they are doing and that they will succeed with the project?
27. How is the contact between management and the project team?
28. Do you find that managers have enough knowledge about AI and the possibilities of it?
29. Is there close cooperation between management and developers?
30. What is the communication between management and developers like?
31. Do developers have a business understanding?
32. Will the developers be included in the company's strategic goals for the project?

33. How is knowledge about AI developed in Norwegian companies?
34. How do you develop knowledge about AI in your company?
35. Is the knowledge shared internally within the company?
36. Is knowledge shared with others in the same industry?
37. Are courses/training held?

38. What does the culture have to say for the success of AI projects?

Attachment 2 – Codes

Codes	Number of references
Maintenance	2
Trust	14
Development	24
Competence	41
Black Box	3
Organization	19
Integration	8
Data Management	13
Regulations	9
Business Opportunities	11
Skepticism	2
Lack of Knowledge	41
Maturity	19
Data Collection	5
Data Quality	10
IT-infrastructure	7
Model Development	6
Customers Trust	4
Willingness	11
Culture	20
Learning	16
Interdisciplinarity	16
Success	11
Communication	28
Business Understanding	8
Willingness to Invest	2
Problem Definition	6
Budget Overrun	7
Knowledge Sharing	6