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Machine Learning Project Management

A Study of Project Requirements and Processes in Early Adoption

Master's Thesis in Master's Programme International Project Management

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Department of Architecture and Civil Engineering
CHALMERS UNIVERSITY OF TECHNOLOGY
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Abstract

Machine learning projects have increased in numbers and appropriate project management processes and methodologies are needed to ensure project success. Insufficient research has been done on the subject which could support corporations and organisations that are planning to start, or have recently started, with applied machine learning.

The purpose of this thesis is to provide project management guidance for machine learning projects, by filling the knowledge gap in the literature. This study has focused on applied machine learning projects in the Gothenburg area of Sweden, where data from 13 interview subjects from 10 corporations and organizations have been gathered.

Cross-Industry Process for Data Mining (CRISP-DM), Team Data Science Process (TDSP), Scrum and Kanban have been found to be used in machine learning projects, but with modifications. Digital transformation and organizational change management have strong relevance for machine learning projects. The study found and elaborated on the three ML solution procurement options: in-house development, outsourcing and Commercial Off-the-Shelf (COTS) solutions. Finally, trust in the technology, the team and external collaborations were found important for machine learning project investments.

Keywords: project management, project process, methodology, machine learning, data, trust, team competence, problem framing, external competence.

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Christoffer Brasjö & Martin Lindovsky, Gothenburg, June 2019

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List of Abbreviations

AI	Artificial Intelligence
AGI	Artificial General Intelligence
ANI	Artificial Narrow Intelligence
ASI	Artificial Super Intelligence
CAPEX	Capital Expenditure or Capital Expense
COTS	Commercial Off-the-Shelf
CRISP-DM	Cross-Industry Process for Data Mining
DL	Deep Learning
DMME	Distributed Modeling and Distribution evaluation
KDD	Knowledge Discovery in Databases
ML	Machine Learning
MVP	Minimum Viable Product
NLP	Natural language Processing
PMI	Project Management Institute
PMLC	Project Management Life-Cycle
POC	Proof of Concept
QM-CRISP-DM	Quality Management CRISP-DM
R&D	Research and Development
ROI	Return on Investment
SE	Software Engineering
SEK	Swedish Crown
SEMMA	Sample, Explore, Modify, Assess Data Science process
TDSP	Team Data Science Process
WBS	Work Breakdown Structure

1

Introduction

1.1 Background

Digitization has become the new norm of the twenty-first century, where the amount of data continues to increase at an exponential rate (Hashem et al., 2015). In some cases, the term *big data* is used for extremely large data sets, which are defined by their volume, variety, velocity, veracity and value. People in modern society are used to computers and use them for communications while feeding on *information*, which can be defined as the set of patterns, or expectations, that underlie the data. The hunt for this information is termed *data mining* which is the extraction of "implicit, previously unknown, and potentially useful information from data" (Witten et al., 2016, p.xxiii). To be able to extract this information from raw data, clever data mining tools are needed to find patterns in the data. *Artificial intelligence* (AI) can interpret data, learn from it, and use these learnings to solve problems by simulating human brain functions. For instance, an artificial neural network can make conclusions in a way which resembles human intelligence. Even though the understanding of its attributes of logical reasoning, learning and self-correction are abstract, the AI mimics human intelligence in an extremely useful way. It possesses the ability to perform tasks in complex environments without constant guidance by a user and has the ability to improve performance by learning from experience. Most AI machines are narrow in the application and can solve a specific problem, while a more general AI machine is intelligent in a wide area of activities. General AI does not exist today but is believed by experts to have a 50% chance of being developed around 2040-2050 and a 90% chance of being developed by 2075 (V. C. Müller and Bostrom, 2016). With many years still to go until 2075, narrow applications of AI is the main focus of AI practitioners to create products and services, through different AI techniques.

Machine learning (ML) is a subcategory of AI and provides the technical basis of data mining and is used to extract information from raw data in databases. This information can be used for a variety of purposes, such as finding historical patterns in data to make better decisions and predictions for the future. By using machine learning, practitioners are trying to make sense of data and create products and services based on the outcome of data mining. This is not an easy task as more than 50% of data science and data analytics projects fail to deliver the benefits agreed on at the start of the project (Larson, 2018b).

Much research has been done on the use of data science and algorithms to generate useful data mining results. However, there is significantly less research done on project management processes and methodologies on how to effectively plan and execute data-driven projects, which include AI, machine learning and *deep learning* (DL), a class of machine learning algorithms. “There is a clear lack of well-functioning tools and best practices for building DL systems” (Arpteg et al., 2018, p.50). The information that is out there is found in blogs by practitioners or in corporate documents, created by project managers or data analysts in machine learning projects. There is a need for academic approaches to help AI and machine learning teams to be more efficient and effectively do big data-related projects (J. S. Saltz, 2015).

Currently in Sweden, new investments into AI research, with the purpose of transitioning Sweden into becoming a globally leading collaborative environment for AI. One initiative is AI Innovation of Sweden, national and neutral arena with the aim to accelerate applied AI research and innovation in Sweden (BRG, 2018). The first node is at Lindholmen Gothenburg, with planned nodes in both Stockholm and Malmö/Lund. The expected outcome of this initiative is an increase of applied machine learning projects in the area and the results of the thesis are expected to increase their success rate.

The findings of the study are expected to contribute to both economic and environmental sustainability. In regard to economic sustainability, by considering the final recommendations it may allow Project Managers to make project investments e.g in solution procurement, that support and drive the long term corporate machine learning strategy. For the environmental perspective, training machine learning models can require extensive amounts of computing power with correspondingly high energy consumption (McIntosh et al., 2018). By pointing out requirements to start machine learning projects, Project Managers can make better decisions when to apply machine learning and avoid starting machine learning projects that are doomed to fail from the beginning and waste large amounts of energy.

1.2 Purpose

The purpose of this thesis is to provide project management guidance for machine learning projects. The aim is to support corporations and organizations planning to start, or have recently started, with applied machine learning.

1.3 Research Questions

To be qualified and prepared for the challenging project environment it is crucial to have the right skillset as a Project Manager. Consequently,

> **RQ1: What competence is needed to lead machine learning projects as a Project Manager?**

Before deciding to start a machine learning project there are important things to consider for a Project Manager. Therefore,

> **RQ2: What are the requirements to start a machine learning project?**

It is important to make reasonable decisions in procurement of machine learning competence. Thus,

> **RQ3: What are the options and implications of machine learning solution procurement?**

Process frameworks and methodologies are the backbone for many projects in other domains. For that reason,

> **RQ4: Which project management methodologies or process frameworks are used, or can be used, in machine learning projects and why?**

1.4 Context of the Contributing Organizations

The thesis is written in collaboration with AI Innovation of Sweden and some of their partner corporations and organizations. Established in February 2019, AI innovation of Sweden is a resource hub with the aim to accelerate the implementation of AI by means of sharing knowledge and data, providing a co-location open space environment, and creating collaboration projects, to partner companies, organizations and academia. AI Innovation of Sweden contributes to the research by providing access to their shared open space office at Lindholmen and connect the researchers with organizations of interest for the research. One of the contributing organizations was not an official partner of AI Innovation of Sweden. Further details on the context of the respective organisation and interviews is provided in the Chapter 4 - Empirical Data.

1.5 Scope Limitations

This thesis focuses on applied and narrow machine learning and does not include artificial general, or super, intelligence.

Interviews with 13 different people from 10 different companies and organizations are included in the study. All companies were conducting machine learning projects in some form, with office location in Gothenburg. The interview subjects needed to have work experience in machine learning projects. Some of them had leading roles; Head of AI, Digital Transformation Officer, Director of Research, Deep Learning Product Owner, Co-founder, Innovation Team Leader and Development Lead. Other interviewees were Data Scientists, Software Developer, AI Researcher and Software Engineer. Project role diversities was a requirement to try ensure a full cover of project context.

2

Theory

This thesis creates value and awareness beyond technical challenges to the organizations that are considering their participation in the global AI trends through applying machine learning. This chapter focuses on explaining different topics, processes and models concerning machine learning project management, which are connected to the empirical data.

2.1 Background

In this thesis, words such as *machine learning*, *hype*, *training* and *testing*, *AI evolvement*, and other technical terms will be discussed constantly. Therefore, a background defining these terms and a better explanation of the field of machine learning, will follow.

2.1.1 Artificial Intelligence and Machine Learning

Artificial intelligence (AI), in short, can be explained as machines which think (McCorduck, 2004). The term "artificial intelligence" was first proposed 1956, six years after Alan Turing's published paper on *Computing Machinery and Intelligence*, who later became famous for the competition of creating the most human-like chatbot (the Turing test). Six years before that, McCulloch and Pitts (1990) had come up with the idea of creating a computer model inspired by the functions of brain neurons, to try mimic the intelligent design created by nature. But what does it mean for a machine to be able to think? Without becoming too philosophical, Russell and Norvig (2002, p. 2) say there exist many definitions for AI which they summarized in the 1990s as:

- **Systems that think like humans** - The exciting new efforts to make computers think. Machines with minds.
- **Systems that think rationally** - The study of mental faculties through the use of computational models
- **Systems that act like humans** - The art of creating machines that perform functions that require intelligence when performed by people, or the study if how to make computers do things at which, in the moment, people are better.
- **Systems that act rationally** - Computational intelligence is the study of the design of intelligent agents. AI is concerned with intelligent behavior in artifacts.

Thus, the term "think" means that the machine can mimic some intelligent human characteristics and learn from examples, apply the reasoning to new information and reach conclusions based on data. But since AI is still an emergent technology, the definitions are constantly re-evaluated and what used to be considered intelligent behaviour by a machine five years ago, barely receives any notice today. Kaplan and Haenlein (2019, p. 15) define AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". Dependent on how well the AI can perform on a

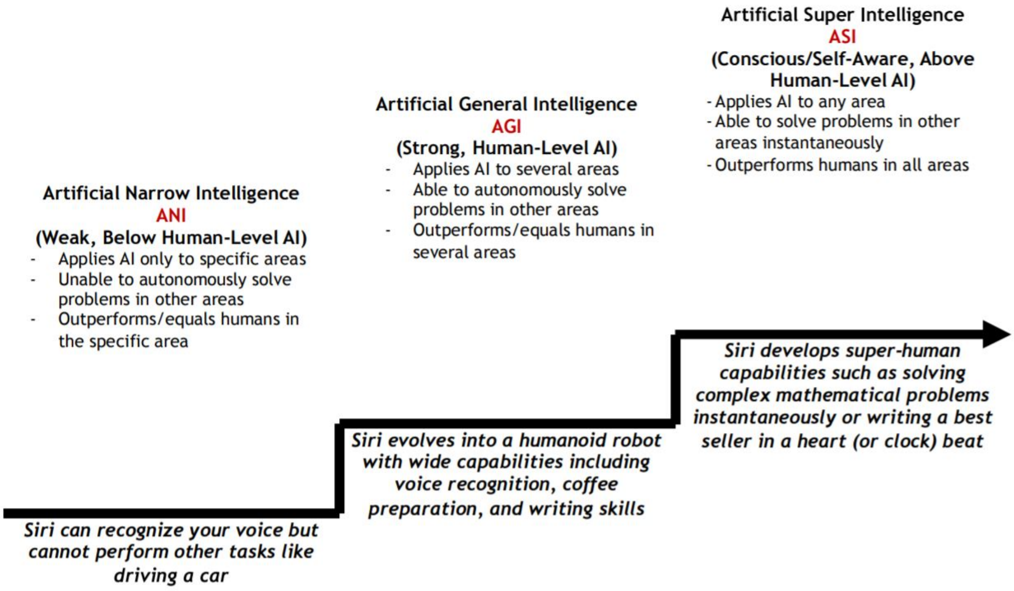

Figure 2.1: Stages of Artificial Intelligence (AI) according to Kaplan and Haenlein (2019, p. 16).

specific task, or multiple tasks of different complexity, Kaplan and Haenlein (2019) say it can be categorized into different generations, or stages, which can be viewed in figure 2.1. The first generation goes by the label *artificial narrow intelligence* (ANI), which refers to an AI designed to a specific task. They can recognize faces on Facebook, or make Apple's Siri understand and act upon voice command, or help Google drive its cars autonomously (Kaplan and Haenlein, 2019). The second generation of AI, called *artificial general intelligence* (AGI), can solve problems autonomously for tasks they have not been designed for. The last stage show the third generation of AI called *artificial super intelligence* (ASI). These systems are truly self-aware, conscious and will make humans redundant, in comparison.

Machine learning (ML), a subset of AI, is the scientific study of computer systems, where statistical models and algorithms are used by the system to perform a specific task *without any explicit instructions* (Witten et al., 2016). Instead, ML relies on patterns and inferences drawn from data.

Deep learning (DL), a class of ML algorithms, uses multiple layers of nonlinear processing units for feature extraction (pattern recognition in image processing) and transformations (Deng, 2014). Each layer is given as an output for the next layer or the final layer.

2.1.2 Applications of Machine Learning

Witten et al. (2016) say that where there is data there is a possibility of ML application. This is one of the reasons why ML has been given so much attention lately. But for corporations to be involved in ML projects a business understanding investigation is needed, which determines if the data mining will be profitable. Good business solutions are often found on problems which (1) require prediction rather than causal inference, and (2) are sufficiently self-contained or relatively insulated from outside influences. The first means that what is interesting to know is how certain aspects of the data relate to one another, according to statistical averages. This information comes without intuition, theory or domain knowledge of human analysts. The second problem type means that assumptions of the data fed to the learning algorithm includes almost everything there is to the problem. If the things which are tried to be predicted changes and no longer matches prior patterns in the data, the algorithm will not know what to make of it.

To be a bit more technical, ML enables acquisition of structural descriptions from examples in many applications. These descriptions can be used for predictions, explanations and understandings (Witten et al., 2016). Fields of application today are autonomous drive, content recommendation, image and video processing, cancer prognosis and prediction, video game bots, marketing, drug discoveries, machine automation, facial recognition, text-to-speech and vise versa, writing sport articles, and education, to name a few (Kourou et al., 2015; Libbrecht and Noble, 2015; Witten et al., 2016).

Examples of good ML problems include predicting the likelihood that a certain type of user will click on a certain kind of ad, or evaluating the extent to which a piece of text is similar to previous texts you have seen. Bad examples include predicting profits from the introduction of a completely new and revolutionary product line, or extrapolating next year's sales from past data, when business markets are dynamic and new competitors have to be taken into account.

2.1.3 Types of Machine Learning

Dependent on the problem at hand, ML is often divided into subareas, namely *supervised learning*, *unsupervised learning* and *reinforcement learning* (A. Müller and Guido, 2016). With supervised learning the AI is fed, for example, an image (input) of a street sign and told to classify it as a stop sign (output). By seeing many images of stop signs the AI learns to classify new images of stop signs it has not yet seen. This data often has to be labeled, or *annotated*, manually by a human, which decides what is a stop sign and what is not. With unsupervised learning there are no labels or correct outputs. Instead the task is to discover the structure of the data. For example, grouping similar items to form "clusters" or reducing the data to a small number of important "dimensions". With reinforcement learning the AI is asked to make decisions based on specific predefined rewards and learns through experimentation. It is commonly used in situations where an AI *agent*, an autonomous entity which acts upon its environment, must operate in an environment where feedback about good or bad choices is available with some delay (A. Müller and

Guido, 2016). Examples are self-driving cars and games where the AI has to respond in real time and make decisions which, in the prior example, have outcomes of life and death. Combinations of these types of ML are also used, where *semi-supervised learning* is partly supervised and partly unsupervised (Witten et al., 2016).

2.1.4 Training and Testing

To evaluate how well an ML model performs different methods are needed to compare different types of ML algorithms. For classification problems the performance can be measured by its *error rate* (Witten et al., 2016). The model predicts a class of each fed instance and if it is correct it is counted as a success and if it is wrong it is counted as an error. It would be easy to compare different models this way but having the performance only measured by the error rate on data it has been trained on, it says nothing about the number of errors when fed with new instances which it has not yet seen. Thus, this is not an optimal way of measuring performance in classification problems, where the interest lies in how well it performs on new data. Therefore, the data is divided into three subsets: *training* data, *validation* data and *test* data.

The training data, as the name implies, is only used to train the classifier, not to measure its performance. When training the classifier, in some learning schemes, there exist two stages. One is to come up with a basic structure, the training data, and the other is to optimize the parameters, which is where the validation data comes in. The error rate is than calculated on the test data, with the optimized model. It is important that these datasets are independent and that the test data has not been part of training the classifier. When the model error rate is satisfactory the test data can be incorporated into the training data to produce a new classifier for actual use, as a way to maximize the total amount of data used in generating the classifier. More data generally generates a better classifier but the rate of improvement decreases when a certain volume of training data has been exceeded (Witten et al., 2016).

The problem, instead, arises when there is insufficient amount of data. Then decisions have to be made on how to make the most out of the limited dataset. In many cases the training data needs to be classified manually, which is both time consuming and expensive. Another problem arises when the data is missing or incomplete. A common solution to deal with incomplete data is to fill in missing values through different imputation methods (Sovilj et al., 2016).

2.1.5 Issues with Machine Learning

There are issues with ML which can be linked to project failure. For instance, many patterns recognized by ML models will be banal and uninteresting, while others will be accidental coincidences in the particular dataset used (Witten et al., 2016). The project manager or project team needs to have an approach which deals with this potential problem, in order to keep stakeholders satisfied.

Another issue regarding ML, according to Clemmedsson (2018), is having insufficient amount of data. This can be traced to data not being stored in the first place, unauthorized data or unethical data, or data that is too expensive to acquire. Having a high quality dataset is essential in ML (Bosch et al., forthcoming). Some ML algorithms require a large amount of data to perform satisfactory and in most cases a mediocre ML algorithm applied to a large and high quality dataset outperforms a better algorithm on a smaller dataset (Witten et al., 2016).

2.2 Digital Transformation and Emerging Technologies

Many companies have strong digital transformation ambitions to digitalize and pervasively automize their products, services and repetitive processes which often lead to ambitions in applying AI through ML. For successful Digital Transformation it requires a large range of business context specific capabilities (Zinder and Yunatova, 2016) and rapid and relentless experimentation (Rogers, 2016). To keep up with "born digital" pioneers, companies attempt to re-invent business models to remain competitive. However, Digital Transformation initiatives tend to take longer time than anticipated by companies and face many problems on the transformation journey, despite many guidelines for implementation (Zinder and Yunatova, 2016).

Emerging technologies are drivers and enablers of digital transformation. ML is one approach to achieve AI and "AI is disrupting every industry from manufacturing to retail, from agriculture to health care" (Quan and Sanderson, 2018, p. 22). Even the construction industry, often described as reluctant to innovate (Lindblad, 2019), is exposed to new interfaces between technical project management and computer science through the use of supervised ML to appraise a projects constructability (Kifokeris and Xenidis, 2019). To thrive in a highly competitive market environment companies need to be efficient and respond quickly to changing market demands and emerging technologies (O'Reilly III and Tushman, 2008). It requires to be innovative to respond to and incorporate emerging technologies in products and processes since the commercialization of new technologies is perceived as an engine of economic growth (Rahim et al., 2015). In many cases "academic entrepreneurs"(Rahim et al., 2015, p. 54) understand the profit potential of a new technology and create start-up companies to commercialize the academic knowledge. In opposite, Christensen (1997) said many entrenched organizations fear the threat of technical innovations which have the potential to disrupt and change the competitive environment, which indicates that incorporating new technologies in existing products and processes is challenging. Much contemporary research on innovation is in accordance with fundamental concepts developed by Christensen (compare Schuh et al. (2018), Rasool et al. (2018) or Kumaraswamy et al. (2018)).

Chalmers University of Technology Professor and Researcher, Jan Bosch, visualizes a typical digital evolution path for traditional companies in figure 2.2. One big challenge in the evolution path is that the coexisting different cultures, priorities and ways of working coexist in the different stages. For instance, from a focus on efficiency and cost optimization in mechanics to innovative and experimental approaches in the AI stage. It is essential to apply new technologies to generate value for the customer. However, monetization of customers and technology investments are not certainly aligned, thus it requires careful prioritization and resource allocation to stay competitive in the long term.

Figure 2.2: Typical evolution path for traditional companies (Bosch, 2019)

2.2.1 Hype

The pressure of adopting emerging technologies and lacking knowledge on the application lead to inflated expectations. Gartner (2018) provides an annual figure on current emerging technologies with two underlying theories, the expectation hype and the technology s-curves. Deep Learning has been on top of the curve in 2018 which describes the latest advancements in ML. This indicates that the technology reached the peak of inflated expectations and it is expected to take 2-5 years before it reaches a state of productive application. The academic validity of Garter's hype cycle model has been scrutinized by Steinert and Leifer (2010) due to questionable methodological set up and analysis procedure of the studies. However, the hype cycle visualizes the expectation hype of emerging technology and provides an initial idea if the a technology is potentially applicable to solve real business problems. Large national funding for AI research, registration growth at conferences and strong efforts of global leading industrial players are further indicators of the trend (Holzinger et al., 2018).

2.2.2 AI Evolvement Stages

If a company embarks on the journey to become a digital company and apply AI, there are five stages how companies evolve in application of AI and corresponding challenges in these stages are expressed by Bosch et al. (forthcoming) in figure 2.3.

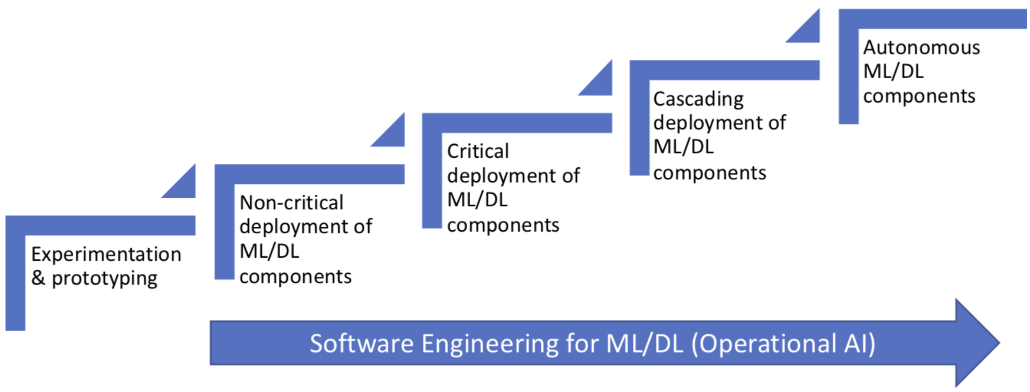

Figure 2.3: How use of Artificial Intelligence (AI), Machine learning (ML) and Deep learning (DL) evolve in industry according to Bosch et al. (forthcoming).

The first step involves companies engaged in experimentation and prototyping, where ML and DL models are conducted in-house without any connection to other product or services offered by the companies. In this stage organizations face the biggest challenges in data acquisition from different data silos, data labelling and data bias. In the second step the developed basic models are tested in production environment and it requires deep analysis of elements and algorithms of the models to improve the performance to achieve the desired output (Bosch et al., forthcoming).

2.3 The Role of Project Management in Machine Learning Projects

From an operational perspective the major aspects of project management are to provide a framework for tasks and actions aligned with the project vision, set milestones and coordinate activities, communicate with stakeholders, identify and recruit resources and ensure efficient project delivery (Kerzner, 2017). Project management practice is concerned with the efficient delivery of outputs but is evolving from the pure operational role to a strategy delivery role (Zwikael and Smyrk, 2019). Duggal (2018) describes project management as the DNA of strategy execution in transformation efforts, showing the importance of leadership and strategic management skills of project managers. Strategic change management skills is one of the crucial project management abilities and at the core of any analytics related project (Shah et al., 2018). From the perspective of digital transformation, many of today's organizations create business value through projects to respond to the dynamic and competitive business environment. Projects are an efficient method to organize and drive innovation and, therefore, project management plays a central role in corporate innovation processes (Lenfle, 2016).

When looking at data science projects it becomes clear that most data science teams approach project management in an ad-hoc manner and do not follow a systematic project process. However, teams believe that their data science projects would improve with a systematic process methodology since data science projects have grown in complexity (Jeff Saltz et al., 2018). ML can be applied in predictive analytics projects and Shah et al. (2018) concludes that it is critical for a project manager in analytic projects “"to understand the experimental nature of discovery and development while balancing these loose requirements against organizational and political constraints to ensure that experimentation drives toward a solution-oriented deliverable that can benefit the organization"” (Shah et al., 2018, p. 93). This requires strong communication skills and awareness of the implication of changes to balance conflicting stakeholder needs. Further, the project manager needs to have the ability to build a team of people with contrasting opinions and priorities and ensure working towards a common goal (Shah et al., 2018).

“Projects, where neither the goals nor the means to attain them can be defined at the beginning”, require extreme project management methods (Lenfle, 2014, p. 921). Wysocki (2013, p. 352) describes it as “a hunt in a dark room for something that does not exist in that room but might in another room, if you knew where to find that other room”. It is described as an experimental learning process and traditional project management becomes redundant when facing dynamic environments with abundant unpredictably uncertainties (Loch et al., 2011). In conditions of stability of the projects production system, the deterministic traditional project management paradigm of planning and control can be followed e.g. Project Management Institute (PMI). This paradigm received much attention in project management research but the legitimacy of traditional planning processes is questioned if the activities cannot be anticipated or assumption based planning leads to false expectations (P. A. Daniel and C. Daniel, 2018). This project environment leads to the non-deterministic paradigm of emergence which enables project managers to learn from reality through feedback loops, to improve their project management model and quality of decisions over time. More complex and unstable project environments will eventually lead to research attention how to build, adapt and apply project decision models e.g. project plan and work-breakdown-structures (WBSs), to the project management loop.(P. A. Daniel and C. Daniel, 2018).

These exploratory project situations require special conditions (Lenfle, 2014). Essential for success is to have “individuals who are both undisputed technical leaders and central management figures” (Lenfle, 2014, p. 928).

2.4 Established Approaches to Managing Data Science Projects

In figure 2.4, the Adaptive Project Management Life Cycle (PMLC) model by Wysocki (2013) aims to discover solutions during the project process and applies to exploratory projects with a high level of complexity and uncertainty when the functions and features are unknown upfront. Consequently, the iterations of the adaptive PMLC continuously define new solutions by discovering functions and features. Each cycle is completed though a feedback loop involving the client. The minimalistic planning qualifies the model for recurrent changes in functions. In extreme project environments a cycle can even loop back to the scope definition (Wysocki, 2013).

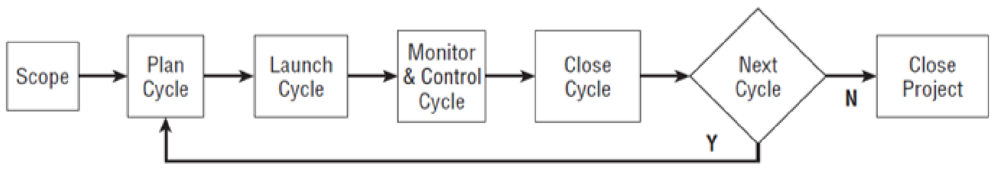

Figure 2.4: Adaptive PMLC (Wysocki, 2013, p. 341)

In case of projects with high uncertainty and scope changes and, agile project management methodologies respond with adaptive and iterative project phases. In IT related projects, agile methodologies are commonly used which allows projects to kick-off without a defined goal and scope (Kerzner, 2017) and “explore feasibility in short cycles and quickly adapt based on evaluation and feedback”(PMI, 2017, p. 7). The Agile Software Development Manifesto with 12 guiding principles has been developed in 2001 and methodologies based on these values have been largely adopted by software development teams (Abrahamsson et al., 2017b). Mathur (2018) recommends to follow modern software development methodologies in ML projects to create team democracy, transparency, early feedback loops and stakeholder involvement. Good working systems are self-documenting and all created assets, functioning or incomplete should be shared with team members and, as soon as possible, with end user (Jurney, 2017). It needs to be considered that many ML applications are developed by non-software organizations which have no experience in agile ways of working (Mathur, 2018).

Two commonly applied agile frameworks in software development are Scrum and Kanban which can be used in data science related projects (Jeffrey Saltz et al., 2017). ML projects have parallels to the domain of software development while having the significant difference of strong data focus (Das et al., 2015; J. S. Saltz, 2015). Arpteg et al. (2018) explain there are differences between traditional software engineering (SE) and ML, especially deep learning (DL), resulting in challenges specific for ML. ML, compared to SE, is heavily dependent on data from the external world, where data partly replaces code for ML systems.

This indicates that ML project methodologies can be similar to agile software development methodologies but require adoption. The scientific research and experimental phases in ML projects makes the work ambiguous and difficult to predict and measure. Therefor it needs to be considered that software engineering practices do not automatically apply to ML projects (Matsudaira, 2015). Jeffrey Saltz et al. (2017, p. 1015) identifies "a lack of adoption of mature team process methodologies for data science projects"." However, there is significant Software engineering challenges in ML projects, especially in the deployment of ML models into production (Arpteg et al., 2018), which requires close collaboration between Data Science and Software Engineering.

2.4.1 Agile Scrum

Scrum is a widely applied process framework to implement agile project management. The main idea behind Scrum is that systems development is exposed to an amount of environmental and technical project variables, which is probable to change during the project process (Abrahamsson et al., 2017a). According to the scrum creators Schwaber and Sutherland (2011), Scrum has clearly defined roles, responsibilities and frequently scheduled meetings. The core of Scrum is that the product is developed in *sprints*. Sprints are iterative cycles in which the functionality of the product is developed by producing new increments. Each sprint includes all the traditional product development phases with the outcome of a releasable increment. The sprint length should be between 1-4 weeks and every sprint is the same length. Every sprint includes stakeholder feedback at the end, however, intermediary results are not supposed to be shared before the end of a sprint. Scrum focuses on delivering customer value, empowers autonomous teams and is a well know methodology but organizations experience cultural challenges when adopting to the methodology (Rigby et al., 2016).

2.4.2 Agile Kanban

Kanban meaning billboard in Japanese, was developed for lean manufacturing, but has been adopted across domains, including software development (Ahmad et al., 2013). In the context of data science Jeffrey Saltz et al. (2017) suggest Agile Kanban in combination with basic data science life-cycle phases. The Kanban board visualizes the work progress in the different phases and limits the work-in-progress tasks for the respective phases to avoid bottlenecks. This Kanban pipeline process management requires prioritization of user stories by the team or project manager. Kanban has no defined meetings, time boxes and roles as e.g. Scrum. Kanban can provide some structure for data science teams but allows flexible execution (Jeffrey Saltz et al., 2017).

2.4.3 Data Science Life-cycle Processes

For data science related projects exist process models. Among the most commonly applied are the *Cross Industry Standard Process for Data Mining* (CRISP-DM), the *Sample, Explore, Modify, Model*, and *Assess* (SEMMA) data mining process and *Knowledge Discovery in Databases* (KDD). These models vary in detail, but are fairly similar on a high level (Jeffrey Saltz et al., 2017). Due to lack of academically-grounded research, the acceptance and actual use of the models are unclear, but CRISP-DM appears to be common in use (Piatetsky, 2014).

CRISP-DM Overall process methodologies are useful to understand the project steps of an ML project. The Cross Industry Standard Process for Data Mining (CRISP-DM) is an “industrial standard”(Azevedo and Santos, 2008, p. 182) and commonly used process model for data mining (Piatetsky, 2014). It provides a general approach to structure and plan a data mining project which can be adopted to specific project environments (Huber et al., 2019). Established in the 1990s The process consists of six high level phases (Wirth and Hipp, 2000) with focus on delivering business value.

1. **Business understanding:** The first step is the definition of project goals and requirements from a business perspective. This is followed by the derivation of specific data mining objectives and required tasks to reach those. The output of the first phase is a description of the indented project plan.
2. **Data understanding:** This phase is characterized by initial data collection and identification of the data’s quality and underlying structure.
3. **Data preparation:** Building of the final data set for the following modelling. This includes attribute selection, reduction, reprocessing and data cleaning.
4. **Modelling:** Selection and application of e.g. ML models or other modelling techniques on the data, including calibration through optimizing parameters.
5. **Evaluation:** Evaluation of the models with the initial business and data mining objectives to decide whether a model can be applied or requires to be refined. The outcome of this phase is a decision on a selected model which is best aligned with the objectives.

6. **Deployment:** Development of a deployment plan with all required steps for implementation of the designed model in production, including a monitoring process plan and maintenance strategy.

Working with CRISP-DM requires close team collaboration. In a controlled experiment, Jeffrey Saltz et al. (2017) applied the framework with bi-weekly status update meetings to track status and issues. If needed the framework allows to loop back to previous stages but CRISP-DM, according to Jeff Saltz et al. (2018, p. 4), resembles a "waterfall-like" approach. According to PMI (2017), traditional waterfall project management approaches require defined deliverables, a specified time period, and a determined budget and quality that is not aligned with the context of innovation to which many data science projects are exposed to. Innovation entails discovery and unforeseeable uncertainty through continually changing requirements and expectations, which does not fit with waterfall approaches (Lenfle, 2016). Larson (2018b) states that the CRISP-DM phases are compatible with agile values and would benefit from the application of agile principles.

When applied, the framework is exposed to several problems if a corrupted version is used (Taylor, 2017). The lack of clarity in the actual business problem is a common issue because project teams are satisfied with knowing the overall business goals and a few metrics how to measure success. Instead it would require detailed knowledge and clarity on the business need before starting to analyze the data. If the analytic results do not match the vaguely defined business objective, it occurs that mindless rework is done on finding new data or models instead of re-evaluating the business problem. Another problem is that some analytic teams do not consider the deployment of their models and are not engaged with the IT-infrastructure work. This leads to the large number of models that never have a valuable impact in the business. Companies tend to fail on iterating on the whole process because maintenance work of aging models is time demanding and it is more attractive to start new projects than monitoring and revising models which are already in production. Undefined business problems are linked to this issue because it requires clarity in the definition of the business problem, to be able to track the model's business performance (Taylor, 2017).

Some research has been done to improve the CRISP-DM framework. For instance, Schafer et al. (2018) developed the QM-CRISP-DM cycle after concluding that the six phases appear to be too general and lack appropriate quality management tools. Huber et al. (2019) developed the DMME framework and provide a holistic extension to the CRISP-DM model with focus on production scenarios.

In the previously described experiment by Jeffrey Saltz et al. (2017), CRISP-DM outperformed agile Scrum and agile Kanban in the quality of the delivery. This was explained that the team applying CRISP-DM strongly focused on the business objectives and data before focusing on the modelling.

TDSP The *Team Data Science Process* (TDSP) can be considered a hybrid version to interconnect knowledge discovery processes e.g. CRISP-DM, and agile practices e.g. sprints and clearly defined team roles. This concept has been researched by Schmidt and Sun (2018). TDSP is an agile, iterative data science methodology developed by Microsoft to guide organizations in successful execution of data science projects. TDSP is compatible with other data science life-cycles e.g. CRISP-DM and the standardized structure supports organizations in building institutional knowledge (Azure, 2017).

In the business understanding phase, the project manager is responsible to develop a project charter on which all further project phases are based on. Eventually the project manager is in charge for the final project report in the acceptance phase. The TDSP Project Charter contains several aspects that demand to be defined by the Project Manager (Azure, 2017).

- Business background, including required business domain knowledge and what business problem is addressed.
- Scope definition of planned data science solutions to be build and general approach, including the final use of the solution.
- Involved and required personnel.
- Definition of quantifiable metrics based on qualitative objectives, desired improvements and method to measure the metrics
- Planning of project phases and milestones
- Data availability and system architecture for deployment
- Communication, including frequency of meetings and contact persons

On a daily basis the project leader e.g. a senior data scientist, not the project manager, is responsible for the sprint planning for work items involved in a project and code review (Azure, 2017).

2.5 Deciding on ML

Before deciding on using ML as a tool to solve problems there are a things to consider regarding the importance of data, problems which are suited for ML, and financial aspects, which are discussed below.

2.5.1 Importance of Data

Witten et al. (2016) say that where there is data there is a possibility of ML application. the world increases at an exponential rate and a massive amount of data will be created in different areas in the next few years (Hashem et al., 2015; Al-Jarrah et al., 2015). Witten et al. (2016) say that ML models require a large amount of data to be able to make predictions and give insights. The increase in data and the need for large amount of data in ML models implies that ML will be applicable to more business areas in the future. The data also needs to be structured in a way which the models can handle (Witten et al., 2016). Having knowledge about the underlying mathematics of different ML models gives a better understanding of which data that can be used. ML models can be fed data with many different variables and the variety of these variables can lead to unforeseen and interesting correlations between them (Gandomi and Haider, 2015). This can create large business values for companies, if the correct tools are applied (Grover et al., 2018).

Furthermore, real data is imperfect due to missing data, duplication of data and wrongfully labeled data (Clemmedsson, 2018). Any discoveries by the ML models on this data will be inexact and exceptions to every rule, and cases not covered by any rule, will follow as a consequence. Algorithms, therefore, have to be constructed in a way to cope with imperfections in the data, to find regularities which are inexact but still useful (Witten et al., 2016).

2.5.2 Good Problems for Machine Learning

For corporations to be involved in ML projects a business understanding investigation is needed, which determines if the data mining will be profitable (Ng, 2019). Good ML business solutions are often found on problems which (1) require prediction rather than causal inference, and (2) are sufficiently self-contained or relatively isolated from outside influences. The first means that what is interesting to know is how to predict new data based on previous data, rather than how certain aspects of the data relate to one another, according to statistical averages. This information comes without intuition, theory or domain knowledge of human analysts. The second problem type means that assumptions of the data fed to the learning algorithm includes almost everything there is to the problem. If the things which are tried to be predicted changes and no longer matches prior patterns in the data, the algorithm will not know what to make of it.

Fields of application today are autonomous drive, content recommendation, image and video processing, cancer prognosis and prediction, video game bots, marketing, drug discoveries, machine automation, facial recognition, text-to-speech and vise versa, writing sport articles and education, to name a few (Kourou et al., 2015; Libbrecht and Noble, 2015; Witten et al., 2016).

2.5.3 Financial Investment and Business Case

Some of the largest technology companies in the world, such as Microsoft, Google, Apple and Facebook, are investing heavily in new applications and research in AI (Popenici and Kerr, 2017). Google continuously publishes their latest research effort and provide open source ML tools (AI, 2018) without any cost for organizations using it. This shows that the value in ML use comes with data. To start an ML project, investments in data acquisition, creating data infrastructure, using or acquiring the right resources and creating a data culture within the organization is needed (Kashyap, 2017b). This can quickly become a costly endeavour and since data-science related projects have a high risk of failure (Larson, 2018b) and the experimental nature of the projects often requires many iterations which consequently prolongs or may never reach a return on investment.

For projects to be approved it usually requires a business case to define the value the project will deliver. Herman and Siegelaub (2009) present several forms of business cases:

- **Return On Investment (ROI)**: The gain generated by the investment is expected to exceed the money spent in the development.

- **Strategic**: The project supports and drives the strategy and/or mission and is not expected to pay off in the short term
- **Investment**: Development of new products for eventual expansion into money-making products but not all products are expected to pay off.
- **Research**: Money will probably be lost on the project but the learning will help us set the organization's future direction."

2.6 Machine Learning Problem Framing

The ML *problem framing*, or *problem definition*, or *problem formulation* is the way to translate components of a business problem into *observations* that comprise *features*, or *attributes*, and a *target label* (Chaoji et al., 2016). In an online store which tracks user data, wanting to predict what and when people will buy their products and to make recommendations, an observation could be that a customer bought a pair of red shoes for $30 on sale. Examples of features are *shoes*, *red color*, *price=$30* and *on sale*. The target would be if the customer bought the shoes or not, which in this case was yes. By tracking data of customers, what they have viewed, what they buy and so on, an ML model can be created to make predictions for future customers.

ML requires explicit and specific definitions that refer to something measurable, to be able to predict specific outcomes or quality of interests (Passi and Barocas, 2019). For example, when creating an ML model to aid in hiring employees, to find a "good" employee the word *good* has to be broken down in order to be successfully measured. Then, dependent on the work, some feature, for example sales, will be more valuable than others, implying that a "good" employee is someone who is competent in sales. Issues which arise are (1) illegal discrimination, (2) some groups will be less accurately measured for a chosen target, and (3) some target variables will be harder to predict than others thanks to uneven available training data. Passi and Barocas (2019, p. 2) suggest that "we should be paying far greater attention to the choice of the target variable, both because it can be a source of unfairness and a mechanism to avoid unfairness".

A common Project Management practice is to break down the project into activities to make reasonable estimations and plan in complex projects (Kerzner, 2017). A similar approach can be used to systematically break down complex problems in solvable bits (Jones, 1998) and can create understanding of underlying sub-problems (Bonyadi et al., 2019).

2.7 Machine Learning Solution Procurement

If an organization decides to apply ML it faces a procurement decision with three options (Gartner, 2016).

- In-house development of solution with own ML team
- Outsource building a solution to an analytics service provider
- Purchase commercial off-the-shelf (COTS) ML solution

The following sections elaborate on the development of customized solutions, both in-house and outsourced.

2.7.1 Team Competence for In-House Development

ML projects are of technical nature and team members must possess mathematical, statistical, computational, programming and data management skills. Further it requires business understanding to be able to answer the *why* of a problem, competence in communication, both visually and verbally, change management and positive psychological skills for relentless experimentation and have courage to fail (Kashyap, 2017a). It needs a small dedicated team which works in close collaboration with the product or service user, while working in a protected and, to some extent, isolated environment (Lenfle, 2014) to be free from the organizational bureaucracy and hierarchy (Kashyap, 2017a). Continuous support from the executive or/and senior management is essential for the ML team (Larson, 2018a).

The most common roles and critical key staff in ML teams are ML engineers, Data Engineers and Data Scientists (Kashyap, 2017a), but role descriptions are not consistently used. Saltzt and Grady (2017) identified a widespread problem with ambiguous team roles in Data Science Teams.

Both an ML Engineer and a Data Scientist extract various types of knowledge from data and tasks are overlapping. Despite the shared characteristics can clear distinction be made. (Kashyap, 2017a) Data Scientists posses deep scientific knowledge of e.g. ML algorithms and focus on research and statistical analysis. For instance can a Data Scientist determine which ML approach to use. (Kashyap, 2017a) They work in close relations with other researchers, engineers, web developers and designers by exposing either raw, intermediate or refined data (Jurney, 2017). ML Engineers are often considered the intersection between Software Engineering and Data Science and develop and program ML applications (Kashyap, 2017a). Data focused ML engineers are also often concerned with creating the data pipeline, data sets, and data ingestion.(Saltzt and Grady, 2017). In agile Data Science projects, generalists are valued over specialists according to Jurney (2017) which indicates the importance of end-to-end knowledge.

In order to find and recruit Data Scientist with expert skill in data analytics as well as team communication and business insights the company needs to compete with other Data Scientist recruiters. As of today, Data Scientist is a relatively new occupation and Data Scientist experts are scarce (Davenport and Patil, 2012). Demand clearly outstrips supply. This creates challenges not only for the recruiting department but for the company and the contents of projects as well. Davenport and Patil (2012) say that the best Data Scientists in the field want opportunities to work on interesting big data challenges, to curiously explore and dive deep into problems and create hypotheses that can be tested. Many Data Scientists come from an pure academic background and often lack the share-mentality needed to effectively communicate with other team members. Other valuable skills for the Data Scientist, especially in ML projects, are data cleaning and organizing large data sets, since data rarely come in structured formats (McAfee and Brynjolfsson, 2012). The best Data Scientists, according to McAfee and Brynjolfsson (2012, p. 8), are also comfortable speaking the language of business to help leaders “reformulate their challenges in ways that big data can tackle”. Qualified candidates may be found in data analytics heavy fields like neuro-science,space-science or bio-informatics and can be trained on ML and project requirement. Also, the candidates may be hired from fields like space science, bio-informatics, or neuro-science, where a lot of data crunching and any analytical skills are present. Once these candidates are hired, training specific to ML and project requirement would be helpful (Kashyap, 2017a).

Kashyap (2017a) recommends to search internally for curious data engineers or developers and train them on ML technology and techniques. Hiring the best people from hackthons or competition does not always lead to success. Many ML Engineers fail to meet business objectives in applied ML projects because the state-of-the-art techniques are not applicable as in competitions when the provided data set is large and clean (Mathur, 2018).

A well researched stakeholder management phenomena is bias in project appraisal (Mackie and Preston, 1998) and the role of an external analyst can play a valuable role in decision making (Crosby, 1992). However, the literature review provided no results on bias in project appraisal in the context of ML.

2.7.2 Procurement of External Competence and Vendors

A benefits of using third party service provider is the access to data scientists and ML experts in times when skilled personnel is scare and hence expensive and time consuming to hire (Davenport and Patil, 2012). However, it requires business domain expertise for building successful ML solutions. If the exact type of project has not been done before, external competence e.g. consultants with deep technical ML expertise, often lack the specific domain knowledge and need time and numerous exchanges with business units to acquire the domain expertise (Ahrens, 2014).

In general, outsourcing parts of the operation bears the risk of losing control and can lead to overdependence and organizations should avoid outsourcing parts of the core business (Nasir and Ivanouskaya, 2018). This leads to the importance to determine the long term strategic role of AI and ML in the organization to understand if outsourcing to a third party service provider is reasonable (Burgess, 2018).

2.8 The Role of Trust in Machine Learning Projects

“Trust is the willingness of a party to be vulnerable to the actions of another party based on the expectations that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party.” (Siau and Wang, 2018, p.48). Three areas were identified in the context of ML projects where this definition applies and trust is considered important.

2.8.1 Trust in the Technology

Trust in the technology within the organization is crucial because “systems that are not trusted are not used” (Schaefer et al., 2016, p.393). Trust in ML technology is one of the current research trends attempting to answer how ML results can be trusted.

There is a correlation between performance and interpretability of ML models. The high performance state-of-the-art ML models are described as in-transparent black boxes which makes machine decisions non-understandable, even to experts which reduces the trust in ML applications (Holzinger et al., 2018; Zhou and Chen, 2018). Taddeo (2017) claims that people tend to trust digital technologies e.g. ML and the trust is only broken by serious negative events. To avoid these events it requires reliable testing frameworks, especially for safety critical application in e.g. autonomous drive (Tuncali et al., 2018).

2.8.2 Management Trust in Machine Learning Project Team

Significantly less research has been done around the issue of management trust in ML project teams. Constant monitoring and micro management of agile working ML project teams is not recommended since the self-management concept is at the core of agile methodologies (Gutierrez et al., 2019). The evaluation of the work results can be difficult for executives when lacking the technical ML knowledge. Continuous support from the executive management is therefore largely based on trust, and unforeseeable failure should not undermine the trust. It requires tolerance for failure from the management side and transparent and understandable ways of communication of progress from the ML teams (Matsudaira, 2015).

2.8.3 Trust in External Collaborations

Very little research has been done in the field of trust in external collaborations in ML projects, but the use of external competence and vendors are common in ML projects (Gartner, 2016). For instance are data annotation tasks for supervised ML common to be outsourced (Koyama, 2018) or external resources are used to build customized data science platforms for ML application (Gartner, 2016). The customer needs to have a holistic experience, so called “conceptual integrity” (Kashyap, 2017a, p.310) on the system to identify the value delivered. Kashyap (2017a, p.310) defines conceptual integrity as the understanding how the solution “is being advertised, delivered, deployed, and accessed, how smart the utility is, the price, and most importantly how well it solves problems”.

3
Method

In this chapter, the research methods and approaches used in this thesis are described. The study has focused on a literature review and unstructured interviews.

3.1 Research Strategy and Research Design

To secure the validity and reliability of the research it is vital to choose the research strategy which is most appropriate for the occasion. The research methodology has to support the research questions. Bryman and Bell (2011) says that a *qualitative* research method, which creates theory from research conducted on people interaction, is preferable to a *quantitative* research method. Since project management involves social interactions, a qualitative research method was chosen to

- Understand the social world through an examination of the interpretation of that world, by its participants.
- Be aware of the subjectiveness caused by emotions when gaining access to 'inside' experience.
- Use appropriate conversation analysis.

A critique of the qualitative research method is the difficulty of replication. Conclusions made by the thesis researchers are based on interviews, observations and own interpretation of situations, which cannot be replicated. However, since ML is a fast developing field, there is no meaning in trying to replicate this study. The application and validity of the thesis is limited to a short time frame.

3.1.1 Research Approach

An *abductive* methodology was chosen to cover both practical reasoning and scientific inquiry, instead of a *deductive* or *inductive* methodology (Svennevig, 2001). The field of AI is changing rapidly and is updated constantly with new algorithms and insights from newly published research articles, which forced an iterative research approach. An abductive research approach is defined by Aliseda (2007) as "the reasoning that proceeds from an observation to its possible explanations or, better put, its most plausible explanations".

A critique of the abductive approach is mentioned by Awuzie and McDermott (2017, p.358) that the approach originally was "nothing more than an act of inferring from guesses". They also say that for the results following an abductive approach to be valid and credible, it must be supported by inductive and deductively sourced evidence. Therefore, the information gathered from the interviews gave insights into which areas to research and to find relevant theory backing, or contradicting, what was said during the interviews. When new insights were found from theories, questions regarding these insights were asked in following interviews.

3.1.2 Research Process

The qualitative research method process is outlined in figure 3.1.

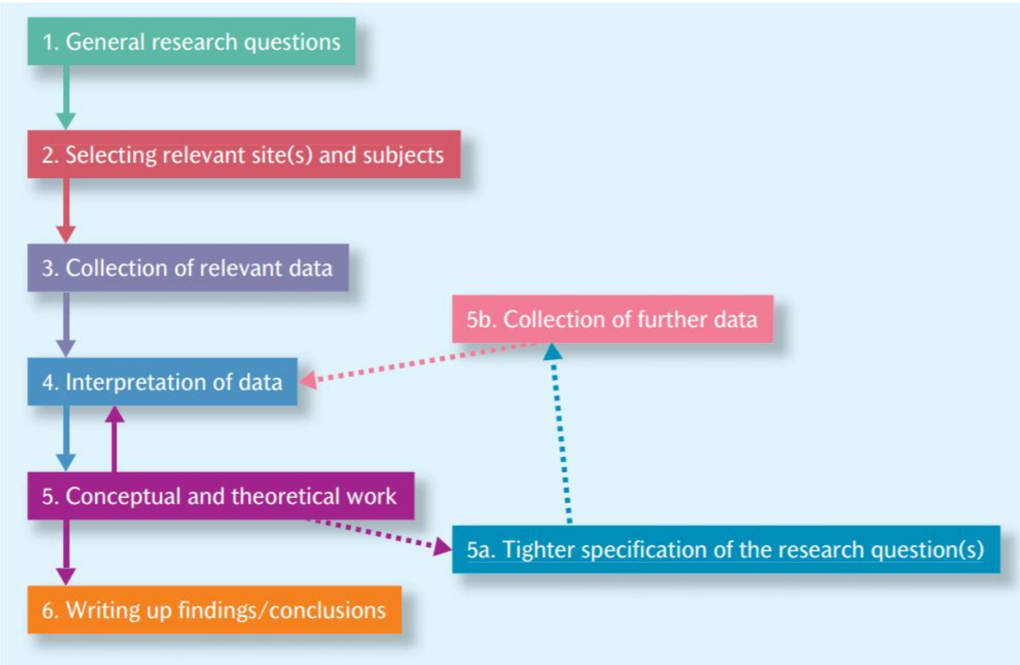

Figure 3.1: An outline of main steps of the qualitative research method process (Bryman and Bell, 2011, p. 390).

Step 1 and step 2 have been iterative, to find research questions beneficial for companies, organizations and researchers involved in the study. This was done by an initial web search of project management challenges in AI and ML projects, followed by contacting companies conducting AI and ML projects, and inviting them to an introductory meeting. During the meetings the companies were told that the researchers had the ambition to aid in the project management process of the projects, by examining problems and trying to solve them. The companies then had a chance to come up with potential research questions which would benefit them.

The data collection in step 3 and step 5b consisted of a literature review and unstructured interviews with different project stakeholders. The iterative process, step 4,5a,5b and step 5,4, was to align the research with what was sought after in the AI community and to improve the quality of the thesis.

3.1.3 Literature Review

The purpose of the literature review was to find already published books and articles about project management methodologies or processes applied to data analytic and ML projects, to find what knowledge the academic society sought after regarding such projects. This was a critical step to find suitable research questions for the thesis. Another reason for the literature review was to compare the literature, and through it the acquired project management theory, to what is actually being used in practice at the companies or organizations. This was a made to point out contradictions and gaps in existing knowledge (Jesson et al., 2011).

The short time frame demanded a *traditional literature review* instead of the more rigorous *systemic literature review*. A traditional literature review is a written appraisal of existing knowledge about a subject with no prescribed methodology (Jesson et al., 2011). It was used to describe the area of ML, the project processes or methodologies used in ML projects and their challenges. The literature was mainly found through the Google Scholar library, but also from other university library databases. The academic community was not up to date with the latest information in ML and, therefore, a few web sources were also used. The evaluation of these web sources were done by considering questions regarding accuracy, bias, level of detail, date published and author authority, according to the guidelines by Walliman (2010)

The literature review was continuously updated and analyzed during the thesis process, to become more relevant as the research progressed and new information and insights were found.

3.2 Data Collection

The data collected was only through interviews with people who have been working in ML projects. Both primary data, through audio recordings and transcriptions, and secondary data, through interpretations of meetings and interviews, have been used to draw conclusions.

3.2.1 Sampling

A total of 13 interviews were conducted at 10 different companies and organizations, in order to receive inputs from many different sources in different sectors (Bryman and Bell, 2011). To qualify as an interviewee the person must have worked in an MLan ML project. There was also a need to have interviews with people of different roles in these projects. Therefore, due to time constraints, if persons working as data scientists had already been interviewed then a person working, for example, as a manager would be prioritized for the next interview. Persons working for consultancy firms, public service or larger companies doing ML projects in-house were contacted, to find similarities/differences between how projects are managed, dependent on work sector. No limitations were made on the interviewees age or gender, even though an equal distribution of young and old, male and female, was sought after. The same is true for the interviewee's experience in ML or working in ML projects. Information was gathered from both novices and experts.

3.2.2 Interviews

The interviews were chosen to be unstructured to allow for both topic specific questions and for the interviewee to share knowledge from experience, by speaking freely about subjects of interest to the interviewee regarding ML (Bryman and Bell, 2011). Questions were picked to get insights which would lead to information regarding new, or answers to current, research questions, without making the interviewee feel threatened to say anything confidential.

The length of the interviews varied between 20 to 70 minutes dependent on the interviewee's availability. The interviewees experiences in ML and working in ML projects were varying between recently started to, approximately, ten years of experience. Four of the interviewees wanted to have an initial meeting with the thesis writers, to learn more about the thesis and how the interviews were being conducted and to establish trust between the parties. Two interviews were held in Swedish due to interviewee convenience. Three interviews were held through the Skype video conference tool because these interviewees were located either abroad (Denmark) or in another city in Sweden than Gothenburg. The rest of the interviews were held in person at the interviewees location of choice. This location was either at the interviewee's office or in a conference room at the AI Innovation of Sweden's open space at Lindholmen.

All interview were audio-recorded and later transcribed into text. Having the the whole interview in text made it easier to search for keywords when analyzing and comparing the interviews. Transcription also allows for a more thorough examination of what the interviewee said and somewhat captures not only *what* the interviewee said but also in what *way* he/she said it (Bryman and Bell, 2011).

3.2.3 Interviewees

The interviewees can be viewed in table 3.1. They are referred to as their name alias and company/organisation alias. An example would be: "The Co-founder & ML Expert at the ML Start-up Company says..."

Table 3.1: The interviewees aliases and roles in their respective company or organisation.

Alias (and Role)	Company or Organisation
Co-founder & ML Expert	ML Start-up Company
Data Scientist	International Consultancy Firm
Digital Transformation Officer	International Consultancy Firm
Head of AI	Large Transportation Company
Data Analytics Manager	Telecommunication Company
Director of Research	Automotive Software Company
Deep Learning Product Owner	Automotive Software Company
Data Scientist and Team Leader	Pharmaceutical Company
Software Developer	Software Company
Innovation Team Leader	IT Consultancy Firm
Software Engineer	Big Data Consultancy Firm
AI Researcher	AI Firm
Development Lead	Public Region County

3.3 Qualitative Data Analysis

A tool used to analyze the data was *coding*. Coding is a process where data is broken down into themes or components and then labeled with a name (Bryman and Bell, 2011). The data from the interviews was analyzed to find these themes, which where separated into subcategories. When an interesting theme was found in the data, which was not found in the literature, questions regarding that theme would be asked in later interviews. With each interview new categories were added while the information in the already established categories grew. When the last interview was done these categories formed a basis for the comparison of the interviews. The themes which had nothing to do with answering the research questions were ruled out. Here follows the categories found and why they were chosen.

Team competence: It was expressed during the interviews the importance of having a competent ML team and it was decided to elaborate on this to be one of the requirements to start an MLan ML project.

Financial investment: To start an MLan ML project an initial investment is needed and it is then crucial to know how to receive this investment.

Business case: A general theme throughout the empirical data is the business case, which has been linked to financial investment and trust in ML projects. It was chosen because interviewees expressed its importance when starting an MLan ML project.

Data: It was found that data was particularly important in ML projects and had to be elaborated on, to show the reader what to consider regarding data before starting, during and after the project.

Trust: Both in-house and external collaborations need to have trust in the ML technology, trust from executives and trust between each other. For effective collaborations a high level of trust has been identified and deemed important in these projects.

Project methodologies and processes: One of the research questions was directly focused on the use of project methodologies and processes and, therefore, had to be included.

Problem Framing: When doing ML with a purpose it was found by several interview participants that the business case needed to be translated into an MLan ML problem and was stated to be "hard", which needed to be discussed.

Procurement of COTS: ML platforms and other commercial off-the-shelf (COTS) products were found common in the empirical data and used by companies to do ML projects.

Procurement in-house: The right resources are needed to do ML projects and through the empirical data it was found that more had to be considered than procuring the right people to the projects.

Procurement external: Many of the interview subjects were outsourcing or used external competencies to do ML projects and, therefore, chosen to elaborate further on.

Project Manager: One of the research questions was to determine the required competence of the ML Project Manager.

Organizational context: The ML projects are influenced by the organizational context and the required support and ideal prerequisites are aimed to be found.

3.4 Ethics

Regarding the ethics of the thesis, the goal of the report is to stay impartial to the fullest extent. This has been done by following scientific praxis work and aligned with the norms of scientific community. Bias is hardly escapable and there is danger coupled to simplifying transcripts (Walliman, 2010). The cleanup and organisation of data is affected by the researchers own interpretations, which introduces bias. Meaning can thus be lost when collecting data. Therefore, all quotes and all information presented in the thesis, gathered from the interviewees, have been sent to each interviewee, for content confirmation. 9 out of the 13 interviewees had comments regarding their statements, which were updated accordingly. This has secured that all information presented has been properly understood, written down, translated from Swedish to English, and without distorting or losing information. Bias can still exist but has been forced to a minimum.

Furthermore, the anonymity of the interviewees have been secured through work title aliases, without giving too much information for readers to find the real names online.

4
Empirical Data

The empirical data was gathered through unstructured interviews, which is explained in the Method chapter 3.2.2. The data is presented in the sections below.

4.1 AI Firm

The firm conducts AI research and provides an ML platform for clients to use on their own. The company's goal is to make AI more accessible.

The **AI Researcher** has a background in Engineering Physics and programming, with a strong focus on mathematics. He has worked at several large software companies before starting at the AI Firm. The data gathered from his interview can be found in table 4.1.

Table 4.1: Statements and quotes by the AI Researcher at the AI Firm.

No.	Statement	Category
S1	Formulate a problem which is relatively easy and advance it step by step with short term wins, to create value while progressing.	Problem framing
S2	Customers have either a clear goal in mind what processes to make more efficient with ML or "just want something cool with AI" and need guidance in application. It is not possible to do cool things in the beginning but provide education to customers in AI, introduce the platform to help them start their AI journey and build up a relationship.	Procurement external, Trust
S3	Companies have been feed the picture that AI can solve all kinds of problems. As an expert you have the responsibility to not promise anything and explain what is possible today by much conversation.	Problem Framing, Procurement external
S4	People working with ML need a deep understanding of the technology. It is preferred to have people that are experts in some specific area but have a general understanding of other involved areas. The job titles are mostly self chosen.	Team competence

Continue of Table 4.1		
No.	Statement	Category
S5	Most small ML teams use something "which resembles sprints but isn't really." The Product Developers, or the Product Team, do work in strict Scrum sprints schedules. The teams plan the work for each week on Monday, and have synchronization meetings Wednesday and Friday, through the management tool *Jira*.	Project methodologies and processes
S6	Strong customer interaction is needed to explain to the customer what is possible to do with ML. Many times the experts have to pull the customer from the skies and tell them what they want is not realistic.	Procurement external
S7	The first thing one has to do when about to do an AI project is to make sure there is data. It is okay to spend two weeks on a pilot study if you can skip spending two month trying to do something which cannot be done.	Data
S8	The developers and the ML specialists are placed together with their own team members. "It's been tried to mix up the teams to increase discussion with people from outside their projects, but people enjoyed more to sit with people who are working on the same things".	Project methodologies and processes
S9	It is important if you find out that the customer does not need ML to solve their problem to share this insight.	Trust
S10	To be leading ML projects a deep understanding of ML and project experience is required.	Project Manager

4.2 Automotive Software Company

The company is focused on applied ML in autonomous drive.

The **Director of Research** has a doctorate in Systems and Production Design. He knows some ML and is an expert in transferring technology into products. He has been leading large engineering firms, built up academic AI centers and is currently supervising research projects. The data gathered from his interview can be found in table 4.2.

Table 4.2: Statements and quotes by the Director of Research at the Automotive Software Company.

No.	Statement	Category
S1	Non-biased persons without personal stake needed to look at the project to decide when to give up a project or pivot.	Team competence

Continue of Table 4.2		
No.	Statement	Category
S2	It requires agile organisation to do ML/DL projects at the core of the organisation. Hard for most engineering organizations to allow for slack time. Have work load of 80 % and have 20 % slack time, in order to fix problems. Not many leaders have the strength to do that and it is rarely applied in reality, but it is needed when doing ML.	Organizational context, Project Manager
S3	Invest in maintenance of employee skills, which is important in fast moving knowledge-intensive industries. Allow time to take some courses and learn something new.	Team competence, Organizational context
S4	Do not sell stuff you do not have with deadline you cannot keep.	Trust
S5	Projects are being prioritized by a committee, moving resources between projects with good gatekeeping functions to only start projects when you have the possibility to do it from a resource perspective. Several ways to do commercial assessment, it is not one shot. Market value, timing aspect, customer need, expertise available, technology risk (reasonable/acceptable risk level required), need to be considered.	Business case
S6	AI based solutions cannot be verified because in a lot of cases the AI system cannot be understood. “You have to trust the system”.	Trust
S7	Separate Product development and R&D: Trying to anticipate the hard problems in the next years to research that, create knowledge now and reduce the risk when reaching the development stage at that point. Usually the development phase will start after an answer is found to the researched question.	Project methodologies and processes
S8	Risk management depends on company culture and needs to be defined. Prepare for different risk levels. Sales people tend to take any risk and R&D is very risk avoiding.	Business case
S9	Good company branding is needed to attract the required competences.	Team competence, Organizational context
S10	Agile based company using agile methodologies. Have a model where you can set up team and apply a method which can be adjusted depending on the project scenarios. Useful model to work in fast moving environment when you do not know exactly how it will develop.	Project methodologies and processes

Continue of Table 4.2		
No.	Statement	Category
S11	The ML team leader needs to have functional skill which is applicable to the area. Does not have to be the expert but need to have functional understanding. It is more about people management, managing risks, motivating, general PM skills.	Project Manager
S12	Measure project progress by gates and review points to see the progress on the risks.	Project methodologies and processes

The **Deep Learning Product Owner** has a background in Electrical Engineering from the university and is specialized in Signal and Systems. He joined the company as a manager for the Deep Learning Group. The data gathered from his interview can be found in table 4.3.

Table 4.3: Statements and quotes by the Deep Learning Product Owner at the Automotive Software Company.

No.	Statement	Category
S1	As a data scientist "95 percent of the work is working with data" which takes time to realize especially for people coming from academia. Academia is focused on creating and defining new models, new networks and training them on a pre-made dataset. Very little focus on how to actually create and managing the data.	Team competence, Data
S2	DL/ML Teams need to have knowledge in software development and agile methods like continuous integration.	Team competence
S3	Big challenge with the cost of creating the data you need to train. The cost of the data annotation is high and the more data is annotated the more compute infrastructure is needed, because the training dataset increases.	Data, Financial investment
S4	Bottom-up approach on finding solutions to problems where the teams have a high-level trust from the product owner. Teams need to feel that they have an ownership of the tasks and by giving them the responsibility and power to actually solve it on their own which often creates a better work environment.	Organisation, Management, Trust
S5	Primarily small and middle-sized AI expert companies need to find a niche. Larger companies can be more general.	Procurement external

Continue of Table 4.3		
No.	Statement	Category
S6	Teams are allowed to decide their own processes. Product owners set some constraints based on requirements from the organization that they need follow and on a high level, *Jira* is used to organize the backlog. The product owners can prioritize the backlog but want the teams estimate as much as possible to decide on their own on their daily or even weekly routines.	Project methodologies and processes
S7	Strong focus on knowledge sharing and processes through presentations of ongoing projects or apply concepts of pair programming.	Project methodologies and processes
S8	The sprints are a few weeks, but with 7 week increments. The Product owner works closely with the business teams to understand the priorities for the next increment from a business perspective.	Project methodologies and processes

4.3 Big Data Consultancy Firm

The company is specialized in search solutions and big data analytics, with projects ranging from building traditional search engines to ML products.

The **Software Developer** has a background in Engineer Mathematics and Computational Science, with specialization in statistics. The data gathered from his interview can be found in table 4.4.

Table 4.4: Statements and quotes by the Software Developer at the Big Data Consultancy Firm.

No.	Statement	Category
S1	Important skills in data science team are being able to parse and clean data and business domain knowledge. Many edge cases to account for and the behavior can be specific to some mechanisms in the domain.	Team competence
S2	Have implemented a data audit before every project to avoid projects to fail because of poor data. Secure to get access, quality is sufficient to avoid developing a model that is depended on a feature which is not consistently available in the data.	Data, Problem framing
S3	Close customer interaction is needed. No value if you only get a dataset and task. Work out the problem together with the client and talk thoroughly about the problem formulation before digging into the data.	Problem framing, External competence
S4	Clients trust them. Have been working with them for many years which makes it easier to do dare to fail proof-of-concepts.	Trust, External competence

Continue of Table 4.4		
No.	Statement	Category
S5	Trying to do the projects in-house and avoid resource consulting at the client, to not be locked to use a certain tool and can always choose what fits the project best. The problem with resource consulting is that you cannot control the process and for instance the infrastructure around the project which often changes.	External competence
S6	Good workplace for data scientist is where you get the wiggle room to experiment with data with high tolerance for failure. Openness in people and communication, knowledge and learning sharing is appreciated.	Procurement in-house
S7	“Scrum with short sprint duration is used and suitable for ML projects.” Gives opportunity to fail early and pivot or adapt and works both for the experimental and product development phase. For each sprint one or two priorities and set and progress and success can be measured through the sprints and product vision. It has been a learning process to understand how to work with the methodology in the best way.	Project methodologies and processes
S8	One-hour per week meetings with client are common in in-house approaches but might not be enough to understand the business domain of the client. Being on site forces you to have in-depth knowledge.	External competence
S9	“A common POC approach is to get 40 hours to show what they can imagine doing for the client.” After that the projects will be scoped.	Problem framing, Project methodologies and processes
S10	More senior and experienced people needed to determine the acceptance criteria for a model. Problem with experience required decision making.	Team competence
S11	Requirements tend to change a lot especially with business-oriented people at the client side.	Management, Problem framing
S12	To set project deadlines is tricky.	Project methodologies and processes:
S13	“To find an MVP [Minimum Viable Product] it is good to start with a simple model and simultaneously develop the infrastructure around it”.	Problem Framing, Project methodologies and processes:

4.4 Global Telecommunication Company

The company offers services, software and infrastructure in information and communication technology.

The **Data Analytics Manager** has worked as a manager in software development projects for 15 years, three of them in data analytic projects. He is currently a driver for change and transformations in data analytics, within the company. The data gathered from his interview can be found in table 4.5.

Table 4.5: Statements and quotes by the Data Analytics Manager at the Global Telecommunication Company.

No.	Statement	Category
S1	Data is the foundation of everything.	Data
S2	Program Owners and Operational Product Owners which are working towards the teams and prioritize the backlog.	Project Manager
S3	Important to mix competences to work efficient because work is interdependent. To avoid that a feature is developed which is not feasible because of data constraints there is separate teams ensuring the quality and flow of the data. Especially in the beginning is tight collaboration between data engineers and data scientists needed to set up the data pipeline.	Data
S4	Strong support from top management for data analytics. Organization puts lots of effort and the momentum is there. Interviewee was an early adapter of ML and Analytics and drives transformation and change.	Organizational context
S5	Bet the money on actual problems and then explore the data with the goal to solve the problem. ML costs money, there are lots of overhead costs.	Financial investment
S6	If possible to not use ML , do not use it. Many problems can be solved without applying ML. Start and see if you can solve the problem simple and if ML, start with the low hanging fruit.	Problem Framing
S7	“The principle is data first. Many are starting at the wrong end with tools like ML.” Data exploration can be valuable but it is more common to bet the money on actual problems and then explore the data with the goal to solve the problem	Data, Problem Framing
S8	Attractive workplace for data scientist: Good use cases and knowledge in the field, it makes it a magnet.	Procurement in-house

Continue of Table 4.5		
No.	Statement	Category
S9	As a software company there are many software engineers with interest in ML and single processing competence which is close to data analytics. It is difficult to find people with data science experience. Hiring based on motivation and attitude and then trained on skill since hard to find specific competence. Very successful to have end to end knowledge in the ML process.	Team competence
S10	Proximity is crucial for effective collaboration and solving problems. Have the knowledge in-house to theoretically solve technical ML challenges and take in consultants if manpower needed.	Team competence, Procurement external
S11	Very agile way of working in the organization. Teams are divided in areas, working autonomously and are connected through product owner. Teams using *Jira* as a PM platform/tool.	Project methodologies and processes, Project Manager
S12	Difficult to estimate work effort for the features and sprints. You need to do as best as you can and be adaptive with iterative processes and short sprints. As quick as possible to gain some first insights or value though a MVP and then scale up the projects.	Project methodologies and processes, Problem Framing
S13	Teams are highly involved in what should be done. Eager and committed to work and come up with new ideas.	Project methodologies and processes, Project Manager
S14	Follow Scrum but break the rules if needed. Continuously sharing results and findings internally but not with the stakeholders. This structure is needed because it is a large organization and it requires defined processes. It would not be healthy to be even more flexible and lose stakeholders on the way.	Project methodologies and processes

4.5 International Consultancy Firm

The firm is a multicultural company of over 200,000 members in more than 40 countries and a global leader in consulting, technology services and digital transformation. They have a unique and holistic AI service portfolio.

The **Data Scientist** has a background, and PhD, in Bioinformatics, a combination between biology and big data analytics. She had just started working at the firm when the interview was held. The data gathered from her interview can be found in table 4.6.

Table 4.6: Statements and quotes by the Data Scientist at the International Consultancy Firm.

No.	Statement	Category
S1	The sales team find clients to work with and as long as the client wants the project it will be started. “We are not so picky when choosing which projects to take on”.	Procurement external
S2	When a project proposal is received, the solution needs to be figured out in very short time to be able to participate in the bidding procedure. For the bidding procedure, assumption on the data need to be made and even solutions are based on imagined data quality. Discussion meetings are carried out to narrow down the assumptions.	Problem Formulation, Data
S4	The data analysis is split into smaller tasks across departments to speed up the process. A common issue is different individual motivation and prioritization levels for the tasks.	Team competence, Project methodologies and processes
S5	Team alignment is essential in all the projects. If there is strong push for the project there are daily meetings with different task groups where the project manager makes sure everything will be aligned within different groups and across different organizational layers.	Project methodologies and processes, Project Manager
S6	“Some of the clients feel like they just want to pay the money and then get things done. They don’t want to be involved and they accept low frequency steering committee meetings. We are fine with that.”	Trust, Procurement external

4.6 IT Consultancy Firm

The firm is a global company with a strong data scientist community. They do data analytics projects for clients, mostly in the production industry.

The **Innovation Team Leader** started his first online ML courses at Stanford University, eight years ago, and has improved his skills since then, to become a data scientist. He focuses on applied research and AI knowledge representation. The data gathered from his interview can be found in table 4.7.

Table 4.7: Statements and quotes by the Innovation Team Leader at the AI Firm.

No.	Statement	Category
S1	Big issues with client’s data quality and data is often not regarded as an asset and thus not properly collected and stored. “As soon as they [the client] have solved the problem they don’t think the data is so interesting anymore.” Further there is missing client understanding in connecting different data sources to create value.	Data

Continue of Table 4.7		
No.	Statement	Category
S2	Many client project requests in the ML and Analytics field.	Hype, Trust
S3	CRISP-DM or TDSP is used. The frameworks are explainable to clients and easy to follow. The method is very dynamic and focus on delivering business value throughout the process which is very important.	Project methodologies and processes
S4	"The ML projects are called exploratory projects, which means that we don't really know what we will find when we start and the quality of the data decides what can be done".	Data, Project methodologies and processes
S5	Projects involve data engineers, data scientists and project lead. Data engineers often have to do a lot of pre-processing on the data.	Data, Team competence
S6	"We try to have the customer involved in the whole process, which means that they have one or two people in the project itself."	Project methodologies and processes
S7	"Sometimes the clients don't really understand what we are able to do and what's not realistic." This requires continuous discussions on arising problems to explain "why it is a problem and how it affects the project".	Trust, Procurement external
S8	If we don't reach the goal for the project, as we set it up, but we still found two or three valuable insights for the client, they can still be happy with the work. We try to reach the goal but it is no always possible. Sometimes this is due to faulty data, which we then ask them to improve, or show them how to improve it.	Data
S9	"I don't think the clients would be so interested in starting these exploratory projects unless they had the trust for us".	Trust
S10	It is hard to recruit externally and takes a lot of time.	Procurement external, Procurement in-house
S11	"Because its a fast moving area, we always have to study and learn new things, to learn new algorithms."	Team competence, Organizational context

4.7 Large Transportation Company

The Large Transportation Company is aiming to become the first cognitive company, in their business area, by using AI and ML.

The **Head of AI** has a PhD and MSc from a technical university, with strong skills in programming and mathematics. He started working at the Large Transportation Company one year ago. Before, he worked at a Pharmaceutical Company as Principal Scientist and Section Head. The data gathered from his interview can be found in table 4.8.

Table 4.8: Statements and quotes by the Head of AI at the Large Transportation Company.

No.	Statement	Category
S1	Hired ML engineers and Data Scientists but also educated staff in ML.	Team competence, Procurement external
S2	Have a clear strategy and vision for the company. “Digitalization is at core of everything”, with the goal to increase efficiency and profit, improve customer experience and interconnect internal processes and people.	Organizational context
S3	Do transformation and ML across the company and not only in a specific area, instead everywhere it benefits. Cross functional objectives to connect the linear business units, since digitalization and data interconnects all units and they benefit from each other.	Organizational context
S4	What is most difficult with AI is not around algorithms and methods, it is about change management. Visionary at the company but realistic with reduced expectations: Strong commitment from leadership, up to the owner. “It’s about saying what’s possible to do and what’s not possible”.	Organizational context, Project Manager
S5	“The main principle to follow the money.” No value to go to automate and apply ML if there is no financial benefit.	Business case, Financial investment
S6	Focus on doing research collaborations for long term research questions to share risks and costs.	Organizational context
S7	Important to properly and continuously evaluate the idea and hypothesis by doing experimental design to get a good statistical answer on costs savings or improvement of efficiency.	Problem framing
S8	Working towards the same goals and share same successes with internal staff brings engagement, enthusiasm and trust. “Everyone understands the core business and have therefore something in common.”	Trust, Organizational context
S9	Product visions needs to be financially reasoned and aligned with the company vision.	Organizational context

Continue of Table 4.8		
No.	Statement	Category
S10	"Be strict about problem formulation and have clear metrics." Leading edge might not always be what you go after. Do not use state of the art in first applied ML projects, instead use something which is simple to explain for the end-user. "It is tempting to improve ongoing ML projects, but try to make it not too complicated and focus on delivering simple solutions first before taking the next step."	Problem framing, Project methodologies and processes
S11	Not using specific PM framework, however, working agile. Work iterative, "don't plan too much ahead instead discover on the way." Always reevaluate progress and question hypotheses, short sprints, avoid taking on too big steps.	Project methodologies and processes
S12	Have an idea on how much profit can be increased, either by saving costs or increase revenue. "That's the metric and the value that is associated with ML and progress can be measured." Have project objectives on a yearly basis for projects as sort of a deadline.	Financial investment, Project methodologies and processes
S13	"Establish a culture that everyone is aware of what creates value for the business which makes it easier to make decisions". Create a dynamic work environment and challenge people by allowing them to do leadership tasks.	Organizational context, Business case, Team competence

The **Digital Transformation Officer** has been a programmer and data hacker since the age of 14, with a degree in Computer Science. He was headhunted to the Large Transportation Company to make the digital transformation of the company, by incorporating ML. He created momentum and showed the company how to do it. Once they knew how, his job was done at the company and changed workplace recently to the International Consultancy Firm. The data gathered from his interview can be found in table 4.9.

Table 4.9: Statements and quotes by the Digital Transformation Officer at the Large Transportation Company.

No.	Statement	Category
S1	"You need to break rules" when digitalizing a traditional business and applying ML.	Organizational context
S2	Public mission statement and strategy with focus on customer experience have proven to be successful.	Organizational context
S3	Bring in young people with the latest ML programming skills. These skilled people can be found at e.g. hackathons	Team competence, Procurement external
S4	First steps for ML is to get data in order and second to go for the low hanging fruits.	Data

Continue of Table 4.9		
No.	Statement	Category
S5	Best way to convince management is through positive financial results.	Financial investment
S6	Outsourced everything regarding ML in the beginning when they did not have the competence, to create a momentum.	Procurement external
S7	Copied all data to run first experiments on it, to not disturb the business through messing up internal data systems.	Data, Organizational context
S8	An initial budget is needed that does not require a business case and can be used for first ML experiments.	Financial investment
S9	Internal competence is needed to understand how to buy in ML services.	Project Manager
S10	Reflect on what data you collect as a company and how you currently measure. If you want to become more efficient and automate processes to eventually increase customer experience, you need actionable metrics and strategic data collection.	Data, Organizational context, Projet methodologies and processes

The **Data Scientist & Team Leader** worked for nine years at the same Pharmaceutical Company as the Head of AI, before joining the Large Transportation Company. He has a master's degree in Chemical Engineering with focus on statistical planning. The data gathered from his interview can be found in table 4.10.

Table 4.10: Statements and quotes by the Data Scientist & Team Leader at the Large Transportation Company.

No.	Statement	Category
S1	When working with ML, deep scientific knowledge and experience are needed to understand the background of the models, to know the type of outcome you can expect and know what you can do theoretically with it. "If you just take a package, throw it at a problem and get a nice results you don't get a deeper understanding of the method".	Team competence
S2	"Start with the data backbone to become efficient later on."	Data
S3	A strong pushing up as long as the ML solution provides value to the company which requires to quantify the value. If it pays off the leadership team supports the solution. The data science team strongly interacts with areas to find things that can be improved. " We are sitting down with people from different areas to see how they work and then develop ideas how to automate things. These are the key interactions right now."	Organizational context, Team competence

Continue of Table 4.10		
No.	Statement	Category
S4	High push at the data driven side of the company. "Great to be part of that and driving it".	Organizational context, Data
S5	"All projects are CAPEX. To do that you need to show that you can do that and that you build a track record of delivering".	Financial investment
S6	"To effectively apply ML you need to make sure that you get a really good definition of the problem. Because ML does not solve everything, especially if you do not have well structured data."	Data, Problem framing
S7	It is always a mix between top-down and bottom-up. One drive pushing up, the available data and a feasibility to put something in production, and one drive pushing down, leader looking at areas that can be improved and automated.	Organizational context
S8	Sometimes you want to have high value and high impact with the outcome. "But you might end up working forever and actually never succeed. Take a step back and work on something tangible which can actually be delivered in a reasonable amount of time."	Problem framing
S9	Biggest challenge is that "there is a lot of people trying to buy ML competence from consultants without knowing how to do it and what to expect." Can take enormous time to deliver because lack of understanding and communication.	Procurement external, Trust
S10	Personally important to have the possibility to do science and engage in research collaborations. Doesn't have to compromise the science work too much when working on corporate deliveries.	Team competence, Organizational context
S11	Better to come up with status and results instead of estimating something in the middle because you can under or overestimate what you can get. "With the amount of scientific components it is difficult to define sprints in a good way, because you are not able to say how much you're able to do in 3 weeks."	Project methodologies and processes
S12	Close interaction with team members to know what was going on as a leader.	Project Manager

Continue of Table 4.10		
No.	Statement	Category
S13	No good push for the AI people to fit into a PM framework. It is essential to have good leadership to compensate for PM frameworks. “You need both confidence in your own skills and for a data science team you need a data science leader, not just a management leader because they can’t support the team with the right decisions. It is crucial to have a knowledgeable leader or leaders that can drive the vision and strategy and make sure that you get the right endpoints and targets and anticipation of the final results so you don’t oversell or undersell.”	Project methodologies and processes, Project Manager

4.8 ML Start-up Company

The company is specialized in ML annotation.

The **Co-founder & ML Expert** has a background in Physics from the university and been active in the field of ML for five years. The data gathered from his interview can be found in table 4.11.

Table 4.11: Statements and quotes by the Co-founder & ML Expert at the AI Start-up Company.

No.	Statement	Category
S1	Increasing interest from clients which do not have a proper ML team in their organisation but still want to do ML.	Team competence, Procurement external
S2	Completely committed to automotive industry. Strong knowledge and experience in the automotive domain is an advantage. Can answer complex client questions. Focus gives them an edge, where other consultants do a lot of different things.	External procurement
S3	Heavy rotation of staff doing different tasks to create a robust team.	Team competence
S4	Ensure that team is not complicated by weird databases with limited access: Problem for large companies since they have proprietary databases.	Data, Project Manager
S5	Data bottlenecks are discovered after putting together an ML team and started working on algorithms and models. Data bottlenecks can kill the project.	Data
S6	ML projects fail because it is an immature technology in an early adoption stage. No one has much experience.	Team competence

Continue of Table 4.11		
No.	Statement	Category
S7	an ML engineer should execute on technically reasonable requirements and not on exactly what is asked for from the management and question the premise of the project. “The problem is that management does not know what they are talking about half the time”. The client needs to be open to expert suggestions how to better solve the problem and let the experts determine the agenda of the product.	Problem framing, Team competence, Project Manager, Procurement external
S8	If labeled data for supervised ML is not generated as a by-product by the business operations, the investment probably takes many years to pay off. “It is a CAPEX intense business which requires much upfront cash”.	Financial investment
S9	Business is based on trust. Clients often cannot specify requirements on, or evaluate, the quality of the delivered product (annotation data).	Trust
S10	It is important to start from the data side, but companies are “buzzword compliant” and tend to start at the wrong end. It is only worth the investment to build the chain backwards if you are certain about the commercial value of the application. If it is exploratory you should start at other end and check what your options are with your data. Important to have clear vision on what the product should be capable of doing at some point in the future. Since there is no use to develop something if there is no useful application that fits with the product vision. Make a data due diligence and map the data streams of the existing business process and fit the vision with the available data.	Data, Problem framing, Business case
S11	Common mistake is that companies are hiring algorithms specialist when they need a systems perspective. To create value with data scientists they need the supporting infrastructure, otherwise it is only expensive and the Data Science PhD person is in the dessert.	Team competence
S12	“Many consultants tend to put too much money on the high risk bets because they won’t have to take responsibility for the consequences.”	Procurement external
S13	Working with agile methods. Meetings every Tuesday and “Stand-ups” every morning to check what people are working on and how it is going. Suggests cross team feature-based meetings in larger companies, to move target from protecting group responsibility and focus on the actual delivery of the product feature.	Project methodologies and processes, Project Manager

Continue of Table 4.11		
No.	Statement	Category
S14	Unless a person has done a very similar task, or has access to results on a very similar task, it is impossible to forecast required time and performance of the model. Short iterations are key.	Team competence, Project methodologies and processes
S15	"Building an ML product frequently involves doing things for the first time. The secret is to underpromise and overdeliver.""A good thumb rule is to add twice the time as the estimate by the ML engineers." These estimates are usually based on uninterrupted work without external dependencies.	Problem framing, Project methodologies and processes
S16	The team leader needs to be clear about goals, manage delivery schedules, timelines, manage external stakeholders e.g. client, and internal demands on the fly. Great product leaders with the ability to bridge technical and non-technical in ML are very rare and expensive.	Project Manager

4.9 Public Region County

The Public Region County is responsible for health care, public transportation and growth and development, in the region. They also provide culture through music, theater, dance, film, art and history.

The **Development Lead** is a self-taught programmer, with a background in Media Pedagogy and Information Architecture, who build his own ML prototypes and informs the region on how to incorporate ML in the organisation. The data gathered from his interview can be found in table 4.12.

Table 4.12: Statements and quotes by the Development Lead at the Public Region County.

No.	Statement	Category
S1	There is a lot of unstructured text in the electronic health records, which is hard to process and access, due to regulation. It is not allowed to store and access most of the data, which hinders application of ML and thus innovation such as personalized medicine.	Data
S2	No one, and everyone, is deciding on the projects. Money and other resources often need to be requested and spent within just above 12 months. Money come from business development funds and investments in the county, different funds for transforming businesses, specific funding and funding from national as well as the the EU level. The AI hype can be used but the right word buzzwords and phrasing is needed in the written request to expect any success.	Financial investment

Continue of Table 4.12		
No.	Statement	Category
S3	The project team setup is a bit unstructured. At the very least someone is experienced in technology and someone is domain expert. We don't have any data scientist, but they are needed. About to establish an AI council in the region. Everyone in region are beginners in this field. Team members are picked from interest. Don't have a clear project process regarding ML.	Team competence, Project methodologies and processes

4.10 Software Company

The Software Company provides contextualized information on a particular subject, to drive fast and informed business decisions. They do this by structuring and organizing text data gathered from different parts of the web, mainly using Natural Language Processing (NLP), including ML.

The **Software Engineer** has a master's degree in Computer Science and a bachelor's degree in Software Engineering. The Engineer is working in the team responsible for data collection and text analysis. The data gathered from the interview can be found in table 4.13.

Table 4.13: Statements and quotes by the Software Engineer at the Software Company.

No.	Statement	Category
S1	Data is everything. You really need to have the right data.	Data
S2	The Product Management makes sure that R&D does things that our clients want and work a lot with stakeholder management. Products are used by different customers and the often different expectations on the product need to be aligned or a compromise needs to be found.	Project Manager, Procurement COTS
S3	"We have an initial meeting inviting many people with different skills and talking about the problem on a high level. People can ask counter questions to make sure that we are not taking on too much on that specific problem or in that specific project. One goal of the meeting is to find people that worked on similar problems before. Then we have a second meeting which is more technical. People in these meetings are not only people who are going to work in the project, others can still help by giving their view on the problem."	Problem framing, Project methodologies and processes

Continue of Table 4.13		
No.	Statement	Category
S4	Often needed to iterate over the problem several times since clients can come with suggestions along the way."Do a quick classifier to check the feasibility of solving the problem. If the results are poor we loop back and see if we missed something in the problem definition." Often intuition used to determine if something can work or not.	Problem framing, Team competence
S5	Specialized on a niche and have different teams in R&D so they have end-to-end knowledge and can develop the full application. For example, full front-end and back-end competence, design, operations and analytics.	Organisational context, Team competence
S6	Each client has two or three contact persons, both sales and tech support, that is helping them and making sure that they are satisfied customers. Often it is easiest for the Project Manager to just talk to these internal contact persons and convey the message to R&D.	Project Manager
S7	Big list of thing that need to be done in specific Kanban board for each team which was recently implemented. Kanban board gives some structure and you can see progress. Changes are no problem if there is agreement how to proceed. Not really using defined sprints but expected time left on the project is re-evaluated every week.	Project methodologies and processes
S8	Important to have agreement between product management and R&D teams on the idea what you are trying to do.	Problem framing
S9	Do not advertise ML product releases with fixed deadlines to the customer. May start estimating a potential release date when 90% done with the work to avoid wrong expectations on the client side.	Project methodologies and processes
S10	"Both project management and R&D come up with stuff they want to do this quarter and these plans must be prioritized against each other by a MUST, COULD, SHOULD stamp."	Project methodologies and processes

5
Discussion

In this chapter, an analysis of the research is conducted by comparing the empirical data with theory.

5.1 Transformation and Change Management Capabilities

To give value to an organization it is essential to understand the organizational environment that is needed to successfully plan and manage an ML project. This has been a strong focus in the interviews. The Head of AI expressed this issue, stating that what is most difficult with AI is not algorithms and methods, but organizational change management. Prior studies by Rogers (2016) and Zinder and Yunatova (2016) have shown that many companies have strong digital transformation ambitions. They also show that these companies face many problems on their transformation journey, despite many guidelines for implementation.

ML being an emergent technology and AI's nature of changing the industry indicates that most ML projects are currently executed in, or as part of, digital transformation initiatives as it is the case for the Large Transportation company and The Global Telecommunication Company. The projects are exposed to frequent changes since it requires rapid and relentless experimentation to succeed with digital transformation (Rogers, 2016).

This study shows, by statements from the Head of AI and the Data Scientist & Team Leader, that ML is a tool that can be applied to corporate data to lower cost and/or increase revenues and increase customer experience. Therefore, companies have to create or acquire data inside their businesses in order to benefit from ML. The Digital Transformation Officer and the Innovation Team Leader pointed out that companies need to systematically collect and store data. But in most cases it is not done even though they want to apply ML. These statements, combined with the digital evolution path (Bosch, 2019), lead to the assumption that companies tend to miss out on establishing a data culture and instead jump directly to the AI level through ML application. The Head of AI pointed out that there should exist cross-functional objectives to connect the linear business units to change their focus into a data-driven mindset, since digitalization and data interconnect all units, and thus, benefit each other.

ML projects apply emergent ML technologies and also a driver of digital transformation. For this to happen, the Head of AI and Analytics Manager state that, a strong commitment for ML from the leadership is needed to lead the way and do transformation and ML across the whole company to create momentum. The Digital Transformation Officer achieved this by announcing publicly a clear digital mission statement and a strategy with a focus on customer experience. This corporate storytelling was deemed very successful because people in the organization were forced to change because it had already been publicly announced and there was no turning back. To overcome the reluctance and fear to change (Quan and Sanderson, 2018) the Digital Transformation Officer expressed that rules need to be broken when digitalizing a traditional business and applying ML.

The transformative project environment explains why strategic change management skills are one of the crucial project management abilities and at the core of any analytics related project (Shah et al., 2018). This important competence was pointed out by the Data Analytics Manager, the Head of AI and the Analytics Manager.

5.2 ML Problem Framing

Chaoji et al. (2016) showed in a previous study that the purpose of ML problem framing is to translate a business problem into an ML language problem, e.g into features. To successfully translate components of the business problem into features, the Head of AI said that all features must have a clear metric, which is in accordance with Passi and Barocas (2019). An observation was that for ML consultants, or engineers working with ML, when having business meetings with clients, it is important to fully understand the client's problem or request. According to the Co-founder & ML Expert, an ML engineer should only execute on technically reasonable requirements and not on exactly what is asked for by the management/client and question the premise of the project. He suggests that clients inexperienced in ML need to be open to expert suggestions on how to better solve the problem and let the experts determine the agenda of the product. Even though the interviewee is biased, working with clients and being the one who wants to be deciding on projects, this study found that clients with little experience in ML tend to have unrealistic expectations of what is possible and what is not. For example, the Innovation Team Leader said that "sometimes the clients don't really understand what we are able to do and what's not realistic". Therefore, the IT Consultancy Firm has continuous discussions on arising problems to explain "why it is a problem and how it affects the project."

The AI Researcher pointed out that it is a good approach to try breaking the problem into smaller problems, which hopefully have been solved before. This is backed by Bonyadi et al. (2019) and Jones (1998), stating that systematic breaking down of problems in solvable bits reveals underlying sub-problems. If no one involved in the project has done a very similar task before or does not have access to the results on a very similar task, the Co-founder & ML Expert said it becomes impossible to forecast required time and performance on the model. The Software Engineer at the Software Company worked on the problem framing in a similar way but expressed their problem framing work process as being iterative, mainly because the clients came with suggestions during the project process, forcing the team to rephrase the problem. In an initial meeting, they invited people with different skills to talk about the problem on a high level. A goal of the meeting was to invite people who had worked on similar problems before, who could then frame the problem in a later more technical meeting. Several interviewees emphasized that, when working on a problem, it can be easy to want high value and high impact with the solution, which might lead to working forever and never actually succeed. It is instead suggested, by the Data Scientist & Team Leader, to "take a step back and work on something tangible which can actually be delivered in a reasonable amount of time".

An interesting finding, pointed out by the AI Researcher and the Data Analytics Manager, was that many problems can be efficiently solved without ML. As stated by Ng (2019), good business ML solutions are found on problems which require prediction rather than causal inference and are sufficiently self-contained or relatively isolated from outside influences. This indicates that there are many business problems that are not suited to be solved by ML tools. The AI Researcher and the Data Analytics Manager suggest ML practitioners to try to solve the problem without ML and only apply it if the problem cannot be solved otherwise.

5.3 Data

In a previous study by Popenici and Kerr (2017), it was shown that many large technology companies are investing in ML research and provide their findings for free. This gives an indication that data is the main concern for ML projects, no the ML models. The interview subjects were consistent in the view that the creation of data and understanding of the available data is crucially important. For example, the AI Researcher said that "the first thing one has to do when about to do an AI project is to make sure there is data" and the Data Analytics Manager said that "data is the foundation of everything". Reasons for this in earlier work by Clemmedsson (2018) and Witten et al. (2016) is that ML models need a large amount of data to function and that data gathered in the real world is imperfect. This results in the need for special care in data creation, design of ML models and data handling. Therefore, a strong indication from the industry is that quality and quantity of big data, defined by its volume, variety, velocity and veracity (noise), is the most important requirement before starting an ML project.

Previous studies by Hashem et al. (2015) and Al-Jarrah et al. (2015) show that data worldwide is currently increasing at an exponential rate and that the data is being created in many different areas, resulting in new possibilities for ML implementation. Witten et al. (2016) say that a massive amount of this stored data is locked up in public and corporate databases, containing information ready to be harnessed by a skilled ML practitioner. The Co-founder & ML Expert at the ML Start-up Company and the Innovation Team Leader at the IT Consultancy Firm have seen this trend and expressed an increase in client interest for ML and data analytic projects. At the same time, The Innovation Team Leader pointed out that a big issue with client data quality is that data, in many cases, are not regarded as an asset by the client, leading to not storing data after a problem is solved. Not many people in these organizations know the potential value of their data.

It was observed that treating the data as a valuable asset is important because no one can say beforehand what is valuable and what is not. If there is available data, according to Witten et al. (2016), there is a possibility of ML application. Therefore, the focus changes to the quality of the data. Numerous interviewee subjects have expressed a challenge to ensure adequate data quality, for ML models to give desired results for the client. To battle this, the Software Developer at the Big Data Consultancy Firm has implemented a data audit before every project to avoid failure due to bad quality data. If the data is faulty, The Innovation Team Leader sometimes ask the client to improve their data or, if needed, show them how to do it. The AI Researcher pointed out that "it is okay to spend two weeks on a pilot study", to experiment with the data and test it, "if you can skip spending two months trying to do something which cannot be done". Thus, this study emphasizes that an important requirement for ML projects is data and data quality and that special care should be taken regarding data, especially in the initial phases of the project.

As as pointed out by Gandomi and Haider (2015), the data should also be varied because ML can find unforeseen and interesting correlations between them, and thus, create large business value for the companies (Grover et al., 2018). For example in an online store, it can be equally important to save data regarding *what* their costumers buy as to *what they do not* buy. As pointed out by the Innovation Team Leader, data should also be stored over a long time, since insights can be time-dependent.

A result from the interviews declared that a common mistake made by people inexperienced in ML is that they start working on algorithms and models without making sure that the quality and quantity of the data is adequate. One reason, stated by the Deep Learning Product Owner, is that when people learn to use ML they often practice on complete and perfect datasets, believing that ML is mostly about creating algorithms and models. Instead, he continues, as a data scientist "95 per cent of the work is working with data", with creation, labelling and maintenance. The data has to be evaluated and, dependent on the outcome of the evaluation, either the data needs to be labelled, and/or new data needs to be added, and/or the ML models need to be tweaked, to be able to robustly handle the imperfections in the data. No information of value regarding how to clean imperfect data was given from the interview subjects, who simply expressed it as being "hard".

Surprisingly, The Data Scientist at the International Consultancy Firm made a lot of assumption regarding the amount of, quality and access of data, when other interviewees made it clear that a thorough analysis of the data is needed. The reason is that the International Consultancy Firm is dependent on clients wanting their aid. If a client comes to the company stating that they have data regarding some domain specifics, assumptions had to be made to "seal the deal". The risk, obviously, is faulty data, which can lead to unwanted results or no results at all. This will lower the trust with the client if promises or potential valuable outcomes have already been made to the client.

5.4 Financial Investment and Business Case

In a prior study, Larson (2018b) stresses the importance of data and data infrastructure, which quickly can become a costly endeavour. The current study supports this as maintaining ML projects, according to the Data Analytics Manager, have high overhead costs and, according to the Deep Learning Product Owner, data creation for supervised ML model training, which is usually sent to data annotation companies, is extremely expensive. In theory, it has been argued that the risks of failure in exploratory ML are high. As pointed out by the Co-founder & ML Expert, the investments probably take many years to pay off and ML "is a CAPEX intense business, which requires a lot of cash up front". Thus, investment in these types of ML projects will require much cash at the start of the project and continuously during the project life-cycle and return on investment can often not be guaranteed. To lower these costs and risks the Head of AI pointed out that for longer ML research projects the focus should be to have research collaborations "to share the risks and costs".

An interesting finding, pointed out by the Digital Transformation Officer at the Large Transportation Company, was that for first exploratory ML projects an initial budget is needed that does not require a business case. The presented theory (Herman and Siegelaub, 2009) does not support projects without a business case but the Transformation Officer further explained that companies aiming for digital transformation need to kick-start their ML projects without the assumption that it will pay off, simply because it is exploratory. This indicates that "no business case" could mean no ROI *Business Case* and instead a *Strategic*, *Investment* or *Research* focused Business Case. After first experiments in the Large Transportation Company, with strategic targets in the Business Case for ML projects, the focus has now shifted towards ROI focused Business Cases. This finding is backed by the Head of AI who said that for ML practitioners, requesting money from management to do ML projects, it is easier to receive a budget if it can be shown how much the investment would reduce costs or increase revenue in the long run.

Following the current trend of ML, business research by (Gartner, 2016) show there is an ongoing investment hype in the AI community. The Development Lead explained that in the public sector this hype has increased the chance of receiving investment money to do ML projects. Money and other resources often need to be requested and spent within just above 12 months. Money comes from business development funds and investments in the county, different funds for transforming businesses, specific funding and funding from national as well as the EU level. The AI hype can be used but the right buzzwords and phrasing are needed in the written request to expect any success. Representing the private sector, the Data Scientist & Team Leader mentioned that there is strong financial support from the executives and budgets for ML initiatives are approved, which can be connected to the hype. This study shows that hype facilitates receiving additional funding for exploratory projects.

5.5 Team Competence for In-House Development

ML Engineers, Data Engineers and Data Scientists are key staff in ML teams according to the majority of interviewees. These results are consistent with previous work from Kashyap (2017b), However, the findings show a special focus on data engineering skills for pre-processing of the data as. For instance, the Software Developer stated that being able to parse and clean data is a crucial skill. This can be explained by the described importance of data. The Data Scientist & Team Leader highlighted the importance of access to senior data scientist knowledge to determine which ML approach to use and the corresponding acceptance criteria of the model. Deep scientific knowledge is needed to understand the background of the models which is aligned with theory as described by Kashyap (2017b). One unanticipated finding, as observed by the Co-founder & ML Expert, was that companies often make a common mistake by only hiring Data Science PhD people with expertise in algorithms, when a systems perspective is needed. Supporting infrastructure is needed to create value with data scientists. Even though (Kashyap, 2017a) stated that hiring young graduates from hackathons bears a risk, the Digital Transformation Officer mentioned that it can be profitable to bring in young people who are familiar with ML programming languages and tools and can efficiently execute ML tasks. Those can be found at hackathons and competitions.

The term ML Engineer was brought up by the Co-founder & ML Expert and Head of AI but was not further elaborated on. The AI researcher emphasized that job titles are mostly self-chosen. This study has been unable to unambiguously demonstrate the role of the ML Engineer as suggested by Kashyap (2017b). A possible explanation can be the widespread problem with ambiguous team roles which was described in earlier research by Saltzt and Grady (2017).

Generalists with end-to-end knowledge are valuable for ML teams as stated for instance by the AI researcher and the Software Engineer. These results match those observed in earlier studies by Jurney (2017). Based on a statement by the AI researcher, this study found that despite being a generalist, to have maximal value to the team it requires specialisation in at least one area. End-to-end knowledge in ML applications can be achieved through heavy rotation of staff doing different tasks according to the Co-founder & ML Expert.

The findings show the importance of non-biased people without a personal stake in ML projects to evaluate the progress and provide input on important decisions e.g. pivot or persevere. This was mentioned by both the Director of Research and Co-founder & ML Expert and appears to be a crucial element. It was observed that it is essential to move the target from protecting the project group and instead focus on the actual delivery of the product. This indicates that for a person involved in the project, who has invested time, company resources and established a satisfying social work environment, to make decisions on project termination, outside guidance could be needed to make the right decision for the company. No previous studies were found in the context of ML projects, but the general phenomena non-biased project appraisal has been well researched and shows the importance of external perspectives on projects across all domains. This study provides evidence that this applies also to ML projects.

Besides the importance of technical competence, prior work by Kashyap (2017a) has noted the importance of business understanding and communication skills in ML team members. This study is consistent with previous work and shows that when looking for areas that can be automated, ML teams need to strongly interact with business areas to understand the business and find things that can be improved and automated, which was pointed out by the Data Scientist & Team Leader as key interactions for successfully ML teams. The Co-founder & ML Expert specified that ML teams need to have the competence to execute on technically reasonable requirements and not accept every request from management. To questions the premise of the project it requires to speak the language of business. This supports previous research by McAfee and Brynjolfsson (2012).

It has been stated by McAfee and Brynjolfsson (2012) that data scientists coming from purely academic background lack a share-mentality which was not considered a serious issue by the interviewed study participants. A more relevant drawback of a pure academic background, identified by the Deep Learning Product Owner, was the lacking experience in creating and managing data because academia is focused on creating and defining new models and new networks and training them on a pre-made and clean dataset.

Based on statements from the Data Analytics Manager, the Head of AI and the Innovation Team Leader, a relevant finding was that a common approach is to educate staff in ML internally or hire based on motivation and attitude since the hiring process is costly and takes time to hire senior data science experts with deep knowledge in ML. The situation that demand outstrips supply as described by Davenport and Patil (2012) has been exacerbated. To attract these scarce competences, a company needs to have good use cases and already existing knowledge in the field of ML pointed out by the Data Analytics Manager. As a Scientist himself, the Data Scientist & Team Leader stated that Data Scientists with an academic background may value to have the possibility to engage in research collaborations and the company should be prepared to be tolerant for failure and allow to experiment. The software developer mentioned that a culture of learning and sharing is often much appreciated.

5.6 Procurement of External Competence and Vendors

Business domain knowledge is essential to develop models that deliver business value as explicitly mentioned by the Software Developer, the Co-founder & ML expert. These results match those observed in earlier studies by Davenport and Patil (2012) and Ahrens (2014). This study confirms that external consultants are often associated with lack of business domain knowledge and indicates that it can be beneficial to work with consultancies or ML service companies that are committed to the respective industry or specialized on specific ML solutions.

As presented in the literature review, outsourcing is common because hiring skilled personnel is a challenge. The majority of interviewees mentioned that clients lacking ML knowledge causes severe problems in communication leading to prolonged and problematic deliveries. The current study indicates that even though most of the tasks are outsourced it requires at least a small and skilled in-house ML team to make reasonable buy-in decisions. Outsourcing of e.g. data annotation for supervised ML is common but needs an understanding of what is wanted and what can be expected. The results further indicate that when a company embarks on the ML journey it has been proven successful to outsource ML, in the beginning, to create momentum and attract ML talent to build an in-house team. This was supported by a statement from the Digital Transformation Officer.

The findings further support the importance to determine the long term strategic role of AI and ML in the company by Burgess (2018). If a company has strong ambitions in applying ML, the results of this study support the idea of having an in-house ML team for applied ML projects. Statements by the Head of AI, the Data Analytics Manager, and the Co-founder & ML Expert were used to support this finding.

This study reveals that in a scenario, as pointed out by the Software Engineer, where a client buys a commercial off-the-shelf ML product, e.g. for threat intelligence, and requests a specific product feature, it is not given that it will be developed. ML products or platforms are often developed to fit a large customer base and a common ground between the customers needs to be found.

5.7 Trust

Trust in the Technology: It was stated in prior research by Schaefer et al. (2016) that systems that are not trusted are not used. A way to tackle this is suggested by the Head of AI who said that at the beginning of the project, “try using simple ML models which are easy to explain to the end-user”. In accordance with Taddeo (2017), the only record from this study of negative trust for ML was when people had experienced negative events in ML projects. Even though it is hard for executives not specialized in ML to evaluate the work results, it was pointed out by the Director of Research that they simply “have to trust the system”, because “in a lot of cases the AI system cannot be understood”. Furthermore, the Digital Transformation Officer said that “the best way of convincing management [to do ML projects] is through positive financial results” with ML projects, because it increases trust in both the technology and the team. For the Large Transportation Company, a corporate vision was made to change the mindset of the whole corporation, which led to an increase of trust in ML by employees not involved in the ML application development.

Management Trust in ML Project Team: According to the Deep Learning Product Owner it is important to give the project team trust and responsibility to solve the ML project on their own and teams feeling they have this responsibility creates a better work environment. The Director of Research expressed that it is hard for executives not specialized in ML to evaluate the work results and it is largely based on trust which is aligned with work by Matsudaira (2015). The Head of AI added to this discussion by saying that “working towards the same goal and share the successes with internal staff bring engagement, enthusiasm and trust. Everyone understands the core business and have therefore something in common." Furthermore, The Software Developer said that "a good workplace for a data scientist is where you get the wiggle room to experiment with data with high tolerance for failure", which is in accordance with Matsudaira (2015) saying that it requires tolerance for failure from the management side and failure should not directly undermine trust.

Trust in External Collaborations: Gartner (2016) and Koyama (2018) said that the use of external competences and vendors are common in ML projects. The Innovation Team Leader agreed to this saying that their clients have an increasing demand for ML problem solving, and for the company to have already established a good client relationship and delivered successful non-ML projects, give them a clear trust advantage in the ML projects."I don't think the clients would be so interested in starting these exploratory projects unless they had the trust for us". A similar statement was made by the Software Developer. The Co-Founder & ML expert pointed out that companies have a hard time assessing the quality of externally annotated data. There is a lack of reliable and cost reasonable testing frameworks (Tuncali et al., 2018) which forces companies to trust their external collaborations. Prior research by Kashyap (2017b) shows that the holistic experience by the client regarding how the work is being advertised, delivered, deployed and accessed, and the smartness of the solution influences the trust. Thus, for external collaborations trust can be increased by showing professionalism in these subject areas. The International Consultancy Firm accepted most of the client projects, even though the majority of the participants in the current study suggested a thorough analysis of the client request and data. This is supported by the Co-founder & ML expert stating that consultants tend to be sales driven and put money on high risk-bets. As an expert, it is important to communicate what is possible and what is not, before making any promises. This ensures not to over-promise and under-deliver, which was pointed out by the Co-founder & ML Expert to undermine trust. The better approach to create trust is to under-promise and over-deliver. The AI researcher pinpointed even though client projects requests are rejected, it can be appreciated by the client and the AI firm can help the client to start their AI journey through education and pilot projects to establish trust. These clients can become very beneficial in the long term due to the trusted relationship.

5.8 Project Methodologies and Processes

The interview results of the Head of AI and the Data Scientist & Team Leader indicate that ML teams can compensate for missing defined processes with strong senior leadership. Jeffrey Saltz et al. (2017) supports that there is a lack of adoption of mature team process methodologies for data science projects. As discussed earlier, senior data science leaders with both technical knowledge and business understanding are scarce and expensive. This combination of findings provides some support for the idea that team process methodologies allow cost-efficient ML project execution with strong empowered teams, without relying on senior leaders. The Co-Founder & ML-Expert pointed out that ML projects are exploratory with many technical and data bottlenecks and require adaptive ways of working and short iterations.

Based on the statements from a broad majority of interviewees the findings indicate that the project requirements tend to change a lot especially with business-oriented people and effort estimations of project tasks are very difficult, which further support the idea of agile ways of working. This study argues that ML projects can be linked to adaptive or even extreme Project Management Life-Cycle (PMLC) models as presented by Wysocki (2013).

Scrum, Kanban, CRISP-DM were found to be used which is consistent with a previous study by Jeffrey Saltz et al. (2017). The IT Consultancy Firm used the TDSP framework by Azure (2017).

Previous studies by Matsudaira (2015) and Jeffrey Saltz et al. (2017) have indicated that ML project methodologies can be similar to agile software development methodologies, but require adoption. This is in accordance with statements by the Data Analytics Manager. The findings show by common consent of the contributing organizations that short planning cycles and frequent team synchronization meetings are of paramount importance to continuously re-evaluate progress and question hypotheses. It was observed that most of the ML teams use sprints but do not strictly follow the **Scrum** process. It is interesting to note that in most cases *sprints* appeared to be used as a synonym for a short, incremental cycle. The companies that stated using Scrum for ML projects have experience in the domain of software development and use it across the organization. It was observed by the Software Developer that it is a learning process to understand how to work with Scrum in the best way in ML projects and, pointed out by the Analytics Manager, that Scrum rules need to be broken to effectively manage ML projects. For instance, important insights are shared immediately internally, which is not aligned with the Scrum methodology. Weak indications have been found in this study that reluctance of sharing intermediary results and strict sprint length, as advised by the Scrum creators Schwaber and Sutherland (2011), can be problematic for efficient project execution.

The statements of the Deep Learning Product Owner and Director of Research show that that prioritization of backlog based on business value is key. The Data Scientist complemented this and stated that when splitting up the work into smaller tasks it is important that the individuals assigned to the tasks are aligned on a similar motivation and prioritization level, for the respective tasks. Prioritization can be done by e.g. product owners or team leaders or by the team itself. Strong team involvement in prioritization is common according to a strong majority of the interview subjects because the team input on effort estimation is valuable. Autonomous and empowered ML teams are allowed to decide on own processes and sprint routines according to the Deep Learning Product Owner. This strongly resembles the characteristics of Scrum described by Rigby et al. (2016) and can be an explanation of why elements of the agile Scrum methodology are used in ML projects. Due to cultural challenges when adopting the Scrum methodology, as mentioned in previous work by Rigby et al. (2016), it can be assumed that it is not useful to implement Scrum only for doing ML if the organization has no prior experience in agile ways of working. The Software Engineer pointed out that end-to-end ML application developments involve software engineering fields following mature agile processes e.g. for developing infrastructure around ML code or front-end design of the user interface. Therefore the findings can support the previous work by Mathur (2018) who recommends following modern software development methodologies to some extent, to be compatible with the software engineering interfaces.

Agile Kanban was found to be used in ML projects and explicitly mentioned by the Software Engineer in the Software Company. The described effect of using Kanban was consistent with previous research by Jeffrey Saltz et al. (2017). The Software Engineer pinpointed that the Kanban board gives structure to teams and visualizes progress and the current study supports that it can be used as a first step in establishing a more structured ML project process. Frequent scope changes are common but if there is team consensus on how to proceed, Kanban is flexible for changes. This indicates that this methodology can be valuable for highly exploratory projects or project phases e.g. data exploration or, as the Data Analytics Manager pointed out, initial value creation through an MVP to find the method that can solve the problem. Once the method is found, the project can be scaled and the study found that processes with more structure can be suitable to coordinate the project team and stakeholders.

Unfortunately, this study can not elaborate on the lacking agility of CRISP-DM (Jeff Saltz et al., 2018) and to what extent TDSP solves this issue (Schmidt and Sun, 2018). The findings show that no company was solely relying on CRISP-DM as a process framework and most companies followed an agile and/or own methodology. It is possible, therefore, that the criticism on CRISP-DM by Jeff Saltz et al. (2018) is justified. Based on the theoretical backbone and the findings on agility, it can thus be suggested that hybrid versions e.g. TDSP, that interconnect knowledge discovery processes and agile practices, can be valuable to projects.

One of the challenges in ML projects found in the current study is to align technology research and product development processes. The findings that companies have different incentives to do technology research. Either to use new discoveries as a source for their commercial products as mentioned by the Director of Research or by receiving external funding to research a specific field of AI, without required commercialization as pointed out by the AI Researcher. The findings show that the AI Firm made an attempt to mix research and product development personnel to increase the discussion with people from outside the projects, but it was not appreciated by the teams. A possible explanation is that much of the research at the company was funded and not pressured by their own development team. Even in a scenario where the development team strongly depended on technology research findings, the current study found that separating the processes can be beneficial. However, this requires anticipation of future technological burdens but reduces the technology risk for the development phase as emphasized by the Director of Research. The results indicate that companies do not need to engage in research to apply ML. The AI start-up Company was not actively doing research, rather implementing the published research of large companies with robust R&D capabilities. But when looping back to attracting skilled staff, it may be required in order to get Data Science researchers to work for the company.

6
Conclusion

The purpose of the current study was to determine the implications of planning and managing machine learning (ML) projects to create awareness for ML Project Management.

One of the significant findings to emerge from this study is that digital transformation and organisational change management have strong relevance for ML projects. Most ML projects are currently executed in a transformative corporate environment, often as drivers of digital transformation. The research has shown that companies tend to miss out on investing in establishing a data culture with strategic data collection before attempting to apply ML, to automate processes and/or increase customer experience. A possible explanation is the AI hype with inflated expectations on ML and perceived pressure to quickly respond to emerging technologies. This study found that corporate storytelling with strong commitment from the executives has proven to be successful to communicate a clear strategy and mission, and thus create momentum around ML. The results suggest that from an ML project management perspective it is essential to understand and support the organisation's transformation journey and ensure that investments in systematic data collection and storage are made. Further, it requires continuous evaluation if the ML product vision is aligned with the corporate strategy. This indicates for a Project Manager leading an ML team it is required to be both a technical ML leader and central management figure with strong change management skills.

This study concludes that data is crucially important in ML projects and should be considered, from a Project Management perspective, to be the *main stakeholder* and be the first thing to look at when assessing the project risks.

When ML practitioners are having business meetings with management executives it is important to fully understand their problem or request. People not familiar with the technology have been linked to having unrealistic expectations of what is possible with ML. The study suggests that a Project Manager should not execute on exactly what is asked for by the executive, instead question the premise of the project to only execute on what is technically reasonable. By asking *why* questions, the root of the problem can be exposed and understood, which facilitates the translation into an ML problem. However, despite ML being a powerful tool, it is not the solution to every business problem.

It was shown that ML projects can require large financial investments upfront and continuously during the project life-cycle for e.g. data infrastructure, skilled personnel, data infrastructure and maintenance. The projects are exploratory with a high risk of failure and a return on investment can often not be guaranteed in an early adoption stage. This study has found that it requires an initial budget for first ML pilot projects that is provided without an ROI Business Case, but when the company becomes more mature in ML, ROI Business Cases for ML projects are useful for budget approval and provide actionable metrics to measure progress and success for the business. This study concludes that the current AI hype facilitates receiving additional funding for exploratory ML projects, both in the private and public sector.

This study discussed the three procurement options, in-house development, outsourcing and COTS solutions. For building up an in-house team, a major finding was that data pre-processing skills, business understanding and the ability to communicate complex ML problems to technology illiterates are considered important skills in ML teams. ML Engineers, Data Engineers and experienced senior Data Scientists with deep scientific knowledge are key staff in ML teams but generalists with end-to-end knowledge and specialization in at least one field are most valuable. Non-biased project appraisal was found to be important and it needs people without a personal stake in the project to provide input on important decisions. This study confirms that demand outstrips supply in the described competences and companies are most attractive for the scarce resources when having good use cases and already existing knowledge in the field of ML. The evidence from this study suggests that outsourcing can be cost-efficient and valuable to create momentum and attract ML talent to build an in-house team. The results of this research strongly support the idea of having an in-house ML competence to either build ML applications or make reasonable buy-in decisions. For outsourcing scenarios, this study suggests working with external partners that have knowledge and ML experience in the project's business domain. It seems that consultant project bidding procedures, which require fast solutions proposals to win a project, are not aligned with the required thorough investigation of data and understanding of the business problem. For Project Managers, it should be considered that COTS solutions are built to fit a large customer base and requested product features might not be developed.

The strong relevance of trust is clearly supported by the current findings and was categorized *trust in the technology*, *management trust in ML project team* and *trust in external collaborations*. ML project teams should be empowered by the Project Manager and it requires tolerance from the management side for experiments and project failure should not directly undermine trust. Trust in ML technology needs to be established across the organisation, and the study indicates that a corporate AI vision can change the mindset of end users and increase their acceptance of ML generated results. The study found evidence that trust in external collaboration is crucial because the quality of delivered ML applications or externally annotated data is difficult to assess. This is a current issue but could be less important in the future if cost efficient and reliable quality testing frameworks are developed.

This study has shown that ML project teams mostly use their own methodologies or processes which resemble, or have certain elements of, Scrum, Kanban, CRISP-DM or TDSP. This study concludes that an agile way of working with short iterative cycles and frequent team synchronization meetings, are of paramount importance to continuously re-evaluate progress and question hypotheses. Agile Kanban was found to be used as a first step in establishing a more structured ML project process, because it visualizes progress, is flexible to change, prioritizes tasks, and gives structure for the teams. This methodology can be valuable for highly exploratory projects or project phases e.g. data exploration or MVP phases that aim to find the method that can solve the problem, Once the method is found, the project can be scaled and the study found that a project process with more structure than Kanban can be suitable to coordinate the project team and stakeholders. Further can be concluded that it is not useful to implement Scrum only for doing ML if the organisation has no prior experience in agile ways of working. Based on findings on agility, it can thus be suggested that hybrid versions e.g. TDSP, that interconnect knowledge discovery processes and agile practices, can be valuable to projects. However, no explicit findings on missing agility of CRISP-DM could be provided. Furthermore, the TDSP framework provides clear guidelines on how to develop an ML project charter, which can be beneficial for a Project Manager. In general it seems that the use of an ML process model with a focus on data and delivering business value throughout the project is valuable.

The findings of this study have to be seen in light of some limitations. The geographic scope of contributing organizations was limited to the Gothenburg area and the majority of selected organizations were partners of AI Innovation of Sweden. This makes it a local study and the participants, even though not mentioned, possibly had previous knowledge exchange through the collaboration hub or AI conferences in Gothenburg.

The research discovered a lack of previous research studies on the topic and provided a broad spectrum of considerations for managing ML projects. However, an in-depth research is needed in the respective aspects, primary in the identified ML project methodologies and processes to provide evidence on the actual effect on the project outcome.

7
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