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AI Paradox and How to Overcome the Barriers for Scaling: Multi-Company Case Study

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Abstract

PURPOSE OF STUDY

The purpose of this thesis is to understand the difficulties related to successful scaling of Artificial Intelligence projects and implementations. The aim is to find and study the potential barriers for scaling and provide actionable solutions to these challenges.

THEORETHICAL BACKGROUND AND METHODOLOGY

The literature review consists of overview on AI technologies and different aspects of novel technology project implementation, change management practices and briefly inspecting AI as a tool for decision making. The data for this thesis is gathered by conducting 7 qualitative interviews in 6 different case companies.

FINDINGS

The findings of this thesis illustrate that AI implementation is multi-disciplined challenge and that there are some barriers for scaling, especially for SME organizations. However, by anticipating and addressing the challenges early on, AI team leads can have better chances at succeeding.

Keywords Artificial Intelligence, Change Management, Scaling, Technology

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TUTKIELMAN TAVOITTEET

Tämän diplomityön tarkoituksena on tutkia haasteita liittyen tekoälyn skaalaamiseen ja käyttöönottoon. Tavoitteena on tutkia mahdollisia esteitä onnistuneelle skaalautumiselle sekä tarjota mahdollisia ratkaisuja näihin haasteisiin.

AINEISTO JA METODOLOGIA

Kirjallisuuskatsaus koostuu katsauksesta eri tekoälyteknologioihin, sekä kirjallisuutta muutosjohtamisesta ja teknologiaprojektien luonteesta. Lopuksi esittelen vielä lyhyesti kirjallisuutta liittyen tekoälyn käyttöön päätöksenteon tukena. Data diplomityötäni varten on kerätty haastattelemalla seitsemää henkilöä kuudessa eri yrityksessä.

TULOKSET

Tämän diplomityön tulokset osoittavat, että tekoälyprojekteihin liittyy tiettyjä teknologiakohtaisia, monialaisia haasteita, jotka voivat johtaa tekoälyhankkeiden skaalautumisen epäonnistumiseen, erityisesti PK yrityksissä. Ennakoimalla ja vastaamalla näihin haasteisiin hyvissä ajoin, tekoälytiimien johtajat voivat parantaa skaalauksen onnistumisen todennäköisyyttä.

Avainsanat Tekoäly, Muutosjohtaminen, Skaalaus, Teknologia

Preface and Acknowledgements

The process of writing my master’s Thesis started early on in 2019 with the help of Sisua Digital who commissioned this thesis. During the spring we found a topic that was interesting to both me and them and I was able to start the writing process in May of 2019 which lasted until the end of 2020.

First and foremost, I would like to thank my thesis supervisor Timo Vuori who provided me with steering and detailed comments during the different phases of writing my thesis. Based on his advice, I was able to focus on the right aspects and trust that my writing process was on the right track. I would also like to thank my employer Sisua Digital for providing me with the topic, guidance, contacts for interviews and valuable support during the writing process. Especially Tomi Torri and Marko Vanhatalo have been key to scoping the topic and finding right contacts for my research process. Lastly, I would like to thank all the people I had a chance to talk to and interview and who gave me great insights related to AI industry in Finland. Due to the promises of anonymity, I cannot name the participants here, but you know who you are!

I also received huge amount of support and trust from my family, friends and from home. Without you this whole journey would have been a lot harder.

Helsinki, January 2021

Aleksi Hentunen

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List of abbreviations

AI = Artificial Intelligence

SME = Small and medium-sized enterprises

RPA = Robotic Process Automation

ML = Machine Learning

POC = Proof-Of-Concept

1. Introduction

The introductory section of this thesis elaborates the motivations and aspirations behind the subject of Artificial Intelligence as project implementation challenge. Research questions and the objective of this research is discussed here in detail as well as the structure and the scope of my thesis.

Since AI can mean different things to different people, in this thesis I have defined Artificial Intelligence as:

"Different sciences have different subject matters, and AI is the study of intelligent behavior in computational terms." (Levesque, 2014)

1.1. Background

Even though the talk about Artificial Intelligence (AI) and its different applications have been circling around different industries for decades, the adoption rates and investments on the technology outside the front-runner tech companies have only now started to increase. Expectations for Artificial Intelligence are high but the difference between ambition levels and actual performance is large in most companies and is highlighted by a big gap in adoption rates between the front-runners and laggards (Ransbotham *et al.*, 2017). Sometimes this failure to scale after initial pilots and early successes is called the AI Paradox. (Gerbert *et al.*, 2018)

AI Paradox and How to Overcome the Barriers for Scaling

Many companies that are now on path to adopt AI for the first time have to operate on the basis of old management principles that are developed for traditional IT implementations. According to my experience there are considerable growth pains associated with the first AI cases, as companies need to learn fast and often ad hoc how to implement AI and how that differs from the traditional ways of doing IT implementations. This typically leads to prolonged projects that do not meet their budget constraints or in failed implementations that do not reach the production. The main purpose of this thesis is therefore to investigate the observed differences and the reasons behind the AI paradox and available methods to overcome these challenges.

Artificial Intelligence is a wide umbrella term that covers many different types of computing technologies that try to mimic the ways humans use their brains to make decisions. Such technologies include different Machine Learning (ML) algorithms, Robotics and Artificial Neural Networks (Statista, 2017). These technologies allow computers to utilize huge quantities of data and can be used to complete task such as classification, regression, clustering, and estimation of distributions (Statista, 2017). Other possible commercial solutions include Image Recognition, Speech Recognition, and multipurpose ML software. These different methods and examples of their use will be described and discussed in length in the literary review section of this thesis to give reader an understanding of capabilities and limitations of Artificial Intelligence as they stand today.

However, looking AI purely through technical lens would tell only a part of the story when applying AI in the real world. Important challenge with any new venture that changes the way organizations conduct work or business, be it technology or process, is the internal opposition to change by managers and employees. According to the research survey by Accenture, the Artificial Intelligent solutions divide strongly the opinions of managers and senior executives, other camp believing the strong potential in change and "others viewing it as a harbinger of doom." (Kolbjørnsrud, Amico and Thomas, 2017) The same survey revealed that the enthusiasm vanishes when moving further down the line of hierarchy, as the senior executives were described being most optimistic, while the line managers are fearing for job losses. (Kolbjørnsrud, Amico and Thomas, 2017) As with any potentially groundbreaking changes to the business operations, these fears should be properly addressed and communicated before launching development projects of any kind. In this thesis I will then investigate how the change management challenge differs when implementing AI as opposed to some other traditional technology.

Different Artificial Intelligence technologies can bring companies that implement them many benefits, including customer satisfaction through better customer service experience, productivity increases, revenue growth or process lead-time reductions. However, in this thesis I will focus more on the mechanics of the project implementation, instead of analyzing the results on which these successes or failures can be measured by. Which qualities of the AI implementation project brings successes, and which are the common pitfalls to avoid? By answering these questions, I hope to ease the task of managers and project teams that are implementing their first Artificial Intelligence projects and bring actionable suggestions on how to manage AI based projects or scale AI operations in general.

1.2. Research questions and objectives

Despite the recent advances on computing power and availability of "Big Data", Artificial Intelligence continues to face challenges when applied to everyday business and production environments. The word AI or more generally just Intelligence is currently on everybody's lips especially in my field of work of business process automation. Taking part in projects that include some AI related solution has turned out to be much different experience compared to projects that only implement more traditional solutions where simple routine-based tasks are automated. This realization led me to the formulation of hypothesis and research questions for my thesis.

Starting hypothesis for this thesis is that there are some inherent Artificial Intelligence specific challenges in the implementation projects that currently prevent the effortless wide scale adoption of said technologies. The purpose of this study is to then to assess whether this assumption is true and then try to pin-point the qualities in the projects that bring successes or failures.

The research question in this thesis is formulated as:

"Why AI projects are hard to scale?"

A possible outcome of this research could be to use the accumulated knowledge to help future strategic and operational implementations. The explicit know-how of the way these technologies are used optimally and what side effects might manifest during these projects can be taken advantage of when planning future AI implementation projects.

1.3. Structure of the thesis

I will start my thesis with a literature review which dives into key technologies that are often called AI and how new technologies are implemented in practice, including the proper change management principles. Lastly, I will briefly explore the possibility of using Artificial Intelligence in strategy work and assisting humans in decision-making in complex and dynamic environments. After the literature review, I will describe the research process in length, after which the results are analyzed. I will conclude my thesis with a discussion chapter and propose future research possibilities based on my findings.

2. Literature review

In this literature review section, I intent to give reader a look on different Artificial Intelligence technologies currently in use and how these are implemented. In addition, the technology implementation concepts are described for two chapters as a part of strategy work as well as project and change management challenge in the context of project implementation frameworks. I will conclude this literature review section by looking on how Artificial Intelligence could be used to enhance strategy work and decision-making processes. Artificial Intelligence can be studied and analyzed from multiple different angles and perspectives, but to limit my approach in this thesis, I will focus on the most important factors concerning AI as a project implementation challenge.

2.1. Introduction to Artificial Intelligence

As is true with any specific field within computer science, Artificial Intelligence research is a novel discipline, despite its philosophical roots of which can be traced all the way back to Ancient Greece (Luger, 1993). The research of Artificial Intelligence is a multi-disciplinary effort, combining elements from areas such as philosophy, mathematics, economics, neuroscience, psychology and computer engineering (Russell and Norvig, 2003).

To understand better the current state of the Artificial Intelligence research and implementations, it is useful to know its history. In the next chapter, I will present a short introduction to how Artificial Intelligence transformed from philosophical discussions to applicable technology. It is also useful to know the type of problems practitioners faced or best practices they used when the technologies were less mature.

2.1.1. Background for Artificial Intelligence

"Those who don't know history are doomed to repeat it."

— Edmund Burke

<u>AI Paradox and How to Overcome the Barriers for Scaling</u>

Even though the first known calculating machine called "The Abacus" can be dated back over two thousand years to Ancient China, it took a long while for humans to progress in building machines that could emulate human cognitive behavior. The major advances were first made when leading Western philosophers started to view human thinking as a form of computation. This eventually led to the first attempts to formalize logic, introduced by Gottfried Wilhelm von Leibniz in his work *Calculus Philosophicus* (Leibniz, 1887). The other important conceptual tool that is used in many Artificial Intelligence solutions, namely "state space search", was formalized with the help of "Graph Theory" roughly the same time and most famously studied and represented by famous Swiss mathematician Leonard Euler in the 18th century. His analysis of connections and paths through seven bridges and islands of the German city of Köningsberg led the creation of graph theory, which explains reasoning about the structure of objects and their relations (Euler, 1735) (Luger, 1993).

One major problem in translating the human intelligence to a format that is readable by computers is to formalize the way logic and language of the brain is represented. The first major advances in this field came from the works of English mathematician George Boole in the 19th century, who is best recognized from his mathematical formalization of the logic knowns as "Boolean algebra", which forms the cornerstone of modern computer science. Boole's major accomplishment can be represented as the three logical operations "AND", "OR" and "NOT" that he devised. The characteristic representation of Boolean values includes only two numbers 1 and 0 (can be interpreted also as "TRUE" and "FALSE"), that may satisfy any equation. From this it is straightforward to deduce the standard definitions of Boolean multiplication (AND) and addition (OR). This overly simplistic system forms the basis of all the future endeavors to formalize logic all the way to the modern reasoning systems. (Luger, 1993)

After the advances made in logic formalization and mathematic theories, the advent of Artificial Intelligence as scientific discipline as we see it today can be attributed to the invention of digital computers in the mid-20th century. The modern computers had finally the necessary memory and processing power that is required by intelligent systems. The evolution of the computer technology through the 20th century has enabled researchers and practitioners to create, test and implement new theories based on theories of intelligence. (Luger, 1993)

One of the first research papers combining the two subjects, machine intelligence and modern digital computing, was written by Alan Turing in 1950 (Turing, 1950). The famous "Turing test" for intelligent computers was first coined based on this paper. The question Turing posed was whether computers could imitate humans to a such degree that it would be impossible for outside interrogator (human) to distinguish if they are interacting with a computer or other human being. Turing also introduced the idea of learning machines that would learn like child does, instead of trying to merely build machines that are direct copies of adult human intelligent capabilities (Turing, 1950). Criticism of Turing test includes the debate whether it is feasible to use human cognitive abilities as a comparison to computers which perform better in fields such as mathematics and raw processing power. When giving answers to the interrogator, intelligent machines would have to seriously dumb down or make occasional errors in some of its answers to avoid “getting caught”. Measuring intelligence only in terms of human cognitive capabilities would therefore sidetrack AI development which should be focused on solving real life practical problems the most efficient way possible. Despite the criticism, Turing test is an important measure in verifying and validating modern AI software. (Luger, 1993)

The birth of AI as a scientific discipline can be traced back to the first official AI related conference held in Dartmouth College in 1956, where the name “Artificial Intelligence” was first chosen to represent the research focused on integrating computation and intelligence. Many of the modern technological frameworks were also introduced, including Neuron Nets and Self-Improvement i.e. Machine Learning. (Luger, 1993) The same year, a group of researchers at Carnegie Institute of Technology produced the first program that is said to be Artificially Intelligent, called Logic Theorist. The research on the area was also continued at facilities within MIT and IBM. (Paris *et al.*, 2017)

The rise of the “Expert Systems” catapulted the commercial AI investments during the 1980s to billions of dollars. (Russell and Norvig, 2003) The Expert Systems in the fields such as mineral mining and medical care helped to implement domain specific human knowledge in a program that would be both effective, and seemingly intelligent in its performance. For these early Expert Systems to work, the problem domain had to be well understood and have clear problem-solving strategies in place. (Luger, 1993) One such example was commercial R1 system that helped the user to configure orders for new computer systems, bringing the company that launched it roughly $40 million in yearly savings. (Russell and Norvig, 2003)

Initially the development of "Intelligent Machines" was slow due to the lack of computing power and proper data. The rise of these "Expert systems" in the 80s propelled the research and development of Artificial Intelligence back from the so called "AI winter" of the 70s. During that time much of the early enthusiasm, funding and support of research was in many places cancelled, when the results from the first simple experiments didn't scale up as easily to wider and more challenging problems. (Russell and Norvig, 2003)

More recent development of Artificial Intelligence has been emphasizing the importance of the data, instead of which specific algorithm to apply. This has become ever more relevant as bigger datasets and faster computational power are readily available since the beginning of the new Millenia. The most recent Artificial Intelligence research has thus focused more on how to utilize this data in different applications areas such as speech recognition, robotic vehicles and logistics planning. (Russell and Norvig, 2003)

Artificial Intelligence research community has always been keen to give optimistic future visions and predictions about the development capabilities of different solutions, which have in turn resulted in many "AI winters" in which the funding has been frozen due to slow developments and lack of faith. However, recently many Artificial Intelligence related systems and technologies have been successfully embedded into various commercial uses which might hint that the promises of the last century are finally starting to come into the daylight. (Paris *et al.*, 2017) The goal of this thesis is to study how well the research and development has transformed into the use of commercial enterprises and what problems still lie ahead when implementing and scaling these solutions in the current business landscape.

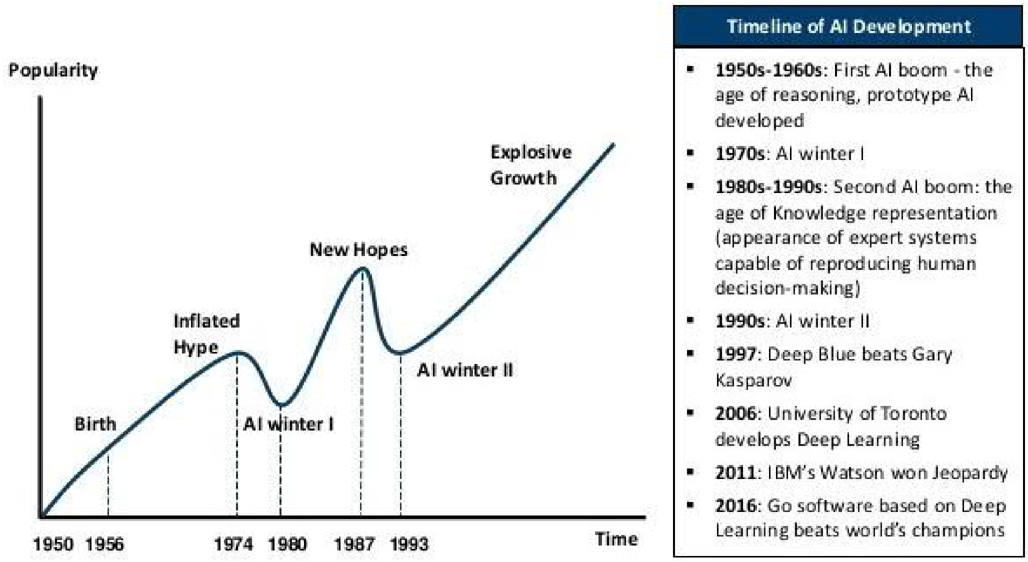

Figure 1. An illustration of the history of AI with some key dates. Source: https://www.actuaries.digital/2018/09/05/history-of-ai-winters/

Next, few of the key technologies that can be classified as Artificial Intelligence are introduced until the focus is turned back towards the key subject of this thesis, the Artificial Intelligence project implementation challenges.

2.1.2. Different Artificial Intelligence technologies

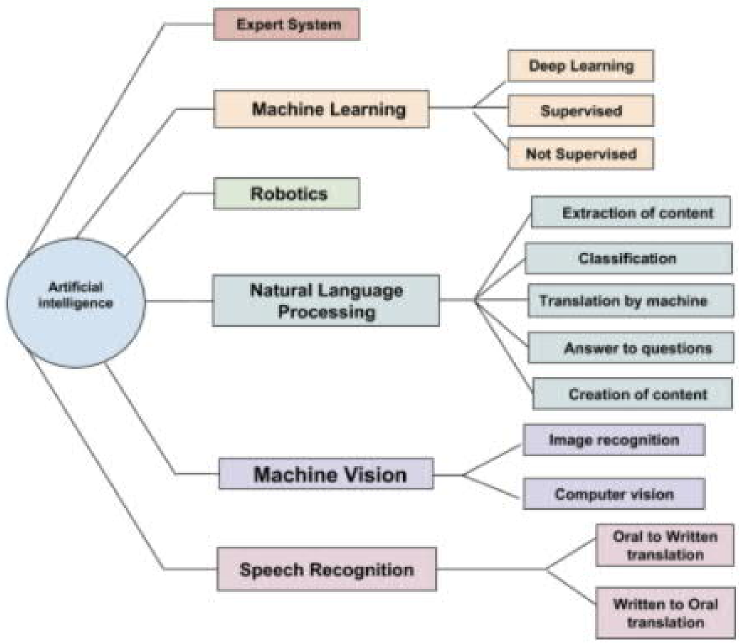

Figure 2. Key AI related technologies mapped. (Dejoux & Léon, 2018)

Artificial Intelligence is a term that covers the many ways to automate intelligent processes and functions. I have decided to include a short description of few of the most used or researched solutions as their own sub-chapter as a background information for this thesis since many of the following concepts are currently either in regular business use or under research and development. Understanding the technical aspects of AI implementation is also of importance when considering potential challenges from implementation point of view.

The most relevant concepts for the current Artificial Intelligence landscape are intelligent search, Machine Learning and deep learning, automated reasoning, neural networks, and natural language applications. If we one day wish to claim to have captured human intelligent capabilities, the problems related to natural language understanding, automated reasoning and learning are the key. (Luger, 1993) There already exists multiple thick textbooks and article compilations written on technological aspects of Artificial Intelligence theory, so the goal in this thesis is not to give a comprehensive look, but rather a short introduction to the different concepts that are usually behind the solutions used by Artificial Intelligence program developers.

The basis for many Artificial Intelligence solutions is an algorithm that can be understood as specific rules or instructions that the program must follow. The other component of Artificial Intelligence is the search function that the chosen algorithm uses for problem solving. Typically searches emulate closely the way humans solve problems: by considering alternative options and choosing the best fit for the current situation. One problem solver technique often used is called state space search. According to this technique, the problem can be represented as decision trees in which a single decision is a node in the structure that has depth and width qualities. (Luger, 1993) In optimal situations the program could go through all the possible states of the state space tree and choose the best one based on the goals it is programmed to achieve using a method called exhaustive search. However, in most real-life situations the size of the decision three grows exponentially with every new layer of decisions. For example, the game of chess has 10^{120} possible board configurations and trying to solve the best moves with exhaustive methods goes way beyond our current computing capabilities. (Luger, 1993)

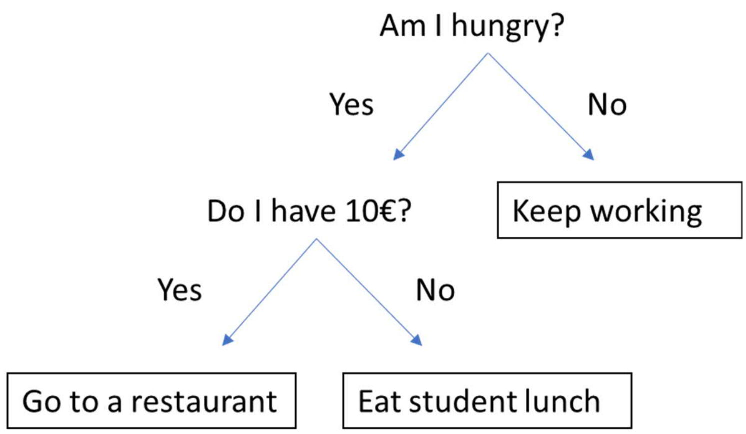

Figure 3 A simple illustration of a decision tree with a limited state space with the possible end states inside boxes.

Instead of exhaustive search, an intelligent search using simple programmable heuristics creates a problem solver that operates much like the way humans solve problems. These heuristics are judgement rules that intend to confine the problem space by focusing on the most "interesting" paths along the state space tree that have the highest probability of giving good solutions. This does not mean that the solution is by default the best possible, but as is often the case in real-life scenarios, good enough suffices as the processing power or available run time act as limiting factors. Heuristics form the backbone of typical Artificial Intelligent research. (Luger, 1993) Typical examples of these kinds of state space programs are chess engines, with their performance enhanced by applying complicated heuristics developed by chess Grand Masters. However, the rise of self-learning neural networks is challenging this type of human assisted programming.

Next, I will present the two most common techniques that are typically classified as Artificial Intelligence and currently in use within variety of business settings i.e., Machine Learning and Neural Networks.

2.1.2.1. Machine Learning

Machine Learning program is in its simplest form a software that uses different mathematical models to make useful predictions from given datasets. The Artificial Intelligence program can be claimed to be learning when its performance is increased as it gets new inputs from the surrounding world (Russell and Norvig, 2003). These inputs are often called *learning data* or *training data* in industry lingo. In more general terms Machine Learning solves the problem of how to build programs that improve automatically through time and experience. (Jordan and Mitchell, 2015) Additionally to make things more interesting, there are different levels of learning, ranging from simple memorization tasks to profound extrapolations about current knowledge to create new knowledge (Russell and Norvig, 2003). The difficulty of the challenge therefore depends on the goals that are set for ML programs.

The benefits of learning algorithms are clear, but the approaches to building a learning machine are complex and are therefore cornerstones of modern Artificial Intelligence research and development. Within this field, Machine Learning is often seen as the most practical technology, as it already has wide adoption for different uses. These solutions include computer vision, speech recognition and natural language processing, among others. These data-intensive Machine Learning models are in use across society in science, technology, and business. The industries currently focused on developing these tools include health care, financial modeling, manufacturing, education, and marketing. Machine Learning models help the practitioners within these industries to have more evidence-based view on their decision making. (Jordan and Mitchell, 2015) The application of AI and Machine Learning is studied and discussed more thoroughly in the following chapters.

Before explaining the different ways on how machines can learn from experience (or data), it is useful to go through the difficulties and challenges related to this pursuit. Firstly, there is the problem of generalization, i.e., how the computer can recognize patterns in the data to extrapolate to future instances that are similar but not identical to the examples in learning data. The program designers cannot possibly anticipate all the situations the learning machine can run into or don't even know how to program the solution themselves, as is the case in many image-recognition challenges (Luger, 1993; Russell and Norvig, 2003). Other design related challenge is the tradeoff related to fitting data to models, called overfitting vs. underfitting. Complex model can be tuned so that it gets local solutions correct, but this usually is not backed with enough learning data points to be accurate enough. The opposite is then to make a simpler model, that cannot as easily adapt to small local differences, but can be used to track general trends within data. (Jordan and Mitchell, 2015)

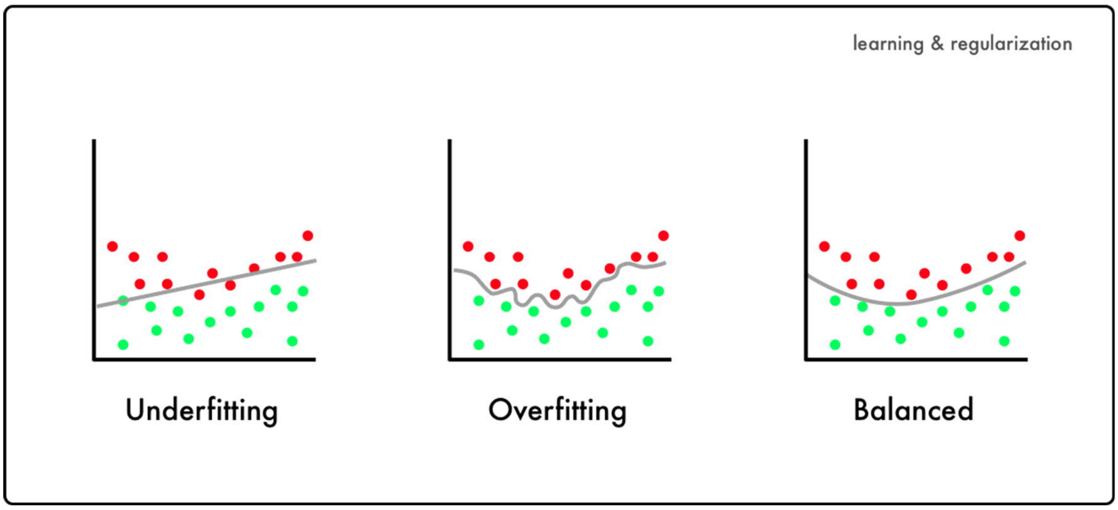

Figure 4. The difference between over and underfitting. Source: https://towardsdatascience.com/8-simple-techniques-to-prevent-overfitting-4d443da2ef7d

The second problem called "inductive bias" relates to the way learning algorithms are programmed to value concepts. By making early design choices, programmers of these systems enable learning algorithm to focus on important aspects of the data, but simultaneously can as a consequence limit what the algorithm can learn, leading to biased results when operating in real business environment. These important design decisions include the choice for the neural net architecture or the search algorithms. (Luger, 1993)

The way AI solutions are designed can have major impact on the result. The quality of the learning data and feedback the program gets from outside environment has also huge implications on the performance of different algorithms. The main research problems are in fact typically related to practical goals of how accurately the algorithm can learn from different types and volumes of learning data, as different learning algorithms vary greatly depending on the problems they are designed to solve. (Jordan and Mitchell, 2015) There are no ready answers on how much data is enough to have accurate models or how much computational power these algorithms require to operate. The research on this area is called "Sample and Computational Complexity". (Jordan and Mitchell, 2015) Next, I will present a few key concepts about different ways an Artificial Intelligence can be made to learn.

There are three main types of learning: unsupervised, supervised and reinforcement learning. When the Machine Learning algorithm works unsupervised, it receives no outside feedback on the input data, and thus must learn patterns by itself. The most common method for unsupervised learning is clustering, where the inputs are grouped by the algorithm based on the quantified qualities of the input data and where the distances between these datapoints are then calculated. The new inputs are then valued based on similarities with these different clusters. (Luger, 1993; Russell and Norvig, 2003) Below is a visualization of clustering of two different types of tree species, based on their width and height. This allows the algorithm to classify future instanced based on their distance from cluster centroids.

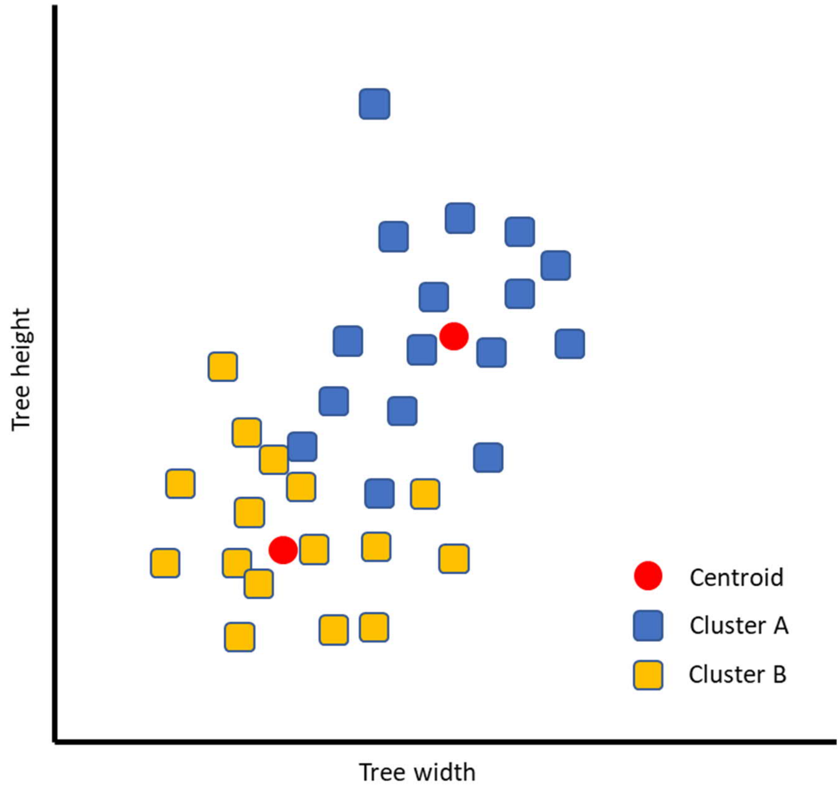

Figure 5. Clustering of two different types of trees. Adapted from Google materials: https://developers.google.com/machine-learning/glossary/

Reinforcement learning means that the algorithm receives additional information about the qualities of input data to aid the decision making and learning process. In AI language these are often called rewards and punishments. For example, in a chess game algorithm the win is rewarded by two points and a loss gives -2, so that the move sequences can be valued based on the final positions they achieve based on these rewards. (Russell and Norvig, 2003) Finally, for supervised learning algorithms, the program is given clear input-output pairs to base the different decisions and functions on in the future. (Russell and Norvig, 2003) This is also the most common way to address problems with Machine Learning. (Jordan and Mitchell, 2015)

The learning is said to be inductive, when the learning agent tries to find hypothesis that fits the given examples. Here the concept of Ockham's razor is very useful in choosing the most simple and consistent hypothesis to fit all new datapoints. There will always be a tradeoff considering how well learning data will be generalized versus the performance of the learning algorithm. Deductive learning on the other hand starts with a general rule to classify the data and with every new datapoint tries to generate a new rule that is more efficient but still logically sound. (Luger, 1993; Russell and Norvig, 2003)

Above I explained in general terms the most common problems Machine Learning programmers face when developing algorithms. These problems can be further divided to subclasses, as is illustrated in the table below:

Problem type	Description	Typical example
Classification	Pick one of the N labels	What type of animal is this? - Cat, bear, horse etc.?
Regression	Predict (numerical) values	Will the user click this advertisement?
Clustering	Grouping of similar examples	Is the document relevant (unsupervised)
Association rule learning	Infer likely association patterns in data	If you buy a toothbrush, you are likely to buy toothpaste (unsupervised).

Structured output	Create complex output	Natural language parse trees, image recognition bounding boxes
Ranking	Identify position on a scale or status	Googles search result ranking

Table 1. Different types of the most common supervised and unsupervised Machine Learning problem types. Adapted from Google Developer materials: https://developers.google.com/machine-learning/problem-framing/cases

As mentioned, Machine Learning is an active research field, that combines elements from computer science, statistics and other academic disciplines that are concerned with decision-making under uncertainty and learning. Part of the challenge currently is to link Machine Learning techniques to the way's humans learn naturally or even how economies function. The way humans learn is typically called *natural learning* and a way to mimic human brain even further comes from the introduction of Neural Networks, discussed in the next chapter. Machine Learning aids in this part of Artificial Intelligence development, as many of the theoretical results acquired from Machine Learning research can be applied to all kinds of learning systems, be they computer algorithms, animals, organizations, or natural evolution.

2.1.2.2. Neural Networks (non-linear models)

Neural networks are systems of layered nodes or other simple components that take their inspiration from the human brain structure of neurons and synapses. These "artificial neurons" consist of input signals and set of weights that describe the connection strengths between layers. The activation level of each node is a cumulative sum of the weights and the strength of the input signals and biases which then results in a final state of the node that is usually in an on/off state (1 or 0), calculated by a threshold function. (Luger, 1993) Neural Nets can be programmed by devising learning algorithms to finetune these weights and biases automatically without human intervention, as a response to external stimuli (i.e. learning data) according to the algorithm humans have programmed it to follow in the beginning. (Nielsen, 2015)

Neural networks are also called the connectionist approach to Artificial Intelligence and due to their distributed representation are typically more robust solutions than their symbolically represented counterparts. (Luger, 1993) As opposed to a more traditional approach to programming where the computer is explicitly told what to do by breaking large problems into many sub-problems that can be easily computed, in neural networks the solution to a problem is formulated through observing data, instead of directly coding the solution. This comes handy in cases where the solution would be extremely hard to find by conventional methods. (Nielsen, 2015)

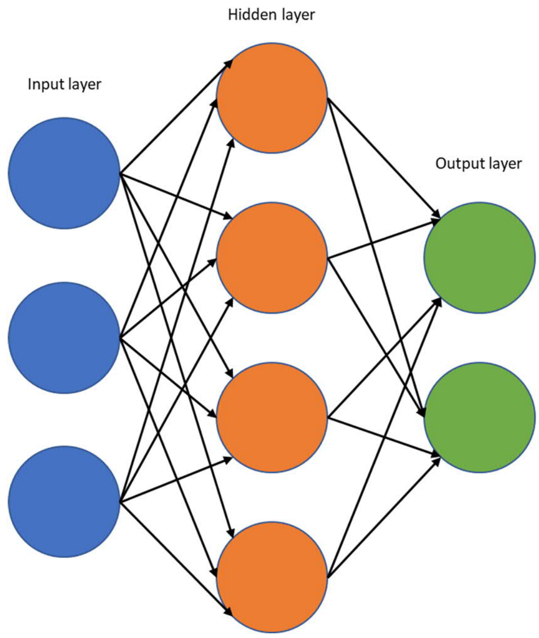

Figure 6. Very simple illustration of neural network architecture. Adapted from (Russell and Norvig, 2003)

In addition to the properties of single artificial neuron, there exists some global properties such as the way the network is build, called the network topology, and the choice of learning algorithms that are used. Neural networks however are not static structures but instead evolve when learning and interacting with the environment. The neural networks learn in surprisingly similar way humans do as the percentage of correct answers increases rapidly at first but stagnates when the share of correct answers is higher. (Luger, 1993) The main problem with neural networks is that they require huge amounts of data to learn.

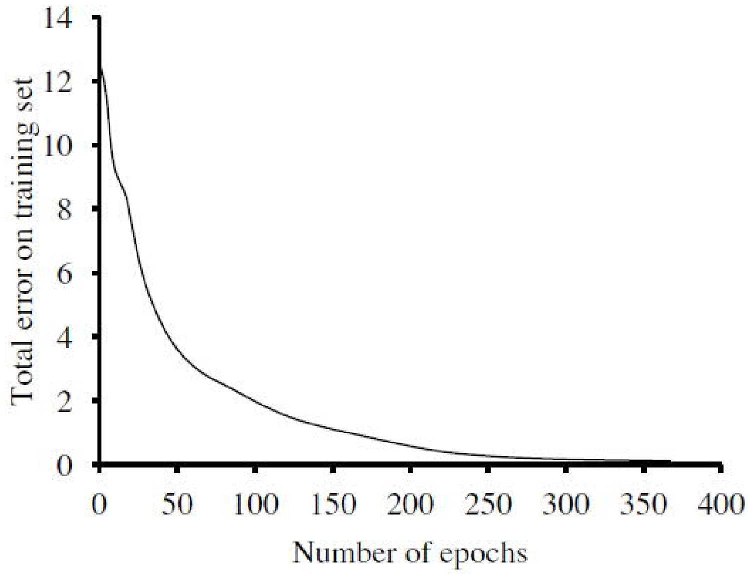

Figure 7. Illustration on how the system learns: The number of errors decrease as the function of time. (Russell and Norvig, 2003)

Even though neural networks and backpropagation algorithms have been introduced already back in the 1970s, the strength of this approach was only recently realized in practice through the introduction of deep neural nets that allow deep learning. These new techniques are based on two key mathematical concepts, stochastic gradient descent, and back-propagation, that allow for much deeper and larger networks that can span up to 10 hidden layers as opposed to 1 hidden layer illustrated above. The main benefit for this is that the deep net can represent a much more complex structures and hierarchies of different concepts. (Nielsen, 2015) Networks that have two or more hidden layers are called deep neural networks. (Nielsen, 2015)

In modern business context, neural networks have good performance in solving wide variety of problems, including speech recognition, natural language processing and computer vision. These technologies are deployed on a large scale by the leading tech companies such as Google, Microsoft and Facebook, just to name a few. (Nielsen, 2015) True edge compared to other learning methods is that Neural Networks can work with “messy” and unstructured data where it can extract patterns that are not obvious. (Syam and Sharma, 2018) This is especially useful in cases mentioned above where the quantity of data is not a problem, but inferring meaningful concepts from it is, such as a car driven by AI that needs to recognize possible threats or instructions from huge amount of irrelevant inputs. Similarly, Natural Language Understanding is a hugely complex but useful problem to solve and the recent developments in deep learning has allowed an explosion in related products and services, such as Siri from Apple and Alexa from Amazon.

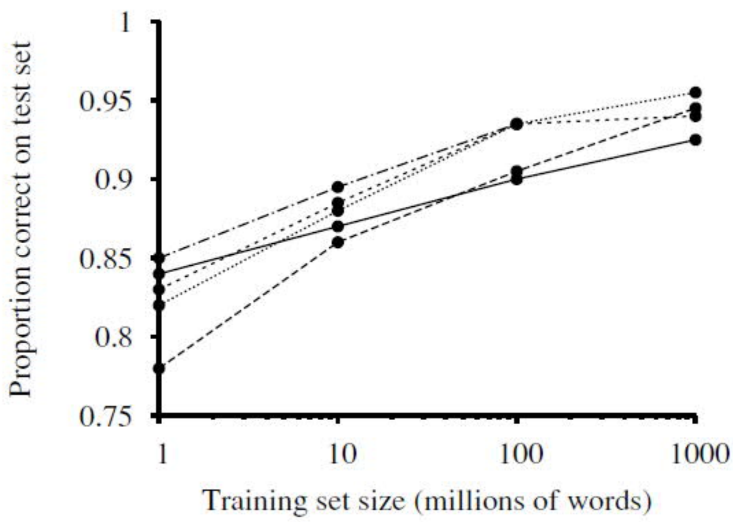

Figure 8. Illustrates the learning curves for five different learning algorithms on a simple task and how the size of training dataset affects the proportion of correct answers. (Russell and Norvig, 2003)

In this chapter I have briefly discussed about the history of AI research and presented two common techniques, Machine Learning and Neural Networks that are passed as AI. Next, I will dive into how these technologies are applied in real world within business context to be able to compare these sources with the findings that I have accumulated during my research process.

2.1.3. Artificial Intelligence in business context

When done correctly, Artificial Intelligence can bring considerable value and competitive advantage to the company implementing it. The most popular deployed AI related capabilities are, according to the survey by McKinsey & Company, Robotic Process Automation (RPA), Computer Vision and Machine Learning. The companies that are making the most out of the progress in digitizing core business have also the edge in AI adoption. (Webb, 2018) My thesis studies the use of AI in business context and therefore researching how AI is currently used in practice and scaled successfully is of high importance to my thesis. Additionally, the potential challenges and barriers for scaling AI have been already well documented by few industry reports and benchmarking this knowledge can guide me to right direction when conducting my own research. The goal of my thesis is then to add to these existing studies by offering a fresh context of Finnish companies.

AI Paradox and How to Overcome the Barriers for Scaling

AI can have major effect on at least three different types of tasks (Gerbert *et al.*, 2017):

1. Tasks that are easy to handle by individuals but require a lot of effort when compounded, such as classifying unstructured data
2. Tasks that are difficult for humans to perform effectively such as credit scoring or fraud detection
3. Tasks that require human interaction or knowledge

Customer service and enhancement of user experience were regularly mentioned uses for Artificial Intelligence in a study conducted by McKinsey Global Institute (Paris *et al.*, 2017). Even early stage Artificial Intelligence adoption, coupled with strong overall digital capabilities has potential to improve forecasting and sourcing, and in addition automate and optimize operations and processes and to develop marketing and pricing. (Paris *et al.*, 2017)

AI powered machines can currently perform many complex tasks, such as recognizing complex patterns in the data and draw conclusions from it, synthesize information, and forecast. However, there are certain limitations and technological barriers to the applicability of AI in the real world. Part of this challenge is the need for specific data that is also vulnerable to biases. The way data is used and analyzed is also of importance. (Paris *et al.*, 2017) Luckily, the data and its use are most typically an issue within industries that are already heavily regulated, such as insurance and banking, where the profiling based on e.g. sex and religion are unacceptable. Sometimes regulations outright ban or limit the use of the black-box ML solutions due to problems concerning backtracking of the decisions. In these cases, Machine Learning algorithms can still be used as a benchmark for how well the traditional model performs. (Ransbotham *et al.*, 2017) As AI technologies require some type of data to get going, the importance for available and high-quality data is omnipresent in all current AI implementations.

Main worry according to the analysts behind the discussion paper by McKinsey Global Institute does not seem to be the technological capabilities but unclear true economic benefits. (Paris *et al.*, 2017) The aspects business leaders are most unsure about include: the exact use for AI, where to obtain these technologies and other AI-powered applications and how to integrate them into their companies and even how to assess the ROI of these projects and technologies. (Paris *et al.*, 2017)

A discussion paper by Paris et al. identified a gap between AI investments and commercial application, which follows the theories of typical early phase technology development curves. (Paris *et al.*, 2017) In the context of AI, the gap is also called the "AI paradox", where scaling is seemingly hard after easy piloting phase. (Gerbert *et al.*, 2018) The adoption rates are also heavily weighted in favor of the tech sector, including telecom and financial services, and outside of these fields companies are still at an early stage of implementation, making their first experiments. According to the survey of 3000 C-level executives by Paris et al., only 20% of the respondents had Artificial Intelligence related technology in use at scale or as a part of core businesses as of 2017. The most common reason for the abstinence was said to be the uncertainty of the ROI or business case that would deploy Artificial Intelligence. (Paris *et al.*, 2017)

In many cases there are also documented attempts to implement AI on wrong types of cases where significant financial loss was accumulated without any major gains (Lacity & Willcocks, 2018). According to the survey conducted by the McKinsey & Company, many organizations lack the basic level practices that help create value from AI, especially at scale. As the capabilities have grown, so has the potential utility in many new fields. These foundations include mapping the potential AI opportunities and having clear strategies for data mining and sourcing, the fundamentals that many AI solutions require. (Webb, 2018) Additional explanation on why the general deployment rates are lagging behind is that the investments are currently targeted for tech giants internal R&D, focused on improving the firm's internal performance, whereas the public solutions and AI start-ups are quickly acquired including the talent that they employ. (Paris *et al.*, 2017) This leads to a wider disparity between front-runners and laggards in terms of complexity and scale.

The main Artificial Intelligence project guidelines, as suggested by one of the biggest commercial Artificial Intelligence solutions provider IBM are: (IBM, 2018)

- *Have a planned AI strategy and road map*
- *Build internal AI capabilities*
- *Begin small but try to scale up quickly*

Especially the major IT focused frontrunner companies are better equipped to follow these guidelines, as is pointed out by MIT Sloan Management Review research report (Ransbotham *et al.*, 2017). What slow reacting companies most typically lack are easily accessible data in usable format and expertise that is required for these projects, be it analytical skills or leadership support. (Ransbotham *et al.*, 2017) The early adopters are in contrast more agile when launching different technologies to solve variety of problems, not relying on any specific solutions. In these companies the C-suite support is also vastly greater compared to the companies that have not yet adopted AI at scale. (Paris *et al.*, 2017)

As happens with any disruptive technology or product, people eventually get worried about the implications on their life, work, or well-being. There exists many whitepapers and business reviews on AI implementation with large quantities of responses from general managers and decision makers, conducted typically by large consulting houses such as McKinsey, BCG and Deloitte or Artificial Intelligence service providers such as IBM (Ronanki, 2018)(Gerbert *et al.*, 2018)(IBM, 2018)(Webb, 2018), that address these claims and also try to make sense of how to advance Artificial Intelligence to a wider scale. My thesis is a continuum of these reports and is specifically focused on Finnish based companies.

The discussion paper by Paris et al. highlights results that could alleviate these worries. Authors reveal that leading AI adopters are more interested in revenue growth and market share than reducing costs. The contrary was found within the

AI experimenters, who had mainly focused on costs, either labor related or otherwise. (Paris *et al.*, 2017) Typically, new technologies are not fully matured when first introduced to the public and the expectations tend to be higher than the actual performance can deliver. Additionally many AI experimenters don't have coherent technology strategy in place which affects the scalability and the full potential of systems integration. (Philip, Sales and Hackett, 2006) . For front-runner companies, AI acts merely as the next logical step of their digitalization processes as they have a long history of trying out different technologies. (Paris *et al.*, 2017)

If new technology proves to be more efficient or reliable than its predecessor, a pull to implement will typically appear. This can be either management-imposed pull, as performance gap to competitors leads to a need to change or technology could have a pull itself as it proves promising enough to solve the critical problems that companies face. The point in both cases is to improve how things are done currently, be it faster or better than humans without the new tools could. (Beyrouti, 2006) However, after the initial experiments, the needed changes to organization's structure and work arrangements are usually left undone. It is important to remember that companies are complex entities with many different aspects affecting the whole all the time. To pin-point the effect of technology on all the wins and all the challenges is too greedy approach. (Philip, Sales and Hackett, 2006)

Other potential sources that could hold back Artificial Intelligence development and adoption include ethical considerations, workforce resentments, and legal or regulatory challenges. (Paris *et al.*, 2017) Computing has displaced humans for a long time now, from the inventions of ATM to robotic welders. This has often led to the creation of higher-skill jobs and an important implication of this has been that the total number of jobs does not tend to decline over time. (Cascio and Montealegre, 2016) Even though machines are very good at problem solving, they still lack the ability to piece together a bigger picture. This indicates that the jobs that are in danger are not managerial, but rather white-collar jobs. (Cascio and Montealegre, 2016) This might be true also for AI but as the technologies matures in the future, this premise might not hold forever.

How AI changes companies that implement them and what can be done from managerial point of view to pre-emptively combat the changes? These topics are discussed in the next chapters when the scope is widened from implications of AI implementation to introducing new technologies in general as part of technology strategy and how the change that follows should be addressed from change management point of view. The topic of Artificial Intelligence as a tool to aid decision making will then be investigated briefly in the chapter 2.4.

2.2. Technology implementation project challenges

The role of technology, be it hardware or software, in organizational life is vastly understudied, as according to Orlowski and Scott nearly 95% of published top management research do not take the presence of technology in organizations properly into account. (Orlikowski and Scott, 2008) Technology is omnipresent in our current work. Annual budgets are huge for technological development and these projects are typically one of organizations largest investments, becoming almost as important to organizations as labor. (Dewett and Jones, 2001) To stay competitive in the modern business environment, companies and organizations often need to change course and follow the technological advances. (Schlesinger, 2008) I therefore argue that to review technology implementation and project literature is important part of researching Artificial Intelligence project related challenges and successes.

Technology implementations have many strategic dimensions that change organizations, and the way work is done. Efforts to change companies based on strategies that are either inconsistent or not clearly planned run into predictable problems. (Schlesinger, 2008) This is especially true when novel groundbreaking technologies such as AI are considered as they often bring new kinds of solutions to old problems and change the way the business is conducted. This type of strategy work is also called technology strategy or more generally development strategy. It should be viewed as one element of the whole strategy process, not in isolation. Technology strategy addresses what technologies to develop, whether to aim for technology leadership positions and should the technologies be implemented in-house or licensed. (Porter, 1986)

Technology as a concept is hard to define, but in more general terms it can be divided into two core aspects: The scope, or what is defined as technology, be it hardware, software or databases and secondly the role of technology, i.e. the interaction of technology and organization. (Orlikowski, 1992) The role of technology and the success of its implementation can undermine the strategic objectives of the implementors and management especially if the end users will not use the technology as intended. (Orlikowski, 1992) In this chapter I will link technology development and project literature together and discuss how technology implementation works in refining organization strategies and competitive advantage. In the next chapter I will then move on to review the change management practices of disruptive technology implementation.

In many technologically advanced industries that are also the most typical front-runners in Artificial Intelligence adoption, the project business approach is of increasing importance. This is due to the fast-phased disruptive nature that the development projects bring. Despite of their importance, many projects are still unsuccessful implementations, either in the way they are managed or because of the results they produce. (Magaña Martínez and Fernandez-Rodriguez, 2015) This may be due to the inherent and increased complexity, lack of control over stakeholders or the inherent uncertainty and continuous changes that make the planning difficult. (Magaña Martínez and Fernandez-Rodriguez, 2015)

Dimensions	**Failure factors**
Organization	1. Lack of sponsorship from high-up managers 2. Managers are not committed 3. Culture is too conservative or political 4. Organization is too large to implement changes or to coordinate effectively
People	5. Missing skill sets to implement or utilize 6. Project managers are not competent 7. Teams are not functional

	8. Individual resistance that affects larger group dynamics 9. Bad customer relationships hinder co-operation
Process	10. Project scope is not well defined 11. Project requirements are ill-defined 12. Project planning is not done properly 13. Project lacks proper tracking mechanisms 14. Project customer is not present or does not participate sufficiently. The role is unclear
Technical	15. Proper implementation framework is missing. Doing things ad-hoc. 16. Technologies or tools are not suitable for the implementation.

Table 2. List of potential failure factors for typical software project implementation. (Chow and Cao, 2008)

It is important to note that projects must be framed and are thus confined by time and scope. Gaddis defines a project as an organizational unit that is assigned to fulfill a goal within these constraints (Gaddis, 1959). The successful project implementation should be realized as achieving competitive advantage over competitors, growth of the overall business or increased profitability (Artto, Martinsuo and Kujala, 2006) and can be traditionally deemed a success if it accomplished to follow the three budgeted constraints: scope, budget (money) and schedule (Magaña Martínez and Fernandez-Rodriguez, 2015), that are also called "tactical" success factors, in contrast to more "strategic" factors such as long term viability and efficient project implementation. (Fossum, Danielsen and Aarseth, 2018) An article by Fossum et al. defines the measurement of project success. The success can be measured in relative or absolute terms, but what typically occurs in the real world is that the results get calibrated against the expectations. Thus, without clearly articulated expectations, the success becomes hard to measure and value. This might lead to a differing opinion about the success of the project among different stakeholders throughout the project. (Fossum, Danielsen and Aarseth, 2018)

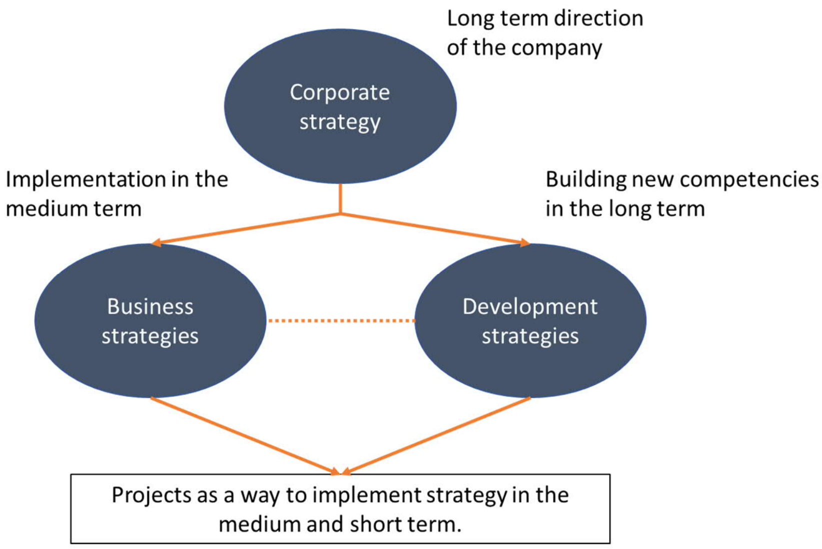

Figure 9. Illustration of the hierarchy of strategic planning and the way projects are linked to each aspect (Artto, Martinsuo and Kujala, 2006)

In the context of new technology projects, the managers have to take into account the type of technology to be rolled out and whether to use outside vendor to implement it and whether the company already have some capabilities associated with the particular technology (Philip, Sales and Hackett, 2006), for example cloud and data analyst expertise in the context of Artificial Intelligence related capabilities. As the customer environment and specific needs differ from case to case, the logic of Artificial Intelligence projects has traditionally been delivering custom tailored solutions instead of mass production of services. A survey by Constellation Research in 2018 revealed that roughly half of the companies that responded are developing their data science and AI related initiatives in-house by building teams using either open-source solutions or cloud-based Machine

Learning and deep learning services offered by external vendors. (MIT SMR CONNECTIONS, 2019) This means that the project nature in half of the cases is delivery based and in other half it is investment of resources by the internal team. The history of the previous development as well as the industry trends and future projections are key factors in determining the correct development strategy and the resource allocations between different possible project plans or whether to outsource the development to external service provider. (Artto, Martinsuo and Kujala, 2006)

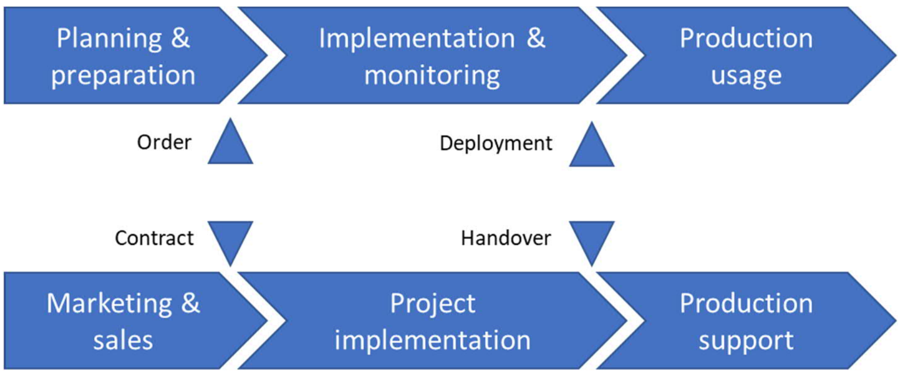

Figure 10. Illustration of the typical project life cycle of outsourced projects, from both the customers and service providers viewpoint (Artto, Martinsuo and Kujala, 2006)

Even if the benefits of the projects are clear to the end users and the project team, sufficient resources have to be allocated for the project to avoid time consuming individual persuasions during the project. (Kraus and Leonard-Barton, 1985) Project managers serve as a valuable link to top-level managers on the necessary information about the actual strategic direction and internal capabilities. This helps the higher-level managers then to choose which projects to actually implement when making the critical decisions about the project life cycles and managing the overall strategic direction of the company. (Artto, Martinsuo and Kujala, 2006)

Front end management focuses on phases before the actual project starts. They decide the budget, timeframe, objectives, and core concepts related to the project. The project planning phase (also called front-end) is crucial as it offers the opportunity to reduce uncertainty and risk. (Fossum, Danielsen and Aarseth, 2018) The information also plays a key part in decision making in early project phases. The problem however is not typically the quantity of available information, but the project managers capability to select relevant information about essential issues. Initiatives should therefore be planned in cooperation with both business and technical managers who have at least a high-level understanding of the capabilities of the technologies related to the project to filter out what is relevant for each case in hand. (Paris *et al.*, 2017) Other issues concerning the project planning phase might be the neglection of opportunity space, which is often caused by path dependency. As Fossum et al. notice, long-term viability of the projects is neglected by emphasizing the short-term challenges, such as resource restrictions or time pressure. (Fossum, Danielsen and Aarseth, 2018)

For new technology implementation project to succeed, Kraus et al. suggest that the implementation team must have the following responsibilities to be issued, either to separate people or divided between key project members: a sponsor that is accustomed to the organizational politics to ensure financial and manpower resources, a "champion" who acts as a diplomat and a problem solver for the innovation, a project manager who is responsible for the administrative details, an integrator who is in charge of managing the conflicting priorities (with other projects or within the current one) and keeps the project group intact through good communication skills. (Kraus and Leonard-Barton, 1985)

Companies often face a choice between developing old mature technologies incrementally or implementing newer but riskier technology projects. This trade-off should be addressed in company's technology strategy. (Porter, 1986) In any case, the final decision should be made on basis of the balance between the cost and benefit as well as the likelihood that the project will be a success. (Porter, 1986) This likelihood of success should be monitored also during the project. As is typical with many projects, the feedback on the actual implementation starts to accumulate after the planning is already done. The responsibility of the project manager is therefore to try to reduce the risks in advance, acknowledging that the perfection is never reached. (Gaddis, 1959)

One distinctive problem to novel technology implementation is that the project managers must often work in dual roles as technical developers and managing the implementation. This is due to the limited resources that can handle new technologies. As this talent is hard to come by, many companies have to outsource the development to outside vendors who might oversell their capabilities, which often leads to disappointing pilot projects. (Gerbert *et al.*, 2017) In addition there is usually a gap at technological skills between the end users and the developers, be they internal or external, which makes the discussions on implementation difficult and may affect the willingness of the customer organization to take responsibility of the solution after the handover phase as they don't feel fully comfortable with the new technology. (Kraus and Leonard-Barton, 1985)

McKinsey Global Institute research paper proposes a straightforward approach to the projects related to AI (Paris *et al.*, 2017):

1. Identify the problem that needs to be solved and the business case first
2. Build the appropriate data ecosystem to support the process
3. Build or buy Artificial Intelligence talent and tools
4. Adapt existing business processes, capabilities and culture to the new tools and technologies.

Even though many companies have already tested varying AI tools, only the most technologically advanced companies have truly been able to embed them to their daily operations. Getting stuck in these types of piloting loops is a real risk for any company that plans to have AI capabilities in the future. (Webb, 2018) Innovations rarely get automatic acceptance within organizations. The risk of overselling a new idea is as equally damaging as underselling a project as failures are more prone to bring even more skepticism about new development initiatives. It is therefore more important to gain small successes early on during piloting than have direct gains. (Kraus and Leonard-Barton, 1985) Proper project management methods alleviate some of these pains and make the likelihood of scaling more likely. For things to advance, the AI initiatives need real commitment and understanding from the managers advancing them in addition to focus on how things might change as a result of implementing AI, all of which require strategic thinking. (Webb, 2018) This change management aspect in the context of implementing new and disruptive technologies is explored in the next chapter.

2.3. Change management in the face of disruptive technology projects

Automating tasks and organizing work are typically the first aspects to be subjected to changes as new technologies are introduced. Novel innovations such as robotics and Artificial Intelligence are quickly replacing the need for humans to work on repetitive processes, freeing the resources to increasingly challenging tasks. (Porter, 1986) The latest wave of digitalization changes the nature of work for many people, which in turn affects people's morale and relationships with co-workers and managers (Philip, Sales and Hackett, 2006). Introducing new technologies might have large impact on the organizational structure or the value chain (Porter, 1986) which is further escalated by the urgencies and complexities of the modern dynamic business environment, including rapid changes in the marketplace, and other external threats and shocks. (Basford and Schaninger, 2016) Organizations should implement new technologies through clear change management practices and address the impact on organizational and operational level as well as on work force. (Gerbert *et al.*, 2017)

Artificial Intelligence among other ground breaking technologies are enabling grand changes in the way we work in addition to helping people do their tasks better and faster. (Cascio and Montealegre, 2016) According to the survey conducted by McKinsey & Company, many companies are lacking the organizational processes that dictate the transformation of core parts of their business through digitalization. (Webb, 2018) In many of the cases, change-management challenge is greater than actual technological challenges related to AI as trust is the key enabler for many new technologies. Especially with black-box AI solutions, the machine-human link can become too obscure for regular workers, which might create tensions and discomfort. Trusting new software and algorithms typically requires a paradigm shift from the people in the workforce, to simply trust the new machines. (Paris *et al.*, 2017) Studying change management best practices is therefore important part of my thesis.

Organizations are always in the middle of change, either at operational or strategic level. (By, 2007) Change management is therefore needed even when the business is running well, for without any obvious challenges to be solved, employees may become too complacent, while at company level there always exists the need to adapt to new industry trends to maintain competitive edge. (Hemp & Steward, 2004) This problem is sometimes referred as the "red queen hypothesis", which emphasizes that the companies must always adapt and "run faster" in order to hold their current position at the market. Change management can be therefore defined more generally, as done by By (2007):

"The process of continually renewing an organization's direction, structure and capabilities to serve the everchanging needs of external and internal customers'". (By, 2007)

Humans are naturally prone to resist change if it causes uncertainties to the potential outcome. (Waddell, 1998) Real resistance to novel innovation is often amplified by mistakes made in the early phase of the introductory period or when clear issues are overlooked in the planning phase. This might come as a surprise for the implementors as their view is limited to the innovation's benefits. (Kraus and Leonard-Barton, 1985) As problems accumulate and resistance grows the attention is often drawn to aspects of the new implementation that are inappropriate, not well planned or even faulty. (Waddell, 1998) To avoid this, affected employees should be given an opportunity to participate during the change project, either by giving feedback or by facilitating teamwork and instructions around the changes (Waddell, 1998) or instructing people on how to operate the new technology, even if the use of it is not required in their daily operations. (Kraus and Leonard-Barton, 1985)

Some of the most common reasons for outright resistance to change or new technology are the natural fears of losing power and skills to handle current tasks or the absence of clear personal benefits. (Kraus and Leonard-Barton, 1985) The ease of implementation of new technologies in workplaces is linked with the basic innate human needs of autonomy, competence, and relatedness. Therefore, new technologies need to be relatively natural and easy to use, efficient, effective (low error rate) and satisfactory to the end user to gain popularity. (Cascio and Montealegre, 2016)

Other key consideration when implementing change, in either tools or processes the organization uses, is the economic aspect of change. Does the new technology bring competitive advantage to the company or the individual users? Peer pressure (everybody else already has "it") has also serious implications on how well new technologies are adopted. (Cascio and Montealegre, 2016) Kraus and Leonard-Barton observe that the productivity usually drops initially when new technology is implemented. This can be mitigated with changing the measurement techniques or include a "phase-in period" when the productivity is not measured as critically. (Kraus and Leonard-Barton, 1985) Philip et al. state in their article that participatory change strategy, where users were properly trained and supported for the use of new technology, produced good results. Additionally, this had positive effects on company culture as whole. In the contrary, when the change was managed top-down with no clear change management practices, the outcomes were mistrust and feeling of inequity. (Philip, Sales and Hackett, 2006)

As larger companies have typically multiple internal markets that are competing for limited resources, the probability of successful implementations is higher if the need for change or problem definition is defined at higher organizational levels. At the same time, the probability of success is higher if the solutions are handled close to the final users. This clear paradox is due to the fact that top management is more concerned of the returns for investments, which filters out the projects that are not financially feasible, but at the same time the solutions are solved at the level where they are best understood. (Kraus and Leonard-Barton, 1985).

According to a study by Beer & Nohria (2000), roughly 70% of all change initiatives are failures. (Beer & Nohria, 2000). In addition to the reasons that rise from the natural resistance to change as discussed above, some blame can be accounted to the managers that oversee these initiatives. Kotter (2007) suggests that typically managers treat changes as an event with clear start and finish dates, whereas it should be viewed as a transformation process that builds gradually through years. When the process is hurried, managers are pressured to skip crucial stages that are required for the changes to stick properly. (Kotter, 2007)

Beer and Nohria (2000) turn the focus on the conflicting variety of methods and advice that make managers to lose focus on the task in hand as change is hard to implement as is, both economically and mentally. (Beer & Nohria, 2000) They also offer a simplistic framework that considers the different emphasis for change. If the change is targeted to bring economic value i.e. "hard approach", the managers can utilize economic incentives, lay-offs or restructuring of the organization (Beer & Nohria, 2000), especially in cases where success and impact of the transformations can be tracked by tools and metrics that can be tied directly to the impact on the bottom-line. (Bucy, 2016) Softer means include measures where the change is intended to address organizational culture and employee capabilities for which managers can implement trust building team exercises and increase communication. (Beer & Nohria, 2000)

People tend to be more trusting towards changes when they understand the "why" behind the initiative. It is crucial during the times of transformation to get the employees on board and to support the change initiatives. This can be achieved be creating a compelling story of the direction of the company, why the changes are happening and why this is important for the situation in hand. (Basford and Schaninger, 2016) The goal of new technology, when the individual workers are concerned should be to:

"Foster self-motivation and well-being, enhance productivity, promote job satisfaction, organizational commitment and citizenship behavior among workers as technology only exists in relation to people." (Cascio and Montealegre, 2016)

Changing the way of work by implementing AI related tools is complicated even when the tasks AI is set to solve are not too complex. In the next chapter I will investigate how these new solutions can be utilized in non-structured work and decision-making process as a part of augmented strategy work, before the focus on brought back to the research part of this thesis, where I explain how I conduct the research process and data analysis.

2.4. Artificial Intelligence as a part of strategy work and decision-making process

In strategy work, it is hard to back up all the decisions with data or actual evidence, which leads executives and strategy workers relying on their intuition. (Kahneman, 2009) However, this is not necessarily a bad thing as us humans are highly capable in connecting seemingly unrelated events and to think outside of the immediate scope of the current situation. This is something machines traditionally cannot do well. (Reeves *et al.*, 2016) But as Kahneman suggests, it is not obvious that human intuition should always be trusted, as even the most highly skilled professionals are prone to mistakes under "zero-validity" environments, i.e. when outcomes are highly unpredictable. (Kahneman, 2009) This can be the case within stock markets or geopolitics, not to even mention the "human-factor" of needs and emotions that affect the decision-making processes in smaller scale. Despite of the hype about the bright AI integrated future, the wide scale usage of AI has been slower than expected. (Davenport, 2005) The logical next step for Artificial Intelligence programs is to start automating this truly hard job: decision making and strategy planning processes under uncertainty.

What are the human skills that AI could replace in the context of strategy work? Literature on human decision making and expert judgement by Kahneman (Kahneman, 2009) and Eisenhardt (Eisenhardt, 1989b) reveal a few key concepts that successful and effective leaders and decision-makers do regularly. One such component is that those who make fast decisions tend to focus on more information than their slower counterparts. This leads to more generated alternatives for possible decisions and larger pool of advisories that the decision maker can consult. These types of patterns along with good conflict resolution skills and strategic integration of said decisions leads to better performance in the long run. (Eisenhardt, 1989b) Using more information and generating alternatives is an asset any AI can and should handle better than humans but the ability to use AI generated results along with other mentioned qualities might still make human expertise highly sought after in the future.

Kahneman in turn elaborates the connection to and the nature of the surrounding environment in determining whether individual decision makers can use their judgement efficiently, even claiming that these links contain necessary conditions to said efficiency. (Kahneman, 2009) He points out that skilled decision makers that have expert intuition might even be unaware of the environmental cues that drive their decision. If the relationship between these cues and events that follow are stable in "high-validity environments", decision-makers can learn to use their expert judgement and intuition, even though the environment might contain uncertainty, such as in the game of poker. (Kahneman, 2009) This would be the optimal yet challenging playing field for AI to operate in, as it can produce objective cue-to-action suggestions based on past events within the same environment. The difference of experts in given field to non-experts are that true experts "know when they don't know – while nonexperts certainly do not know when they don't know". (Kahneman, 2009) It is also possible to generate algorithms that perform better than humans for low-validity environments, but their accuracy would remain low, even though being above random. Kahneman also predicts that introduction of these algorithms will, at least initially, "evoke substantial resistance". (Kahneman, 2009)

As discussed in the previous chapter, the trust is a key enabler when working in tandem with Artificial Intelligence. This means that the most fragile and sensitive use cases are not the first ones on the new technology strategy pipeline. Use cases requiring human judgement and abstract high-level information that are regularly handled by company executives are not seen currently as potential for AI based automation. (Luhtanen, 2018) Once there is evidence that the new AI initiatives are bearing fruit, companies can start to widen the scope of AI adoption closer to strategy work and decision-making processes. People need to have trust that AI algorithms and models' suggestions work, but at the same time feel that they have the authority to execute those decisions themselves, not having to consult people in higher up positions which might inhibit the true use of AI. (Fountaine, McCarthy and Saleh, 2019) AI could at least in theory help with strategy generation and understanding the complex world through more holistic lens. (Luhtanen, 2018)

How could AI then help in practice with decision making and strategy formulation? Firstly, it is very useful to understand how uncertainty affects the decision making. Currently it is difficult to extract knowledge from managers in decision making positions, as the knowledge is typically too dynamic and difficult to maintain over time. (Tulabandhula and Rudin, 2014) The modern tools available are more focused on helping executives to gather, report, analyze and interpret data instead of generating and making decisions. It is also costly to manage such analytical engines, both in money and time-wise. (Tulabandhula and Rudin, 2014) Reeves et al. (Reeves *et al.*, 2016) see that strategy and decision making can only be augmented with a collection of different resources that act together to generate and execute strategies. Their "integrated strategy machine" would consist of many different operations, such as "problem definition, signal processing, pattern recognition, abstraction and conceptualization, analysis and prediction". (Reeves *et al.*, 2016) The key according to them is the integration of all these moving parts, some human, some technological or AI.

Jarrahi in his article Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making (Jarrahi, 2018) shares Reeves et al. view that humans should focus on working together with AI instead of merely replace and automate their work with it. Jarrahi draws his conclusions on the co-operation via categorizing decision-making to three central challenges: uncertainty, complexity and equivocality. (Jarrahi, 2018) AI can be trained to assist humans in each of these challenges.

For uncertainty, many AI solutions can use their speed and algorithms to provide access to different scenarios where human decision makers can choose the most fitting as suggested by Eisenhardt. (Eisenhardt, 1989b) Complexity in high-validity environments can be reduced by having AI look for patterns in the data, and curate that for the humans to interpret. (Jarrahi, 2018) Of these three key challenges, equivocality remains the only category where humans will still dominate most of the work, as solving social issues with AI recommendations would raise many ethical questions, not to mention the possibility of different biases in the data. (Jarrahi, 2018) Currently AI could still assist humans with reading sentiments from a lot a human input, for example gathered from social media.

Even though technically many of these solutions are available, the organizations have not yet built platforms for such a wide scale AI adoption that the benefits could be achieve all the way up the top of the decision-making hierarchy. Currently the broad strategic decisions and questions require a holistic approach, something which analyzing data alone cannot achieve. (Davenport, 2005) AI in its current form can and has been brought to help the executive decision making, but as Jarrahi mentions, strategic thinking requires such a wide array of sense making and understanding the environment beyond single specific decisions that AI would have hard time grasping all the varying components. This is where human strategists currently excel.

2.5. Summary of the literature review

In this review I introduced the most common Artificial Intelligence related technologies and how these are currently implemented in business context. I elaborated further what kinds of implications these technologies have imposed on companies and what could and should be done better, based on findings of many different researchers and organizations. A good starting point to any new technology project is to study the project management principles and change management practices. These are also very relevant when studying AI implementations. Lastly, the potential of AI as a executive decision-making tool was explored briefly in the last chapter before the conclusion of this literature review. This chapter also revealed the possible pain-points or areas of improvement for AI where humans still reign supreme.

As a conclusion, I found out that AI has slowly, yet not steadily, been infiltrating the business landscape over the last few decades. The studies and reports generated the last decade demonstrate that finally AI is here to stay, and that scaling seems inevitable. However, to successfully introduce AI to any organization requires careful planning, good project management practices and foresight to see how the changes to way work is done affect the business.

Next, I will go through the methodology and research design of my thesis, after which I will present my findings on how AI adoption currently looks like in the Finnish business landscape and how well the challenges described during the literature review are recognized and mitigated by Finnish AI teams and their managers.

3. Methodology and research design

In this chapter I will describe and justify the methods that I used to conduct the research part of my thesis. I will first discuss the research methodology and how the chosen approach best supports my research goals and research question. I will then move on to describe the data collection and data analysis processes in qualitative case study context before concluding this chapter by shortly exploring the trustworthiness and limitations of my thesis and the research process. After this, in the following chapters I will present my findings and discuss how they are supported by the existing literature.

3.1. Research methodology and background

The topic of this research was formulated together with Sisua Digital, company specialized in Robotic Process Automation (RPA) consultation, where I am employed during the writing of this thesis. This topic was chosen especially as we have encountered some repeating challenges in projects that combine software robotics with AI tools, that are not typically relevant in standard RPA projects. This led us to wonder whether there exists universal challenges or best practices that might concern Artificial Intelligence related projects in general. Undercovering these possible trends has thus clear business benefit for Sisua Digital as well as academic relevance and value as the results might be possible to generalize for the use of wider audience.

This research is conducted by studying a handful (6) of Finnish companies that have already some experience from the recent years on AI implementation, be it pilots or solutions already in production. The key aspect in my research alongside any possible data released by the companies is collecting knowledge by interviewing the project participants and managers inside the company in order to study the relationships between technology implementation, strategy, and operational business. The comparison of these interviews is then used to relate the strategic goals and aspirations that AI implementations are planned for in addition to the operational successes and failures faced by these companies. Service providers side, whose job is typically the implementation of Artificial Intelligence models is also studied briefly by interviewing key personnel in two of such companies.

The results are masked for the final version of this thesis to protect the anonymity of interviewees. The goal is to study wide variety of companies in order to compare results and to gain knowledge on the implementation motivations, as well as preconditions for successes in implementation such as previous process automation or IT projects and challenges faced when launching AI projects for the first time.

Usually, it is easier to learn from the mistakes of others in the style of "how not to do" and thus trying to minimize these mistakes in the future implementation projects. However, it is also crucial to find successful case projects in order to learn from these accomplishments. By selecting 6 case companies, a wide variety of different situations and outcomes could be observed in order to find possible patterns or best practices, instead of studying just one company more in-depth.

In this thesis, I decided to utilize the case study approach that relies on qualitative research methodology, as presented by Eriksson and Kovalainen in their book Qualitative Methods in Business Research (Eriksson & Kovalainen, 2008). The case study approach and qualitative methods, their use, benefits, and shortcomings are discussed below.

3.2. Case study approach

I argue that in this thesis and in this particular research context, a compromise between intensive and extensive case study approach works best to cover the positive qualities that these two bring and to narrow the scope of this thesis. The positive qualities of intensive case study approach as stated by Erikson and Kovalainen (Eriksson and Kovalainen, 2011a) can be best observed through the quote:

"Imagine an intensive case study describing the adoption process of a new accounting system in an organization. If such a case were to be well researched and documented, it would enable the reader of the research report to form their own insights as to who the key actors are and what the key issues in the process are, what was easy and what was problematic, what could have been done to avoid disagreements, etc. This kind of description leads to theorizing and seeking for understanding by anyone who reads the case study report, not just the researcher." (Eriksson and Kovalainen, 2011a)

This notion clearly aligns with my research objectives. Intensive case study approach intents to discover as much as possible about one or few cases and is also the most classic way to draw understanding of the specific research context. Real-life descriptions are useful when evaluating different mechanics of Artificial

Intelligence implementation projects which can then be directly used in other similar projects in the future. With intensive case study approach the researcher can be seen as the sense-making agent who limits the boundaries of the case by the used perspective and by selecting the relevant experiences, analyses it and then makes the right interpretations. (Eriksson and Kovalainen, 2011a)

However, to limit the scope of the thesis I would have to make compromises on the depth of the research such as how long time period I will choose to use observations from, i.e., will I include all the previous related novel technology projects implemented by the case company as benchmark or focus solely on projects related to Artificial Intelligence. Also, the number of people inside the organization to include would bring different focus on the thesis, since the application of Artificial Intelligence can have implications on the work or job descriptions on many levels of the organization. Lastly to limit the scope I choose to limit the number of external stakeholders such as customers or subcontractors outside of the scope of this thesis.

Even if the problems related to the scope are not considered, if this thesis would be facilitated solely through the intensive case study lens, I would miss the chance to compare the results between successful implementation projects against less successful or in two slightly different environments. The often-suggested goals of extensive case studies within business environments are to test or extend any prior theories that are available (Eriksson and Kovalainen, 2011a) which also fits the goals of my thesis as the intention is not to generate new theories, but rather test previous hypothesis.

As Yin (2001) mentions, if the resources which here are time and availability of potential cases allow, it is preferable to choose multiple cases over single case approach. (Yin, 2001) Adding additional companies to the research does not necessarily bring added value, but instead they should be limited according to the marginal value that new perspectives could bring, as is suggested by Eisenhardt (1989) (Eisenhardt, 1989a).

Extensive case study approach allows me to find and map theoretically interesting or otherwise common patterns between different cases, which I can use to build up the best practices and test the theories presented in the literature. However, the generalizations that can be arrived to even through researching many different cases cannot necessarily be considered as statistical generalizations. One way to overcome this is to use method called analytic generalizations to generalize empirical findings to existing theories. (Yin, 2001).

I argue that the case study approach to study Artificial Intelligence project implementation gives a better understanding on how these technological solutions work in Finnish business context in 2019-2020 where Artificial Intelligence is somewhat recent concept in terms of everyday use and could be used as a comparison if similar research is conducted in the following years to see whether advances are made, be it by new project management practices or technological development. Case study approach also serves as a benefit to better understand the need and expectations of these companies when starting a new project from the supplier and project manager perspectives.

3.3. Qualitative research

The five features of qualitative research as presented by Yin, 2001 (Yin, 2001) are:

1. Studies problems under real-life conditions
2. Presents the views of the people involved in the research
3. Considers the context of the conditions of the subject matter
4. Links the insights to existing theory or frameworks
5. Uses multiple sources of evidence, instead of relying on single testimonies

By studying Artificial Intelligence implementation projects using qualitative case study approach, all these features are supported and taken into consideration.

To focus on the mechanics of Artificial Intelligence project implementation limits how well different project attributes can be realistically quantified. As mentioned, existing studies use large quantity of structured questionnaires to draw general conclusions and trends from, but this does not capture the day-to-day experience of the project teams or does not differentiate the importance between different aspects. (Yin, 2001) This argument also supports my decision to focus on qualitative research methods.

My research relies on unstructured qualitative data gathered by interviewing subject matter experts. In the next chapter I will present how this data is collected and how it is then analyzed in order to present the findings in relevant manner.

3.4. Data collection

In case study approach, in-depth interviews are the most common data gathering source that could be augmented with complementary data if it is available (Eriksson and Kovalainen, 2011a). These other sources such as meeting documents, emails, annual reports, progress reports, budgets, media articles or any other material related to the project can bring better evidence to the case and provide solid background to mirror the interviews on, in order to minimize the possible biases. The rate to which these are available to the researcher might vary between different case companies, so they should be used only to augment the findings and not draw general conclusions from directly. (Eriksson and Kovalainen, 2011a)

The main method of data collection in this thesis are open-ended interviews that are focused on the subject matter. As an inspiration to use this kind of data collection method, I benchmark a research by Brown and Eisenhardt (Brown and Eisenhardt, 1997), which uses grounded theory method to study six companies within computer industry. They gathered data from two and sometimes three different management levels of the hierarchy in addition to mirroring some outside forces impacting the company and the industry. The data was collected through interviews, questionnaires as well as by using some secondary sources. These methods are well within my scope for this thesis as well.

The interviews were split between those responsible for the single project and high-level decision makers responsible for wider variety of projects within the organization as well as participants from the service provider side. This type of division will also serve the purpose within this thesis to capture different aspects of the Artificial Intelligence project implementation. Contrary to the Brown and Eisenhardt's intensive methods, I will not conduct other on-site informal observations outside of these semi-structured interviews. (Brown and Eisenhardt, 1997)

3.4.1. Semi-structured interviews

I conducted 7 semi-structured open-ended interviews during my data gathering process to map out current state of Artificial Intelligence use and methodology in large and well-established Finnish organizations and to test my hypothesis that there are some AI related general challenges to be found and best practices to be shared. Byman (2012) defines for semi-structured interviews that the interviewer asks a series of questions that are prepared in advance but is able to vary the exact order or content of the questions as needed. The questions should aim to be more general and the interviewer also has the freedom to ask further questions outside of the pre-determined ones if needed, for example about the answer's participants have given. However, the interviews are still conducted with a fairly clear focus, so that specific issues that are related to the research topic can be addressed. (Bryman, 2012) One of the advantages of semi-structured interviews is the flexibility of the unstructured nature of the questionnaire, that can be made to fit the multiple different situations of participants without altering too much the interview guide and is especially useful in the context of multi company case study where the cases are comparable to each other. (Bryman, 2012)

For my purposes, the semi-structured interviews are the most obvious and best fit to have natural conversations to approach the subject from multiple different angles without being too restrictive, but at the same time giving me enough structure so that I don't have to do excessive research in advance for each company or alter my interview guide for each separate interview. It can be assumed that the interview participants all have varying levels of experience and knowledge on the subject of Artificial Intelligence adoption and semi-structured interviews allow me to focus on the topics that are most interesting for each interviewee, rather than to force every interview to follow some pre-determined path and to keep the interview informal and conversational. In many cases the follow up questions and off-the-topic discussions allowed me to deepen my understanding of the subject I was studying as I was learning about Artificial Intelligence and technological implementation projects through the process of writing this thesis as well.

3.4.2. Structure and details of interviews

Qualitative semi-structured interviews should be used to study “what” and “how” questions. (Eriksson and Kovalainen, 2011b) I conducted all the interviews using a semi-structured interview technique, aiming for open ended questions, and using follow up questions if necessary. My interview guide is found in the appendix section, however as I conducted my interviews in Finnish, these questions are translated but represent exactly the topics and themes discussed with interviewees.

I was able to tweak the wordings after first interviews to make them more precise, but the content of the interviews proved to be good and no major changes occurred during the interview phase. I started the interview by presenting the topic and leading in with a definition of AI as the term is not exact and could mean different things to different people. This helped me to ground the interview and limit the scope of the subject that I wanted to talk about, leaving outside topics such as analytics or software robotics.

All the interviews were conducted in Finnish and I encouraged the interviewees to use their own terminology and way of expression. I recorded all the interviews which helped me to stay present and be more active with follow up questions. After transcribing and analyzing the interviews I translated the most relevant quotes to English, focusing on not to alter the original message. In some cases, I sent the interview questions before hand, as per request. Five of the interviews were conducted in person while two were conducted via conference call, due to the government or company mandated restrictions regarding COVID-19 virus outbreak during most of 2020. In my view, this didn't affect the quality of the interviews in any way.

3.4.3. Interviewees

In this study, I interviewed seven people from six different Finnish organizations operating in banking and finances, medical care, industry, logistics and consulting. As agreed with the participants, I will not name or describe the positions and backgrounds of the interviewees but in general, most of them were in executive position of their AI unit or team, responsible of the high-level decision making as well as overseeing the implementations.

The goal of this data gathering process is finding and interviewing members of organizations that have done their first implementations and already have some lessons learned. Successful or not, the experience of the existing organization is key for my research, while I still understand that for many of the case companies scaling their AI operations is still work in progress.

3.5. Data analysis

According to the grounded data analysis method, as used by Brown and Eisenhardt (1997), I started by using industry reports to generalize and understand the challenges and best practices related to Artificial Intelligence and its adaption. These reports were mainly used to formulate the questionnaires and to benchmark existing knowledge which was then deepened by interviews that focused on company specific challenges and personal experiences.

These interviews were first transcribed and coded from the original recordings in Finnish. From the initial coding process of the raw data I found 25 general codes. I then divided the codes into five different categories by their similarities in the answers and their topics. These codes and their categorization are shown below in Figure 11. Quotes that illustrated the categories and overlying themes were then chosen to be used in the findings section to demonstrate the key observations and results from the interviews.

Finally, by analyzing the categories as a whole, I was able to find two underlying themes: AI as a project implementation challenge and AI as people management challenge. These themes were then benchmarked with the literature to form conclusions from the data analysis process. These code groups are used as a basis for the chapter 4. for structuring the findings by recognizing the most relevant aspects of Artificial Intelligence projects.

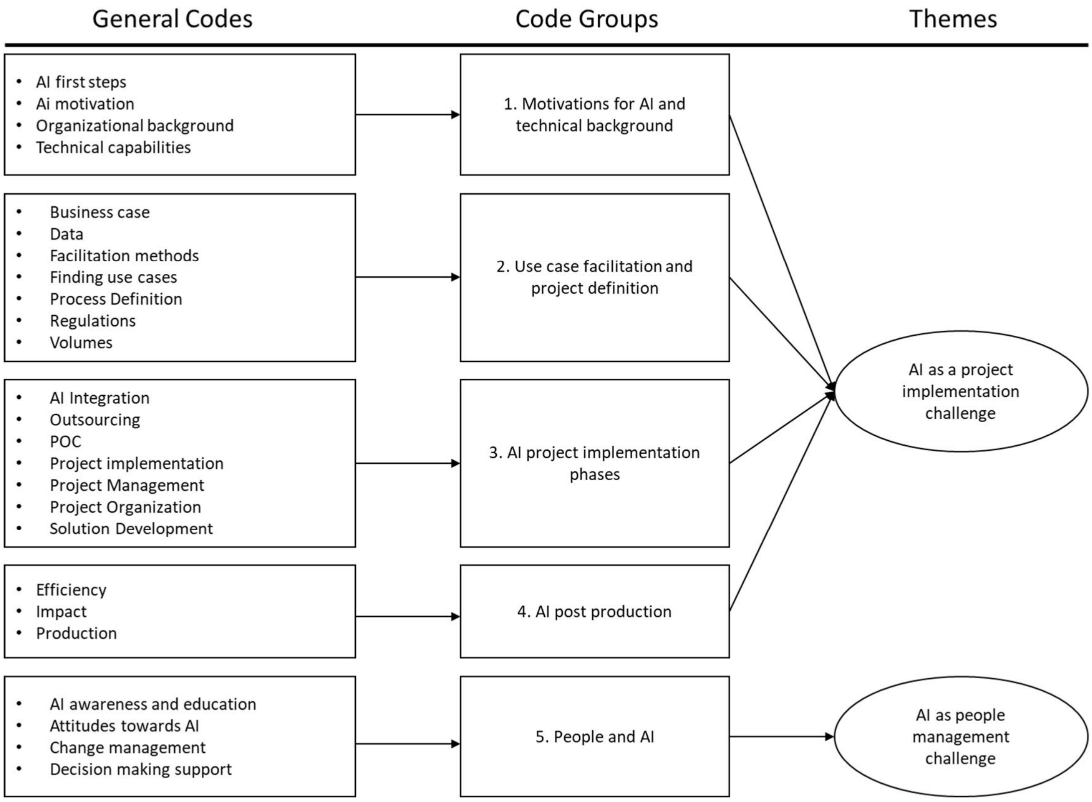

Figure 11. Codes, groups, and themes.

3.6. Research trustworthiness, limitations, and ethicality

As this is my first large scale research process, I must consider some aspects that might affect the results and general research trustworthiness that are due to my inexperience in conducting qualitative research and interviews as well as the overall nature of qualitative case research.

As Bryman (2012) mentions, the direct measurements are not an issue regarding qualitative research as opposed to quantitative research methods where research data plays central role. The limitations regarding the validity of this research include external reliability, i.e. can the study be replicated (Bryman, 2012), since the industry is constantly evolving, even during my own research process. Other considerations include the scoping of the subject and the preparation of my research from the original hypothesis and research questions, which Bryman (2012) calls credibility. The selection of case companies to be studied is largely dependent on who I get a chance to interview and in addition the people within the organizations that I am interviewing. This Bryman (2012) calls transferability. (Bryman, 2012)

I started my interview process already in the second half of 2019 and continued them in three phases: first in the autumn of 2019, second in the early 2020 while the last interviews were conducted during the summer of 2020. These long delays between the interviews allowed me to accumulate my knowledge on the subject matter and I argue that the last phase interviews are the most focused and informed. I somewhat mitigated this in my planning process by starting with AI vendors who I knew had a slightly different viewpoints than the people leading AI organizations from within and I was able to test my questionnaire in vivo and gain firsthand understanding of the interview process.

I mitigated the ethical aspect of qualitative research so that the interviewees privacy was conserved by choosing not to name any one person or company directly in my thesis. As companies that I studied have distinct problems and industries that they operate in, it might be possible to guess some participants, but this is not my intent. I stated directly to each interviewee not to release any company secrets or aspects they are not comfortable sharing and asked to stay on a more general level, as the goal of my research was not to study any of the case companies in depth.

During the writing process of this thesis, I was employed at Sisua Digital which commissioned my research in the first place. Together with my employer we scoped the thesis early on and the subject of the thesis was inspired by our common desire to understand the field of Artificial Intelligence. Sisua Digital is a company focused on software robotics and robotic process automation and part of our offerings consist of intelligent AI related solutions as well. The influence of this background should be considered when reading this thesis.

In the next chapter I will finally present the findings related to my original research question and hypothesis. Does AI have some technology specific challenges that make it hard to scale and what methods and best practices Finnish companies and their AI team leaders use to overcome these challenges?

4. Findings

In this chapter I will present the research context and empirical findings that I accumulated during my research and interviews. The structure of this chapter is based on the code groups I formulated in the previous chapter. The main themes that I recognized during my research are in 1) Artificial Intelligence as a project implementation challenge, and 2) Artificial Intelligence as people management challenge. These themes also loosely reflect the theoretical background presented in chapter 2 and are further divided into sub-categories based on the grouping and coding that I used to analyze the interviews. Within each of these sub-chapters I will then link the recognized challenges with the best-practices currently employed by the case companies.

These sub-chapters combined will examine my hypothesis that AI has some technology related general challenges and will answer the initial research question “Why AI is hard to scale?”. These results are aimed to aid in launching first AI projects and when planning to invest in scaling AI operations further.

As different companies have different names for their AI unit, for simplicity sake, in my thesis I will call the organization that is responsible of developing AI as “AI team”.

4.1. Research context

This research was conducted using qualitative interview methods to study 6 case companies that have already set up their Artificial Intelligence operations and have solutions in production in the time period between 2019 and 2020. The size of these case companies varies but they are generally major industry players either in Finland or globally. My research is not limited to any specific industry in order to cover a wide array of possible scenarios for AI implementation.

Additionally, the interviewees have varying range of technical and managerial backgrounds working with AI.

To generalize the findings to smaller companies and other industries requires some considerations since not every company is able to put forward significant amounts in development without some expected benefits. My findings could therefore help in avoiding some potentially costly mistakes in the early phase of the AI initiatives and to lower the barriers to entry for smaller companies that want to scale up their AI development.

4.2. AI project implementation and the path towards scale

When implementing Artificial Intelligence, the path from initial aspirations of building organizational AI capabilities to the finalized production implementations in scale involves some critical steps along the way. For this reason, I have structured my analysis of key findings in this chapter chronologically starting from the initial motivations for building Artificial Intelligence related solutions and continuing all the way through each phase of the implementation. These phases include use case facilitation and business case analysis for prioritized AI roadmaps, choosing the project organization for each implementation and the decision whether to outsource or build the solution in-house, the actual solution development phase and finally the integration of AI with business, post-production, and maintenance.

There are certain challenges associated with each of these phases that the interviewees have faced during their projects. Building AI efficiently at scale requires that these challenges have been addressed and mitigated systematically. These and other unmitigated challenges are further examined in the Discussion chapter as well as the best practices interviewees have used to solve these challenges.

As discussed already in the theoretical background section of my thesis, the potential failure factors of a software project can be divided into different dimensions as presented by Chow and Cao (2008) in the table 3. below (Chow and Cao, 2008). In their research these failure factors were related to conventional software development projects, but I found out that AI projects don't differ much from this approach and many of these factors were also mentioned by the interviewees. More detailed descriptions of these challenges and how they might exhibit differently in AI related projects are discussed within their own sub-chapters, but this table provides a good overview of the expected challenges based on the literature.

Dimensions	**Failure factors**
Organization	1. Lack of sponsorship from high-up managers 2. Managers are not committed 3. Culture is too conservative or political 4. Organization is too large to implement changes or to coordinate effectively
People	5. Missing skill sets to implement or utilize 6. Project managers are not competent 7. Teams are not functional

	8. Individual resistance that affects larger group dynamics 9. Bad customer relationships hinder co-operation
Process	10. Project scope is not well defined 11. Project requirements are ill-defined 12. Project planning is not done properly 13. Project lacks proper tracking mechanisms 14. Project customer is not present or does not participate sufficiently. The role is unclear
Technical	15. Proper implementation framework is missing. Doing things ad-hoc. 16. Technologies or tools are not suitable for the implementation.

Table 3. List of potential failure factors for typical software project implementation. (Chow and Cao, 2008)

In the first sub-chapter I will examine the organization dimension by presenting challenges and best practices related to initial steps to start implementing AI. I will then continue to the process and technical related dimensions of AI projects and finish my findings section by examining the people related challenges and best practices as its own, separate chapter.

4.2.1. Motivations and technical background for Artificial Intelligence implementations

The research question for this thesis is to study whether there are some AI technology specific challenges that might hinder the scaling of the implementations or prohibit making the AI initiatives profitable in the long run. One way to start examining the fitness of companies who want to begin implementing AI is looking into their past development of other technology implementations to find out possible patterns. Varying needs, problems and organizational background of the companies mean that there are no one route to first AI related projects. However, there are some commonalities that lead to the first initial investments, hiring's, and successful implementations.

The first obvious mark that the organization is ready and, on its way, to implement Artificial Intelligence is observing the previous digitalization development initiatives, such as advanced analytics, cloud technology, chatbots or data-lakes and usage of legacy production systems that could enable further development of said systems by introducing Artificial Intelligence to the mix. The need for data and organization capable of taking advantage of it is in key role for the first steps of AI journey, as mentioned by the interviewees:

"Our AI originates from the evolution of the digital services. Our outsourced legacy servers feed production and financial data constantly to our Data Lake based on Cloud technology."

•

"We received funding for our Data Lake initiative. The main focus back then was not AI, but on the other hand it wasn´t even booming yet."

Any new technology or change initiative often needs an internal champion to justify the investments required to take these projects into action (Kraus and Leonard-Barton, 1985) and guarantee that the projects have enough backing to tolerate some amounts of uncertainty in the short-term (Fossum, Danielsen and Aarseth, 2018). Many of the interviewees stated that the first AI projects came from high level decision makers that had educated themselves about the latest technological trends on the industry and sometimes these new initiatives were heavily personated to one key actor within the company, who had enough strategic power to allocate resources to AI initiatives. Once these funds were internally allocated and the organization around the initiative formed, the actionable solutions were readily available. These findings are illustrated by statements such as:

"Our general director at a time took us to all kinds of interesting directions – our Intelligence-organization was one of these initiatives where we sought new capabilities."

•

"Our chairman of the board visited conferences related to Artificial Intelligence."

•

"Especially our Chatbot initiative was strongly personated with our Intelligence team lead. From the get-go he kept the business case alive since the investments have to be justified."

Once there is a strategic decision in place to focus on internal development, new kinds of solutions and technologies have room to rise. Following a chosen development roadmap allows the organization room to test different solutions and experiment on new technologies such as Artificial Intelligence while having the confidence that even though first projects might prove to be difficult, the plug is not immediately pulled on budgets and resources. Many of the first cases were reportedly challenging and described as learning experiences by the interviewees. Without the support from high level strategic decision-makers, the pressure to deliver could be too high and initiatives carry a risk to be scraped before the benefits are realized in practice. After the initial hype is settled, managing the expectations becomes more realistic.

"From the beginning, it has been clearly a top management strategic decision. The first Data Scientist were hired back then but there were no clear definitions on what they should do."

•

We started with head-on enthusiasm which led to the goals being a bit unrealistic. The expectations have now leveled, and managing has become more realistic."

•

"Some problems [related to data] came out of the blue. Now we have learned from these mistakes and know how to discuss these issues early on."

Sometimes the need for new kinds of solutions come bottom-up when certain pain-points are recognized withing the operating business and there is a match between a technology and need. This is the case especially in the early adopters and technologically savvy organizations that have the technical mind-set to solve problems. (Paris *et al.*, 2017) In these circumstances, the first implementations led by a small initial team or single persons, lead to a formation of more advance organizational structure around Artificial Intelligence development. This in turn can even affect company strategy if it is backed up by solid financial plan as well.

"Single idea that needed a developer. The first idea was implemented as a thesis work, by one of our current Data Scientist and we got started from there."

•

"During the discussions with managers and production employees came up certain pain-points. We who understood where technology is capable of bringing solutions helped to connect the dots."

•

"It [AI initiative] came internally. Our personnel were very enthusiastic when AI boom was the strongest. Often it is useful to say to people that you can experiment and present the business plan."

Enabling these types of experiments with a certain start-up mentality of not casting too much organizational walls or normal burdens might speed up the innovation processes even further as one interviewee mentions:

"One of our unit focuses on new innovations and ways of working. We got a certain kind of start-up mentality working that does not get tangled with normal organizational wall where everybody only oversees their own corner."

Having the enthusiasm or strongly backed business cases however do not guarantee that the AI initiatives are successful and can go ahead without challenges. The way these new projects are selected and framed has major implications on their success in the long run. Without a good planning processes, the projects can be hard to scale or even prove to be unusable in actual use. The next chapter discusses this critical aspect, the planning phase of the projects and what kinds of challenges and best practices are involved in selecting the proper use cases for AI.

4.2.2. AI use case facilitation and project definition

For both of the two possible origins for AI enthusiasm, strategic decision by high level decision-makers or bottom-up initiatives, comes the challenge of finding appropriate use cases or problems to solve with the new set of tools and methods. Not everything can or even should be automated or solved with AI and sometimes the best use cases require seeing the business in completely new light as AI can change the paradigm of how business can be operated in certain areas within organizations (Paris *et al.*, 2017). This challenge is not at all trivial and could inhibit the scaling of AI after the initial trials and successes.

The interviewed case companies have in place a few different ways to solve the challenge of finding appropriate use for AI. The methods vary between structured facilitation and creative empowerment. Following the more traditional and structured approach are the workshops and conducting business case analysis on potential use cases as the first steps for building a road map for future AI implementations. From the managerial perspective, IT and AI teams cannot see or know everything that is happening inside different organizational functions and to mitigate this, they need good communication structures directly to the organizational level. Understanding the work and being part of the planning process as an internal consult is an effective way to handle this issue. Motivating and pushing the people working directly with daily operations to propose ideas and problems to be solved is also an important source for new potential use cases.

"Few times a year we invite internal proposals which we then fund from the AI team and see how we can advance those. Our role is as technical steering."

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"Our ICT organization supports all the business units and functions. We have regular monthly meetings with the business unit managers and go through their case portfolio. We give them then a chance to impact, either by proposing new items to the list or prioritize the roadmap differently.

•

"We organize structured workshops irregularly. We sit down with the managers and find a good angle to discuss how we could improve things."

•

"We collect information and needs from the business functions, which means we are part of their planning, either directly or indirectly. We have Data Scientists as internal consultants that help them in everyday tasks and therefore can understand what is important and meaningful."

•

"We see more general trends and what is going on. We try to bring these to the table and explain that this could be done also, would it be useful? Both is needed, listening to users and their wishes as well as bringing own ideas to them."

However, not everything that is requested from the AI team is feasible or useful to implement and thus the organization needs somebody that is able to see the bigger picture and generalize solutions for the wider use of the company. (Gerbert *et al.*, 2018) The challenge is that this is often tied to single individuals who end up pushing things forward. One mentioned key quality in assessing the use cases is the ability to alter or even dismiss some promising looking cases early on, in favor of others so that scarce resources are not wasted where AI is not necessarily the best solution, or it won´t integrate easily with business. Often times the business users can only see their own task in hand and fail to generalize the solution where it would be scalable which leads to wrong types of cases being implemented. (Lacity & Willcocks, 2018)

There are few ways to address the challenge of how to prioritize use cases. Firstly, there is the business case-based approach. Bringing business value is in the core of AI and doing things just for the sake of it leads often times to failures in terms of economic benefits. (Paris *et al.*, 2017) Key here for finding good use cases is the volume of transactions. The potential to automate even a fraction of a process with thousands or even millions of transactions can bring huge business benefits. For cases with lower volumes, the benefits must be acquired from larger automation potential or better overall processes and work time reductions. Estimating and calculating business cases for these solutions are more challenging task as not all automated work directly translates to personnel overhead reductions, but the work might simply be transferred to other tasks. Here the business understanding and strategic prioritization on what the company wants to improve on and achieve is important.

Understanding and defining clearly what is being solved is the first step in successful implementations and cases that bring the best obvious value should be highlighted early on. From the technical perspective the challenge is then to find cases that are solvable with reasonable resources as the team size or available budgets are usually limited. The business users might have some unrealistic expectations on the AI or conversely, they do not realize what it can do. The responsibility of the AI team is then to select those cases first that it can implement within reasonable budget and time restrictions. One of the interviewees mentioned this approach as the "benefit-difficulty" quadrant. The chance to receive external funding for AI projects might also affect the prioritization since the financial risk of implementing is lowered. One last possible input for prioritizing the use cases are the external signals such as the market situation or some strategic goals that the business tries to fulfill, such as customer satisfaction or production efficiency.

"Business value is in the core of Data Science. You get lost easily when doing AI if there are no clear goals of what should be solved and how."

•

"One challenge is that the majority of the managers or employees are not experts on technology, and they don't know what is possible. There might also be unrealistic views portrayed by media on what technology could do."

•

"The funding determines a lot. Those projects that have received external funding can start to develop their solutions."

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"We have a long list of cases on our roadmap. We then prioritize them based on the business case. Of course, we also look at the market situation and whether we have some areas we want to focus more on, such as customer satisfaction or business efficiency."

Sometimes the ideas for new use cases are so abstract or there are no real correlations to existing processes that building business case is challenging. In these cases, even a rough qualitative analysis is feasible especially if the outcome and scope of the project is unclear without further testing. The challenge is how to value these cases against more provable projects with calculable results and benefits so that the efforts are not wasted on something that seems good on paper but is hard to justify financially.

After the first AI use cases are implemented and the business users gain more knowledge on what AI technologies are capable of doing, finding new use cases becomes easier. One of the interviewees highlighted that in order to select the most useful cases without wasting effort on low value initiatives, up to 80% of the suggestions should be eliminated early on during the process definition. The organization should have enough material and potential cases to facilitate the implementation of couple of the most lucrative cases each year, depending on the resources available to the AI team.

"There should be enough input of use cases that most of them are scraped. Because otherwise the best ones are not filtered through. Good goal would be that 80% of the use cases are eliminated at each step."

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"It's an iterative process. Once you get the first few done, people get new ideas. Some of them work and some do not. We collect them to our pipeline and try to implement business case analysis to prioritize."

•

"Especially working with customer interface, the business case calculations are not so straightforward. Many other aspects are related, for instance you cannot achieve full customer service automation since some people still would insist on calling. Working with raw mathematical models is easier."

As mentioned before, the problem and solution definitions coupled with the business case calculations to prioritize the AI roadmap is a vital part of the success of AI strategy execution. The nature of Data Science however is such that not everything can be anticipated and tested out on paper analysis. Some hands-on testing and trials are needed to confirm that the ideas work in practice before the project can be approved for development. (Rautio, 2019) This path to production and the ways AI teams can organize themselves for these projects is discussed in the next chapter.

4.2.3. Technical implementation of AI

Once the decision is made to invest in AI development and the first potential use cases are recognized, companies face the new challenge of how to structure the implementation of the actual solutions. Should normal development project practices be used and what unexpected challenges might slow things down? What kind of team should be built to develop and maintain the solutions? Should the development be partially or completely outsourced? According to the literature sources that recommend AI project guidelines such as IBM (IBM, 2018), finding right operating models and managing AI implementations correctly is a key to successful projects as well as sources for potential troubles if not done correctly.

Many of the interviewees stressed on the importance of actually understanding what is being solved and how the new solutions could be scaled for wider use. An important part of determining what projects to take into roadmap is defining the challenges correctly and having general business understanding to make the solutions useful to the end-users. AI should be viewed as a tool to solve problems better than before, not an end goal in itself. The organizations planning to implement their first use cases should be prepared to scrape many of the initial ideas to guarantee that the truly best and most useful end up on the final roadmap and the resources are not wasted on trivial challenges where results cannot easily be scaled, or the implementations do not fill the promised gains. One interviewee had in place a concrete way to get good grasp of the needs of end users:

"If we are bringing a solution to production, we might place a member of our technical development team to work side-by-side with the people to see how everything works in practice and have a clear understanding on what we are actually trying to solve."

The early phase of defining the use cases that could be suitable for AI involves testing the initial hypothesis by implementing short and cheap Proof-Of-Concept (POC) projects where the AI team can verify that they can get results out of available data and generally see how well the models work in practice. (Rautio, 2019) During this phase it is typical to work tightly with the end-customer to see if the solution is providing right kinds of results, while making changes to the process or the models is still easy and straightforward. The POC development is often an iterative process where improvements are made based on the feedback. The challenge during this phase according to one interviewee, is getting stuck in long verification loops where the business is hesitant on the approval and constantly seeks minor improvements in places where the benefits are only marginal. Planning the technical blueprint and schedule for the final implementation should be done only after there has been an approval that everything works as planned. During this phase it usually becomes clear for the AI team whether the solutions is also scalable to wider use and what kinds of limitations there are in the data or other technical aspects that might cause problems or delays during the actual development phase.

"First we conduct a very light-weight POC to see if the idea seems promising. After that we can allocate budget for the actual development if the solution works and is scalable."

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"Most typically we start with some kind of POC."

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"We try whether the results based on data are good enough to achieve something. Alternatively, if we already have decided to implement, the first phase is to verify how much resources and time was needed to achieve certain kinds of results and do we need more iterations to continue. Typically, we seek some results to base the future development plan on."

AI deployments are always dependent on accessible data and these data sources are typically build on existing digital foundation. The larger the organization is, the more likely it will have proper data ready to be utilized on AI initiatives. (Paris *et al.*, 2017) Data is indeed an integral part of AI projects but as many of the interviewees stated, the quantity of data is often not a barrier for developing AI, given that the modern data infrastructures are already in place. The lack of available data can however cause significant delays to projects if not anticipated early on. The quality of the data is the most common source for early project failures and typically the first requirement for an AI project to be able to move forward in development. If the existing data quality is poor or some crucial part is missing, it can be mitigated by consciously implementing new and better data gathering processes to collect new learning data for the models to operate on, if feasible. This will obviously prolong the implementation process as the data might take some time to accumulate.

"We have certain areas where data is plentiful and building solutions around those is quite straightforward. But there always comes new ideas or we recognize that there is a problem to be solved and there is no data. Then we have to think about setting in place new processes to collect it."

•

"Data for our core AI processes is plentiful, the development is not dependent on that."

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"The amount of available data grows all the time. Let's say, for every third idea it turns out that there is no data that we collect or its not in a digital format or without labeling and collecting it requires a lengthy project of its own."

There are no set-in-stone rules for how much or what kind of data is needed for each kind of solution. The three categories for the division of learning data, testing data and validation data can have some hundreds or up to millions of datapoints if needed (Jordan and Mitchell, 2015). The business logic and the models can in theory be built even without having data prepared in advance, but the final validation of whether everything works together in production should always be done on real world data, as in the cases where testing data was fabricated, humans can rarely anticipate all the possible real world scenarios beforehand. (Luger, 1993)

"In many cases we have sufficient data but to scale we need to validate the results."

•

"The biggest challenges I have personally faced are related to cases where we don't have all the data that we wanted, for example there are datapoints missing for the cases when something does not happen or is unsuccessful."

•

"Once in a while comes surprises when the data scientist hasn't been able to see behind the data. We build a cool model, optimize results and take it into production, but it turns out that during the data gathering process some variables were grossly misrepresented or real world has cases that were missing in the learning data."

•

"In principle we believed that we had the data, but it turned out that the quality was not what we expected. So, we needed to take a couple of steps back and start over."

Paris et al. point out in their research report the ethical and legal challenges that are involved when using customer related data or personal information to predict certain properties to use as a basis for decision-making. (Paris *et al.*, 2017) However, this was seen only as a minor barrier or not a problem at all according to the interviewees. For most of the legal aspects, especially in the finance sector there are already clear guidelines in place and the team generally knows what can and what cannot be done with the data. AI teams can also anticipate which potential solutions are guaranteed to face these issues and know to avoid them. Focusing on the internal processes and functions is the easiest way to avoid possible legal restrictions and reparations.

"Finance industry is shackled with all kinds of regulations. We want to work ethically with data and for this reason we have quite strong controls on what we can do with data. We start with an idea and early on think whether we can do this."

•

"Once in a while we have to seriously ponder if we can use certain kind of data and if we could commercialize some data. We have mostly focused on improving our own processes to mitigate this challenge. We understand that not all the data we have can be utilized."

From management point of view, next key decision is forming the right project organization for the AI implementation. Some helpful guidelines by Kraus et al. (Kraus and Leonard-Barton, 1985) are already offered in the literature review section of this thesis in chapter 2.2. As opposed to the role-based approach of Kraus et al., the interviewees had more resource-based view on this subject, building developer teams ad-hoc based on the availability and nature of the project. Generally, the project team consists of Data Scientists that work on the development and the business manager who oversees that the solution fits the problem AI is implemented for. The actual solution is then integrated to the production environment in cooperation with general solution developers. It was mentioned that the AI team often is a part of more general IT department and benefits from working closely with the application and user-interface developers.

"When we started to build the team, we wanted to have capabilities to solve most of the problems ourselves."

•

"In our work we don't separate data scientist or different AI fields. We have 30 data scientist and I see that they have the right tools and processes available."

•

"If we talk about the ideal project team – we do not see ourselves as only data scientist, we are software developers as well. This is something we highlight in our recruiting as well."

•

"Data scientist is part of a bigger team, we have those who handle data integrations, API developers and those that develop the end products and how we get the model out into the wild."

•

"Most of our projects are done as agile development so we rarely have some structured project organization. Based on the use case we select the key persons and sponsors to

guarantee the buy in. We have an expert from the business telling us what the data actually means and then the technical developers and data scientists."

•

"We have combined data analytics and AI team of roughly 20 persons."

As setting up internal AI capabilities takes time and resources, it was also stated that especially in the early phase of the AI journey, actual implementations are outsourced especially when the problems are too complicated for the current teams' capabilities. (Philip, Sales and Hackett, 2006) From the case companies' perspective, this requires strong project management and vendor management skills and involvement as the outsourcing process can require a heavy call of proposals and validation of submissions, a process that might in itself take months. The risks and challenges mentioned by the interviewees involve getting stuck in the eternal POC and fine-tuning limbo with the outside vendors as well as the trouble of pricing the maintenance and post-production of the final solutions. For these outsourced projects, vendors typically supply 1-2 developers for the early testing and validation phase. One interviewee mentioned that there are some challenges finding Finnish vendors that could handle wider scale global rollouts which require a larger team to develop and manage. Outside vendors can be used side-by-side with internal AI team, where consultancy and discussions are used to solve more complicated problems that might be outside the current team's skillset – without having to recruit talents for one-off projects.

"From piloting onwards, the project goes to our sourcing which is a really tight tendering process which might take 1-2 months. This requires time, effort, and budget from the dedicated business owner to function properly. If the implementation is really small, we put out a few page long calls of proposals for few vendors. In these cases, it needs to be a project, we need to have some monitoring, in the first phases myself and the process owner. From the vendors side the team is 1-2 developers in the first phase."

•

"Then we have partners, with whom we pass around ideas and if there are more complicated cases or the implementation is so large that we want to outsource the development, then we use resources for that."

•

"The challenge is that who owns the models. The IT support cannot maintain those. In practice it is the business responsibility to monitor, the models do not last forever even with re-learning of the models they get outdated without development. I do not have a proper answer on how to do those. Either they end up back on my desk or we outsource them to some vendor."

•

"Depending on the case, we have some expertise ourselves or if it's something more specific, we outsource."

•

"During the first phase when the project is started, we determine if we should do it ourselves or outsource. Mostly we buy the software development work. We have some

data analyst as responsible working with the project manager, helping with the scoping of the problem and finalizing the documentation. Then we do call for proposals."

The actual developing or technical work of implementing AI solutions was generally not seen as a challenge, according to the interviews, as long as there are data and capable developers available. Most of the resources and time are spent in the definition phase and working with the business to formulate what is being solved, and the importance of these phases was not stressed enough by the interviewees. A good part of the technical work is also spent on working with the user-interface and infrastructure development which is not typically seen as a part of AI challenge but is still a key part of implementing the solutions successfully to production and guaranteeing good user experience. The AI part of the solution itself is typically an API-based and the user layer is then built on top of that.

However, integrating the technically complete solutions to production environment where the model is first time put into the test against real world seemed to bring along certain challenges. The technical and maintenance related issues of post-production is discussed in the next sub-chapter, while the human aspect is the focus of the chapter 4.3. People and AI.

4.2.4. AI maintenance in post-production

The final phase of an AI project is deploying the solutions into production and maintaining their effectiveness. From AI perspective this includes, in most cases, the continuous monitoring of the model to see if its quality is deteriorating due to changes in the operating environment and therefore in the input data (Stoica *et al.*, 2017). Challenges related to moving the solutions to production and how to maintain them were seen as something that most of the interviewees wanted to improve in their current work and it seems that this is where the most confusion and lack of good practices lie within the AI project life cycle.

Before the solutions are implemented into regular use they need to be tested and verified. This requires that the AI team works closely with the final business users to see if the solution is really a fit to the original problem and whether the new solution requires some ways to change the current way of doing by the end user. Scenarios where little or no changes are required are seen as the most straightforward during the deployment phase. However, if people and processes need to adapt to the new solution, some challenges are to be expected. In these cases, change management practices are helpful, as well as educating and demonstrating end users how the solution is actually performing versus the old way of doing. Additionally, the best places to pilot new solutions are not necessarily the most straightforward units or test groups, since some of the challenging or borderline cases might not surface in these conditions, but instead later when the solution is scaled to other locations or units.

"For piloting we have dedicated user groups that use them in production-like environments"

- *"Every project is unique. Sometimes the rollout is straightforward, and AI is regarded just as new tool to take advantage of. In some cases when we have to replace an old process with a new one, the new tool does not work similarly or appears to work worse than the old way. Small bugs might arise, and this is where change management is needed."*

As mentioned, the hand-over phase from the developer team to maintenance and support was mentioned regularly by the interviewees to be the most challenging part of the project. Even though the initial rollout could be small, the phase where the developer team should be released for new development might be prolonged due to constant request for improvements and model optimizations. IT support cannot handle the monitoring in isolation but needs input from the business users who work daily with the process outputs. The model might work well on paper but the decrease in quality can only be seen by the people using it directly, hence the need for good communication between business, IT support and AI team is needed to guarantee that the issues are raised on timely manner. Organizing this can be challenging, but relatively straightforward if the models are in regular use and issues can be recognized easily.

"It is a challenge, who owns the models. IT support cannot maintain predictive models. In practice it is the responsibility of the business users, the models do not work eternally

and due to outdating the models need development. We don't have answers to this, either the models come back to me or we outsource them."

•

"Making a model is a one-off effort. Since its in so regular use, we don't really have a risk that it would erode, left unchecked, since we update and enhance it all the time."

It can be assumed that the first production testing phase is much longer compared to more traditional software and automation projects. This is also dependent on what kind of support the models and the implementations need. If constant monitoring is required, too much of AI teams' resources might be needed for post-production, rather than developing new implementations. One way to mitigate these prolonged rollouts is to include the support team early on during the development phase, rather than working strictly as different organizations with divided responsibilities. The interviewees mentioned however that they are still constantly working on to find good ways of mitigating these challenges and for smaller organizations this could be a barrier for scaling AI effectively, once there are certain amount of use cases in production.

"We are constantly looking for right operating models. We have not made this fully agile yet. Me personally, I would try to eliminate handovers completely, so that our Data Science team would do the rollouts and similarly the support team would be within the same team and part of the project from the start. Currently we share the same office space but belong to different organizations with different objectives and priorities."

•

"The interesting question is that what is our exit plan? I can do many things, including user interface and it does not require massive rollouts. But how am I able to let them go? My calendar has not enough room if I keep taking more and more of these."

•

"We have a post-production team which takes over these projects that include Data Scientist and Data Engineers in Poland. It is more core IT, and the support is based on need, whether it is business hours or 24/7 support."

•

"This has been one of the central areas for the need of improvement. During the past year we have especially focused to make the process better and run more systematically. Trying to make documentation for handover better. Depending on the solution and the work needed during its life cycle, it's not very effective if our own developers need to do the maintenance personally."

The true impact of AI implementation is only fully realized and can be measured after the initial launch to production. As mentioned before, the business case can be sometimes hard to compile and is dependent on the available data and its quality. However, the coverage and possible automation rates should already be anticipated and decided on during the testing and development phases and big surprises are not to be expected after the rollout. The challenge is when the model's performance is lower than expected, due to some wrong assumptions during the process definition or data gathering phases. This could have serious consequences for the final business case and user experience. One interviewee mentioned that if the initial assumptions differ from the final achievable results, similar projects should be estimated more rigidly in the future, if not to be avoided completely.

"If we have calculated that the solution saves a lot of working time, but the measurements reveal that it did not have anticipated impact, the next time we need to seriously consider whether we should implement similar projects.

•

"Challenge that we face all the time is when Data Scientist has not been able see behind the data and the data everything is based on does not reflect the real world."

•

"Despite the problem being easily solvable, we might have not been able to guarantee that the process around it is stable. If we change parameters weekly, it does not work. Adjusting the rest of the organization to the needs of the technology has been a challenge. We didn't anticipate these problems until we already were quite far in the project."

When the development and maintenance is outsourced, the AI team must guarantee that the pricing and the monitoring is handled accurately. The goals of the AI solutions should be agreed beforehand, and monitoring done regularly to assure that the models are working as expected. The challenge in these cases is the decisions of the ownership of the models and dividing the responsibilities on model updates.

"It's a different game, when outsourced vendors do the projects. Then there is no infrastructure development, everything is ready."

•

"We have certain contractual tasks and service levels with outsourced production services. The vendors are responsible that they are available and, in the background, fix the resources to guarantee that. We have product-owners monitoring the quality and directing the vendor operations. Once in a year our analyst then checks how well the models perform and we assess whether the models need re-learning, which is a heavy process especially within certain solutions that need humans validating the data."

Taking AI to production and into use is not just a technical challenge. Involving end users early on during the development was mentioned to be especially important for the success of the projects and scaling of the initiatives. How AI and people work together, challenges related to change management, as well as some benefits that AI could bring to aid in human decision making are the topics of the next chapter 4.3. People and AI.

Phase	Challenges	Quotes & Best Practices
Decision to develop solutions with AI	- Dependent on knowledgeable individuals -Budget allocation	*"Our AI originates from the evolution of the digital services."* *"Our general director at a time took us to all kinds of interesting directions - including AI"*
Finding use cases	-Finding relevant use-cases	*"We collect information and needs from the business functions, which means we are part of their planning, either directly or indirectly."*

	-Active business participation in finding new solutions -Business case analysis	*"Business value is in the core of Data Science. You get lost easily when doing AI if there are no clear goals of what should be solved and how."*
Managing the development	-Make vs. buy -Project organization -Data	*"When we started to build the team, we wanted to have capabilities to solve most of the problems ourselves."* *"Data scientist is part of a bigger team, we have those who handle data integrations, API developers and those that develop the end products and how we get the model out into the wild."*
Integration and post-production	-Rollout -Change management -Upkeep and maintenance	*"Every project is unique. Small bugs might arise, and this is where change management is needed."* *"It is a challenge, who owns the models. IT support cannot maintain predictive models. In practice its business responsibility, the models do not work eternally and due to outdating the models need development"*

Table 4. Conclusions from the most typical phases of an AI project

4.3. People and AI

As already discussed in the literature review section, the latest wave of digitalization has changed the nature of work for many people, which in turn affects people's morale and relationships with co-workers and managers (Philip, Sales and Hackett, 2006). One of the key challenges of implementing AI is how people using it are going to react to the new ways of working. The expectations for AI might be impossible to achieve, as people typically expect error-free operation from machines while at the same time accept human errors in similar processes. (IBM, 2018) The nature of AI on the other hand means that 100% effectiveness is hardly ever possible and accepting these mistakes from a machine is hard to take.

Challenges related to how organization is managed from the AI team's perspective and what kinds of problems AI team might face working with end-users were regularly brought up during the interviews as well as in the literature. AI implementation is not purely a technical endeavor, but having the solution working smoothly alongside humans that operate it requires different kinds of skills than just data and analytical expertise. These challenges and some best practices are the topic of this chapter.

More precisely, in this chapter, I will discuss three key elements related to how people work with AI, including the challenges and best practices highlighted during the interviews. These categories are: AI awareness and education for the people working alongside new technologies, change management practices available for managers making sure the implementations are done effectively and lastly AI as a tool to support decision-making.

4.3.1. AI awareness and education

One of the challenges with any automation project is addressing fears of the employees such as job loss or uncertainty of their role in the future. However, according to different studies, this fear is partially unjustified since automation historically has not eroded the need for humans but rather changed the way people work and the kinds of tasks they operate with. (Cascio and Montealegre, 2016) AI is a part of digitalization wave that first time threatens the white-collar jobs, so many fears still needs addressing which is part of a challenge when implementing and scaling AI for the first time. (Ronanki, 2018) The way people are trained to use AI and understand its possibilities and restrictions is a crucial part of successful AI initiatives within any organization.

One method to address these fears is educating the workforce on possibilities and capabilities of AI and what it means to have these technologies in their work context. (Ronanki, 2018) Interviewees mentioned that they use different kinds of methods to conduct education. Firstly, clear communication is the key. Having demos and examples available on company intranet is one way to bring awareness to the people of what kinds of initiatives are going on in their organization. There might be some initial opposition to the new solutions and their benefits might not be clear to the people adapting to new ways of doing. Showing and communicating clearly how the AI can help and bring benefits is useful in these situations. As one interviewee explained regarding one of their rollouts:

"The benefits should be demonstrated to the workers. For example, do comparisons based on clear metrics. Encourage working one week with the new tool and then one week without when they felt good working and see what the results look in reality. If you can show a clear difference, they tend to believe you."

These kinds of methods might be taking it to the extreme but are necessary in cases of strong objections. Usually, the feel for work has accumulated during a long period of time working on a task and to re-orientate to new methods takes time. To justify why this effort is indeed good and useful is therefore crucial for the success of the adaptation, so that there are no relapses where the solution is left unused after some initial trial period.

Other good methods for raising AI awareness is conducting internal seminars or trainings for business managers so they have the right tools and knowledge to communicate the AI related issues forward to their units. These courses can be challenging and involve some light-hearted certifications related to learnings accumulated, or just common gatherings to inform and educate the workforce on new technologies, without too much required from the participants. The education on ethical issues for AI team managers should not be neglected either to avoid the challenges and potential PR disasters due to privacy or data breaches when implementing new projects.

"We organize trainings where we invite development managers from different units of the organization. Part of our team are all the time in close contact with different parts of organization."

•

"Informing is vital from the perspective of my own job. We film demos of the projects where we explain things and put them on the front page of our intranet. It's the only way to get the message through."

•

"To face the challenges, we have all kinds of education paths and common gatherings where our personnel can familiarize themselves with technologies and their capabilities."

If the education on AI is done correctly, it might create a positive feedback loop where the business gets excited and offers to AI team their own ideas on challenges they want to get solved. Even though some of these ideas might still not be suitable for AI, it is nevertheless useful to have the business working actively for the AI team to raise issues and offer use cases to be solved. It is then AI team's responsibility to recognize the best ones and enforce this iterative process to their gain.

"Once we have few projects under our belts, it becomes an iterative process where people have revelations themselves and come suggesting us ideas. Some of the ideas are feasible and some not."

•

"We educate our organization on what it means to have AI and what is Data Science. And when there is genuine need for Data Science projects, we already have some expertise within the teams."

Sometimes, despite the best efforts to educate and to communicate clearly with the business, the new solutions bring a type of disruption to the traditional ways of working that the projects risk a failure. In these cases, AI team leaders should apply proper change management practices to make sure the projects are implemented correctly. These challenges and methods to overcome them are discussed in the next sub-chapter.

4.3.2. Change management practices for AI implementation

As Gerbert et al. state, organizations should implement new technologies through clear change management practices and address the impact on organizational and operational level as well as on work force. (Gerbert *et al.*, 2017) The main challenge from managerial perspective is that each project tends to be unique in its characteristics with own challenges and new target audience. The projects can however be roughly divided into two people related categories based on their difficulty: The ones where not much changes to ways of working or roles are required but instead the new solutions are just a new tool to aid the workforce. More challenging projects are those that require active changes to either processes or might even displace some workers from their original tasks.

"Each project has unique characteristics. Some users come to the realization that, great, now we have this new tool we can utilize. Some have to cut their old processes and replace them with a new one. Then they have a problem when the new tool works differently than accustomed, or even worse with early unexpected challenges associated to the initial rollout. This requires change management."

Good starting point for implementing AI within any organization are projects that do not involve too much disruption or allows employees to stop doing something that was part of their tasks previously. If the project has good managerial backing and the people taking AI into use do not feel threatened by it, the chances are good that the project will be a success. These rollouts might not even be visible for the end users, but instead they might just be aware that some kind of AI is now being used. Communication here is also important, to avoid possible confusion, but change management is not a key issue with these types of projects.

Many of the interviewees mentioned about the challenges related to implementations that have disruptive qualities attached to them. This is not purely just an AI related challenge, since any new technology or process that requires people to change their behavior will face resistance at first. Technical understanding of the people adopting AI also brings one more dimension to the equation. The more technically savvy people, who might initially resist, might need less persuasion, and catch on the idea faster than their less technical counterparts. To state this aloud is somewhat controversial at face value but is something to consider already during the process definition phase.

"For super-analytical people, you just have to demonstrate the difference between the old manual and the new machine generated results. They catch on quickly without too many arguments."

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"With production people that have engineering background, the implementing is typically really smooth. Closer we get to customer interface and sales; people tend to be less systematic and fitting or modeling new solutions to that kind of environment is more challenging."

One way to mitigate this resistance is giving people the feeling of ownership of the project. If the employees have a chance to affect the outcome and control how AI is being adopted, they might feel less inclined to complain and resists after the launch. Having people educated more broadly on the concepts of process efficiency and change management will also prove fruitful when launching AI.

"If we recognize that the new project might cause some challenges during the rollout, we contact the LEAN responsible of the unit and incorporate them to the project."

In this organization, the access to people that are same time knowledgeable about the challenges relating to project implementation and change management was really useful and the prior decision to place them on each organization pays dividend with AI use cases as well. Mapping and knowing whether employees have these kinds of capabilities is helpful for the AI team when preparing new projects.

In this sub-chapter I considered the challenges related to instances where AI displaces current methods of working or is merely introduced as a new tool. In the next chapter I will dive deeper on instances where AI can also augment the work and decision-making of the people working with the new solutions and the kinds of benefits or challenges that are to be expected with these, more advanced use cases.

4.3.3. AI as a tool to support decision-making

As discussed in the previous chapter, the trust is a key enabler when we consider people working with AI. This means that the most complicated use cases should not typically be selected first for the AI roadmap. Once there is evidence that the new AI initiatives are giving results, companies can start to widen the scope of AI adoption closer to strategy work and decision-making processes. People need to have a trust that the AI algorithms and models' suggestions work but at the same time feel that they have the authority to still execute those decisions themselves, not having to consult people in higher up positions which might inhibit the true use of AI. (Fountaine, McCarthy and Saleh, 2019)

It is rarely the case where AI will do tasks assigned to it with 100% efficiency without any mistakes. When using AI as a tool for decision making, the goal is to help the employees do their job more efficiently, instead of replacing their efforts completely. Sometimes it might be the case that human employees actually will perform certain tasks better than AI. Within these scenarios the benefit is usually that AI will perform the task either faster or more diligently on the vast majority of cases, so that human efforts can then be directed to the challenging ones, which they have now more time to allocate to, enhancing the overall quality of the work.

The challenge is to educate people to see AI as a tool to aid their job development, instead of threat that just automates their tasks. As one interviewee mentions:

"In practice, people are involved in the projects and there are really no confrontations, machine vs. humans. People who have done the optimization work, now they have a machine helping them. It's more of a symbiosis in my view."

To see the human-machine cooperation as symbiosis instead of competition is the key to having well-functioning AI tools that emulate and help with human decision-making processes. Other key challenge to consider when automating human decision-making, is where the most time is spent for each task, and thus what are the most beneficial automation targets. This challenge was described as follows by one of the interviewees:

"The integral part is how you define the question. If the first problem is framed too naively, the solution will not help too much. If AI model that is trained to see irregularities in an image will get similar results with similar processing times as a trainee would, we have a high threshold to automate these due to inherent error rates. You should train the models to do tasks that are as hard as possible for humans and take them the most time to handle. For example, monitoring some small changes across long periods of time or counting multiple things from an image. People are really bad at these, but for Machine Learning it's not really a challenge."

This above statement illustrates the cost-benefit threshold when using AI for automating human work or using AI to help humans with their work and decision-making. The process of how to approach process definition when using AI as an automation tool is already discussed in the earlier chapter. What is interesting here is how the interviewee sees the role of the AI when automating tasks that are hard for humans.

As a conclusion of this sub-chapter, I find that the main benefits of using AI as a tool to help humans make their decisions is to free up resources, be it time or mental capacity to perform their jobs better. At this stage of the development, there seems to be no ambitious efforts to claim that AI would actually have the capability to go beyond human skills on its own. To study the theme of general AI with these types of capabilities does not fit the scope of my research but is in itself an interesting topic of discussion for future research.

As a summary to many findings presented in this chapter, I can conclude that despite of many challenges, be they technical or people related, AI teams seem to be finally on the path towards AI at scale. Some issues especially relate to the later phases of the projects are still missing all-embracing best practices, but the important things is that the AI team leaders are aware of the challenges and working actively to overcome them. In the next chapter I will discuss how these findings can be supported by the AI implementation literature and additionally I will go a little bit beyond of the scope of this thesis to discuss some possible future areas to study.

5. Discussion

In this chapter I will discuss how my findings are supported by the potential AI related issues and challenges recognized in the literature review chapter and whether the proposed theories and best practices are in use within companies that have already managed to scale their AI implementations. Additionally, I will attempt to generalize the results for SME companies that are currently doing or interested in doing their first AI projects or investigating how to apply AI at scale.

5.1. Barriers to wide scale AI adoption

The established AI implementation literature and management consultancy studies have done a thorough job of mapping the potential barriers for entry or challenges that might face companies that are implementing AI for the first time. Naturally, these studies are mostly focused on international enterprises that typically have the tools and resources available to spend on internal research and development of AI even though the companies themselves might not be working directly within IT industry. The studies and related questionnaires are conducted in masse, and to compare these generalized results to a smaller more focused sample is useful to either affirm the existing studies or reveal some novel viewpoints to the issue of scaling AI that could manifest itself in different way that is conventionally though. My data collection method of semi-structured interviews is also different to more generalized and structured methods used by the previous literature and might offer more in-depth view to the issue of scaling AI.

The recognized challenges could be divided into three categories: technological, business and people related challenges. Paris et al. expect that the large companies with strong IT background are the first ones to manage to scale AI furthest as they can leverage their existing digital systems and data infrastructure to smoothly transition their processes and operations to be suitable for AI. (Paris *et al.*, 2017) The research process and my findings back up this prediction. Firstly, when screening for companies to be interviewed, the successful ones tended to be larger and more technologically oriented than the ones that declined the offer to participate due to varying reasons. Many statements from the interviewees also backed up the original assumption as generally all of the companies had already some kind of data infrastructure in place and analytics department working on challenges that AI could also solve. For smaller companies, the issue might thus be the price associated with firstly building the appropriate data infrastructure before even considering the first AI implementations, yet alone scaling of such projects. I therefore propose that the digital maturity is the most important barrier for entry for small and medium sized companies. The success of the implementations from there on depends on the business and people related challenges.

The failed attempts to implement and scale AI after the decision to invest is made can be due to wrong types of use cases and problems AI is set to solve or automate. (Lacity & Willcocks, 2018) These failed trials might dishearten the managers as there are no economic benefits in sight. The AI initiatives with unclear business cases might be therefore overshadowed by competing investments and projects, which was seen as a significant barrier for AI scaling by Ransbotham et al. (Ransbotham *et al.*, 2017). As the organizations I studied and managers that I interviewed were on the path of scaling after some successful implementations, I don't have a good representation of types of situations where the company decides to abandon AI development altogether. Finding these cases and companies is obviously much harder than finding functioning AI departments, but it would be an interesting proposal to add this type of research on top of successful and ongoing implementations.

Chui et al. divide the potential use cases for AI into two categories: consumer-facing and back-office. (Chui *et al.*, 2018) The value for implementing AI for different use cases depends on the nature of the industry the company implementing it operates in, and not the digital maturity or other technical inhibitions companies might have. For some, the greatest potential is in the analytics use cases, especially when operational performance is key source of competitive advantage and other times marketing and sales could create greater benefits. (Chui *et al.*, 2018) My decision to include companies from many different industries takes this disparity into account and the findings reflect this also as the interviewees had recognized different opportunities and challenges related to both use case categories.

The ease of AI implementation was something that was not generally discussed along the potential benefits of certain use cases categories within the literature but was frequently mentioned by the interviews. Implementing customer facing AI projects was considered much harder and caused many more unexpected challenges early on compared to the purely analytical use cases. Chui et al. mention that the analytics uses for AI are mostly enhancements to previous methods instead of purely novel use cases or ideas. (Chui *et al.*, 2018) This observation was also mentioned by the interviews. These use cases were easier to take into regular use, according to the interviews, since the usefulness was easy to demonstrate by comparing the old and the new ways of doing. Finding the right use cases to start with is important and highlighted by many of the interviewees but the limitations and challenges related to user acceptance and organizational as well as skill management is crucial to successfully implement AI at scale.

The disparity of skills available for companies that implement AI is of concern for Ransbotham et al. The best talent that can build AI solutions is rare and in high demand which lead to high costs. The skills related to running AI organizations is also of high relevance as AI projects include multiple different roles and purely technical implementors cannot handle all at once. (Ransbotham *et al.*, 2017) This issue was also shortly mentioned by one interviewee who mentioned the struggle to find properly sized implementors who could handle the larger outsourced AI use cases. Otherwise, there we no direct mentions that the skills would be in shortage, and the team sizes where typically growing steadily along with the number of AI use cases implemented.

Ransbotham et al. also talk about the complexity of managing make vs. buy situations with AI implementations as many different roles are needed for each project, from different disciplines. The front running companies therefore tend to resort on building up internal skills through hiring or training. (Ransbotham *et al.*, 2017) Additionally Ransbotham et al. worry that the smaller and less technologically experienced companies might face problems if they want to rely on purely outsourced AI operations as they also need some internal knowhow on how to screen for AI use cases and handle data. (Ransbotham *et al.*, 2017) This view also supports my findings as many of the case companies had decided to build their own AI team and expand their skills as opposed to purely outsourcing the operations.

Final barriers related to AI implementations are the rollouts and post-production, which success is determined how by well the end users are adopting the new tools to their everyday activities. This challenge is brough up by Chui et al. who observe that most AI implementations are actually enhancements to previous processes and tools instead of completely novel use cases, and where AI has to compete for budget and attention with many other tools and IT projects. (Chui *et al.*, 2018) The challenge of rollouts and convincing users the benefits of AI was the regular worry of the interviewees and many were still looking for good practices that could be used universally to guarantee that the AI implementation would not fall short in the very end of the project lifecycle with failed adoption. Chui et al. calls this the “last mile” problem, where the insights and gains from AI need to be integrated to the behavior of the people and organization as a whole. (Chui *et al.*, 2018)

Recognizing challenges is one thing but to be able to solve them effectively in real life situations is as important. To tie this Discussion chapter to bigger picture, and to guide the reader on how to potentially break down these implementation barriers to kick-start their own AI journey, I will compare the literature and case company best practices in the next sub-chapter.

5.2. Proposed best practices while scaling AI

The literature focused on AI implementation and scaling offers multiple guidelines and best practices that companies can apply and use to scale their own AI operations. In this chapter I compare how these practices are translated to real life in the Finnish context and what other potential best practices interviewees offer that are suited to their own AI teams' purposes. The structure of this chapter follows the project life cycle as in the previous chapter, but the key consideration is how well the advice given by literature and interviewees can be applied to wider audiences' goals and purposes.

How to kick off AI initiatives and guarantee appropriate budgets is typically the first consideration when companies start to think about implementing AI at scale. The recommended process to start off by Küpper et al. is to evaluate the company's pain points and benchmark the industry trends to assess the AI potential. Key part of this is also having solid IT infrastructure in place. The result of this assessment phase should be a clear AI implementation strategy, backed up by company's overall digital strategy. (Küpper *et al.*, 2018) However, Webb (2018) acknowledges that the current state of organizational processes that could allow these types of strategic digital transformations is not reality for most of the companies. (Webb, 2018) My findings also reflect the Webb's findings, as the initial spark was more likely to be a result of a personal interest and understanding of the current technological landscape, which then resulted in first AI projects, rather than well planned and prepared AI strategy initiatives. The size of the companies I research might skew my perception, since it's possible that even larger, more digitally mature companies could be using the methodologies proposed by Küpper et al. But the reality seems to be that this is not the case or possibility for majority of companies that have more acute issues to solve and cannot spare excess resources on forward-thinking technology or AI strategies.

Küpper et al. also stress the need for well thought out implementation roadmap that is prioritized based on the organizations challenges and pain-points and backed up by solid business case analysis. (Küpper *et al.*, 2018) The companies that I interviewed had many different ways to gather possible uses for AI and organize their road map. Based on the answers, I would claim that smaller company size is actually an advantage since the developers and AI team leads can have closer and more personal relationships with different business unit managers who feed the AI roadmap. Workshopping seems to be the industry standard according to both Küpper et al. (Küpper *et al.*, 2018) and the interviewees who facilitated these use case workshops and arranged other roadmap planning sessions regularly. To prioritize the use cases, sometimes the business case analysis was done to back up the decision-making, but sometimes the idea needs to be tested and verified before any real knowledge could be accumulated.

For the early development and testing of a potential concept to be solved with AI, light POCs as "fail-fast, minimum-viable-product approach" (Küpper *et al.*, 2018) is recommended and applied among all of the case companies. Sometimes predicting the results or business case potential beforehand without these trials is hard or even impossible and having the potential to test ideas and data and the ability to quickly scrape ideas that are too tough to handle is the key to fast scaling. One interviewee mentioned that the roadmap should allow for enough options that up to 80% of these early prospects and trials are actually scraped. Committing to full-scale implementations is easier when there is concrete evidence to support the business case. (Küpper *et al.*, 2018)

Fountain et al. also state that the responsibility of the high-level decision-makers is to create appropriate incentives for the business managers to apply AI in solving their challenges, since the threat of people becoming suspicious of AI as a tool or its capability is real. (Fountaine, McCarthy and Saleh, 2019) Demonstrating the differences in results and outputs of AI and "traditional" way of doing hands-on was commonplace occurrence for the interviewees but the more technical the organization was from the get-go, the easier the employees were to convince of the benefits of AI. Working closely with the business managers and working on the roadmap together with them was mentioned to be a good way of motivating and advancing the AI knowledge. Sometimes this even meant organizing info-seminars or informal lectures about AI with certificates for those who completed them.

To compare the actual project teams' compositions across companies is difficult due to the different technological needs and initial company profiles, in addition to the size and internal customer base for these projects. The options range from fully in-house AI team built slowly over time to partially outsourced development. (Chui *et al.*, 2018) Many interviewees stated the need for other skills, such as application programming and user interface design that they are looking from their recruits. The practices vary a bit among companies, but the need to combine AI programming knowledge with the integration and post-production maintenance seemed to be of regular concern for the AI team leads. It could be that the true best practice operating models are still in making, as the field is still young and growing. The literature suggest this multi-disciplinary approach as the preferred one as the different skills and perspectives are usually needed to implement effective AI based tools. (Fountaine, McCarthy and Saleh, 2019) When the project complexity exceeds the limits of the current team, interviewees stated that they were consulting outside vendors for support or altogether outsourced the solution development. Pricing and managing this were said to be somewhat cumbersome, but best practices include keeping yearly checks on the AI model accuracies and pushing the development phase to avoid prolonged POC and testing limbos.

For many AI implementations, the management of the different stakeholders is actually greater challenge than the technical development. (Paris *et al.*, 2017) Once the organization has successfully launched a few AI implementations, the internal opposition and barriers start to melt as the knowledge and trust is gained by the employees and high-up managers and the AI team has managed to internalize good operating models for facilitating use cases, managing the development and maintaining the production. (Fountaine, McCarthy and Saleh, 2019) Especially the rollouts and bringing the developed models to people was deemed as the greatest single challenge among the interviewees that were still looking for proper operating models and best practices to avoid or anticipate delays and challenges. When the number of processes to be maintained raises, the organizations also need to consider how large proportion of the AI teams time is spent on keeping the existing models running versus developing new implementations. Separate maintenance team, but within IT organization was the chosen operating model for one of the interviewees. For this issue to have a good guidelines and clear best practices requires more time to pass in order for the AI teams to mature and learn. Scaling AI is still new challenge for many organizations.

6. Conclusions

To wrap up my thesis, in this final chapter I bring the attention one last time to the research question and my initial hypothesis. I will explain how they are in my view important and under researched currently in the context of Finnish organizational literature on AI. I will then conclude by summarizing my findings and evaluating how relevant the new knowledge is for the reader who is familiar with the other literature on the subject. To close this thesis, I shall propose some areas for further research that I found interesting but intentionally left out of the scope of my thesis.

Adoption of AI has been growing steadily ever since the computing power of the modern machines have achieved a tipping point that allows for complete models to utilize large quantities of data. However, the implementing of AI at scale is still fairly limited to front-running technology companies, whereas the SME organizations struggle especially with scaling. The motivation for my thesis was to research this starting hypothesis in depth to help people in the field understand the potential challenges related to the pursuit of AI implementation at scale as well as offer new implementors some tools to spot and overcome barriers in advance. Allowing AI to be more accessible to different types of companies is important so that the gap between front-runners and laggards doesn't grow too large in terms of technology know-how. Even the Finnish government has stated in their AI strategy reports that the goal is to make Finland a leader in AI adoption and development. (Elinkeinoministeriö, 2017)

By studying the industry literature and interviewing a handful of Finnish companies that have been able to establish their AI operations at scale, I set myself to find out the most typical challenges that leaders of the AI teams have faced during their scaling period. The existing studies are mostly focused on large multinational tech-savvy companies whereas my research context was focused on variety of Finnish companies and organizations that operate in different environments and with different tools and resources available to them.

By interviewing managers and AI developers in different companies and organizations operating in varying industries, I managed to recognize the most typical challenges they have faced during each phase of the AI implementation project life cycle. The motivations behind implementing AI is fairly uncoordinated and lacking proper strategic planning. However, once the decision to invest is made and resources guaranteed, the AI starts to bring the promised benefits. There exist still many challenges to be solved along the project life cycle, that differ from the more typical technology implementation projects. However, interviewees had managed to overcome most of these by trial and error.

These findings support well my initial hypothesis that there exist some AI related barriers of entry and challenges during the early scaling phase, but by addressing these challenges early on, many SME companies can potentially avoid using too many resources during this initial phase of scaling. Implementing AI is a multi-disciplinary challenge and if the project managers or AI team leads fail to see this, and only try to implement AI as technical tool, there might be enough opposition that trumps the initiative before the benefits can be demonstrated. Being mindful of the different aspects discussed in this study helps the implementors to anticipate the challenges.

When reading this thesis, it is good to keep in mind that this is my first large scale research process about a field that I wasn't too familiar to begin with. By having some adjacent knowledge on technology project implementation beforehand, I was able to quickly dive into the subject. With the support of my employer, I was also given opportunities to implement AI personally and face these challenges firsthand. I did not include my own views from these processes in this research, but they definitely had an effect on my research process, as I was able to ask more defined question and have deeper conversations with the interviewees, as opposed to the situation where I didn't have personal hands-on experience on the subject matter. The AI field is evolving rapidly, so it is also important to keep in mind the context of this research and I hope many of the challenges mentioned in this thesis are trivial in the future.

This thesis did intentionally leave out the evaluation of different types of use cases in any other than surface level division as well as potential benefits that AI has managed to bring to different types of organizations. To further deepen the understanding and help future research and AI implementors in their work, I suggest a deep dive in to use case and AI business case analysis as a direct continuum of this thesis, as these areas are important especially in the early phase when the benefits are not yet crystal clear and budget allocations are competed with other potential tools and solutions. I would also suggest widening the scope of this study to even smaller companies, but same time admit that finding good representation could be harder as many of these smaller companies are still in the early phase of scaling AI and have not necessarily cumulated enough knowledge on their path towards AI at scale.

To conclude my thesis, I want to make an optimistic prediction that this time AI is here to stay and the path for many companies to adopt AI has never been better prepared and laden with opportunities and knowhow.

7. References

Artto, K., Martinsuo, M. and Kujala, J. (2006) *Project business*. 2nd editio, *Project business*. 2nd editio. Helsinki: WSOY. Available at: http://pbgroup.tkk.fi/en/.

Basford, T. and Schaninger, B. (2016) 'The four building blocks of change', *McKinsey Quarterly*, (April).

Beer, M., Eisenstat, R. A. & Spector, B., 1990. Why Change Programs Don't Produce Change. *Harvard Business Review,* Issue November-December.

Beer, M. & Nohria, N., 2000. Cracking the Code of Change. *Harvard Business Review,* Issue May-june.

Beyrouti, N. (2006) 'The Impact of Technological Innovation on Organizations , Work Environment and Personal Lives', *Portland International Conference on Management of Engineering and Technology*, 3(July), pp. 1133–1138. doi: 10.1109/PICMET.2006.296680.

Brown, S. and Eisenhardt, K. M. (1997) 'The Art of Continuous Change : Linking Complexity Theory and Time-Paced Evolution in Relentlessly Shifting Organizations', *Administrative Science Quarterly*, 42(1), pp. 1–34.

Bryman, A. (2012) *Social Research Methods*. 4th Editio. Oxford: Oxford University Press.

Bucy, M. (2016) 'The " how " of transformation', *McKinsey Quarterly*, (May).

By, R. T. (2007) 'Organisational change management : A critical review', *Journal of Change Management*, 5(4), pp. 369–380. doi: 10.1080/14697010500359250.

Cascio, W. F. and Montealegre, R. (2016) 'How Technology Is Changing Work and Organizations', *Annual Review of Organizational Psychology and Organizational Behavior*, 3(March), pp. 349–375. doi: 10.1146/annurev-orgpsych-041015-062352.

Chow, T. and Cao, D. (2008) 'A survey study of critical success factors in agile software projects', *The Journal Of Systems and Software*, 81, pp. 961–971. doi: 10.1016/j.jss.2007.08.020.

Chui, M. *et al.* (2018) *Notes from the AI Frontier: Insights from hundreds of Use Cases*.

Claudé, M. and Combe, D. (2018) *the Roles of Artificial Intelligence and Humans in Decision Making: Towards Augmented Humans?* Umeå University.

Davenport, T. H. (2005) 'Automated Decision Making Comes of Age', *MIT Sloan Management Review*, (February).

Dejoux, C. & Léon, E., 2018. *Metamorphose Des Managers:.* s.l.:Pearson.

Dewett, T. and Jones, G. R. (2001) 'The role of information technology in the organization: a review, model, and assessment', *Journal Of Management*, 27, pp. 313–346.

Eisenhardt, K. M. (1989a) 'Building Theories from Case Study Research', *Academy of Management Review*, 14(4), pp. 532–550. Available at: https://www.jstor.org/stable/258557.

Eisenhardt, K. M. (1989b) 'Making Fast Strategic Decisions in High-Velocity Environments', *The Academy of Management Journal*, 32(3), pp. 534–576.

Elinkeinoministeriö, T. (2017) *Suomen tekoälyaika*.

Eriksson, P. and Kovalainen, A. (2011a) 'Case Study Research', in *Qualitative Methods in Business Research*. London: SAGE Publications Ltd, pp. 115–136. doi: https://dx.doi.org/10.4135/9780857028044.

Eriksson, P. and Kovalainen, A. (2011b) 'Qualitative Research Materials', *Qualitative Methods in Business Research*, pp. 78–96. doi: 10.4135/9780857028044.d53.

Eriksson, P. & Kovalainen, A., 2008. *Qualitative Methods in Business Research.* London: SAGE Publications Ltd.

Euler, L., 1735. *The seven bridges of Konigsberg.* Newman: s.n.

Fossum, K. R., Danielsen, B. and Aarseth, W. (2018) 'A project management issue of new technology developments - A case study on lack of human factors attention in human-robot interaction', *Journal of Risk and Reliability*, (April). doi: 10.1177/1748006X17728601.

Fountaine, T., McCarthy, B. and Saleh, T. (2019) 'Building the AI - Powered Organization', *Harvard Business Review*, (July-August), pp. 62–73.

Gaddis, B. P. O. (1959) 'The project manager', *Harvard Business Review*, (May-June), pp. 89–97.

Garvin, D. A. & Roberto, M. A., 2005. Change Through Persuasion. *Harvard Business Review,* Issue February.

Gerbert, P. *et al.* (2017) 'Powering the Service Economy with Robots and AI'. Available at: https://www.bcg.com/publications/2017/technology-digital-operations-powering-the-service-economy-with-rpa-ai.aspx.

Gerbert, P. *et al.* (2018) 'The Big Leap Toward AI at Scale', *The Boston Consulting Group, BCG Henderson Institute*.

Heifetz, R. A. & Linsky, M., 2002. A Survival Guide for Leaders. *Harvard Business Review,* Issue June.

Hemp, P. & Steward, T. A., 2004. Leading Change When Business Is Good: An Interview with Samuel J. Palmisano. *Harvard Business Review,* Issue December.

IBM (2018) *Beyond the hype : A guide to understanding and successfully implementing artificial intelligence within your business*.

Jarrahi, M. H. (2018) ‘Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making’, *Business Horizons*, 61(4), pp. 577–586. doi: 10.1016/j.bushor.2018.03.007.

Jordan, M. I. and Mitchell, T. M. (2015) ‘Machine learning: Trends, perspectives, and prospects’, *Science*, 349(6245), pp. 255–260. doi: 10.1126/science.aaa8415.

Kahneman, D. (2009) ‘Conditions for Intuitive Expertise’, *American Psychologist*, 64(6), pp. 515–526. doi: 10.1037/a0016755.

Kegan, R. & Lahey, L. L., 2001. The Real Reason People Won't Change. *Harvard Business Review,* Issue November.

Kim, W. C. & Mauborgne, R., 2003. Tipping Point Leadership. *Harvard Business Review,* Issue April.

Kolbjørnsrud, V., Amico, R. and Thomas, R. J. (2017) ‘Partnering with AI : how organizations can win over skeptical managers’, *Strategy & Leadership*, 45(1), pp. 37–43. doi: 10.1108/SL-12-2016-0085.

Kotter, J. P., 2007. Leading Change: Why Transformation Efforts Fail. *Harvard Business Review,* Issue January.

Kraus, W. A. and Leonard-Barton, D. (1985) ‘Implementing New Technology’, *Harvard Business Review*.

Küpper, D. *et al.* (2018) *AI in the Factory of the Future - The Ghost in the Machine*.

Lacity, M. C. & Willcocks, L. P., 2018. *Robotic Process and Cognitive Automation: The Next Phase.* First Edition ed. Stratford-upon-Avon: SB Publishing.

Leibniz, G. W. v., 1887. *Philosophische Schriften.* Berlin: s.n.

Levesque, H. J. (2014) ‘On our best behaviour’, *Artificial Intelligence*, 212(1). doi: 10.1016/j.artint.2014.03.007.

Luger, G. F. (1993) *Artificial Intelligence: Structures and Strategies for Complex Problem Solving*, *Pearson Addison Wesley*. doi: citeulike-article-id:1048507.

Luhtanen, N. (2018) *How will automation impact corporate strategy planning process – case Finnish MNC*. Aalto University.

Magaña Martínez, D. and Fernandez-Rodriguez, J. C. (2015) ‘Artificial Intelligence Applied to Project Success: A Literature Review’, *International Journal of Interactive Multimedia and Artificial Intelligence*, 3(5), p. 77. doi: 10.9781/ijimai.2015.3510.

Mehta, D. and Schreiber, K. (2017) ‘Artificial Intelligence’, *Statista Report*.

Meyerson, D. E., 2001. Radical Change, the Quiet Way. *Harvard Business Review,* Issue October.

MIT SMR CONNECTIONS (2019) *Implementing AI : From Exploration to Execution*, *MIT SMR Connections*.

Nielsen, M. (2015) *Neural Networks and Deep Learning*. Determination Press.

Orlikowski, W. J. (1992) ‘The Duality Of Technology: Rethinking The Concept of Technologyin Organizations*’, *Organization Science*, 3(3), pp. 389–427.

Orlikowski, W. J. and Scott, S. V (2008) ‘10 Sociomateriality : Challenging the Separation of Technology , Work and Organization’, *The Academy of Management Annals*, 2(1), pp. 433–474. doi: http://dx.doi.org/10.1080/19416520802211644 PLEASE.

Paris, E. H. *et al.* (2017) *Artificial Intelligence: The Next Digital Frontier?*

Philip, H., Sales, A. L. and Hackett, E. J. (2006) ‘The Implementation and Adoption of New Technology in Organizations: The Impact on Work, People, and Culture’, *Human Resource Management*, 30(November), pp. 113–139. doi: 10.1002/hrm.3930300107.

Porter, M. (1986) ‘Technology and competitive advantage’, *Journal of Business Strategy*, 5(3). doi: 10.1108/eb039075.

Ransbotham, S. *et al.* (2017) ‘Reshaping business with artificial intelligence.’, *MIT Sloan Mangement Review and The Boston Consulting Group*, (September), pp. 1–17. doi: 10.3934/dcdsb.2008.10.925.

Rautio, V., 2019. *Tekoäly, Koneoppiminen ja Data Yritysten Liiketoiminnassa.* [Online] Available at: https://yrityksille.elisa.fi/ideat/kolme-oppia-tekoalyn-hyodyntamiseen/ [Haettu 18.9 2020].

Reeves, M. *et al.* (2016) *The Integrated Strategy Machine*.

Ronanki, R. (2018) ‘Artificial Intelligence for the Real World’, *Harvard Business Review*, (January-February).

Russell, S. and Norvig, P. (2003) *Artificial Intelligence: A Modern Approach*. Third Edit. Prentice Hall.

Schlesinger, L. A. (2008) ‘Choosing Strategies for Change’, *Harvard Business Review*, (July-August).

Sirkin, H. L., Keenan, P. & Jackson, A., 2005. The Hard Side of Change Management. *Harvard Business Review,* Issue October.

Stoica, I. *et al.* (2017) ‘A Berkeley View of Systems Challenges for AI’, *ArXiv*, (December). Available at: http://arxiv.org/abs/1712.05855.

Syam, N. and Sharma, A. (2018) ‘Waiting for a sales renaissance in the fourth industrial revolution : Machine learning and arti fi cial intelligence in sales research and practice’, *Industrial Marketing Management*. Elsevier, 69(January), pp. 135–146. doi: 10.1016/j.indmarman.2017.12.019.

Tulabandhula, T. and Rudin, C. (2014) ‘On combining machine learning with decision making’, *Machine Learning*, 97, pp. 33–64. doi: 10.1007/s10994-014-5459-7.

Turing, A. M. (1950) ‘Computing machinery and intelligence’, *A Quarterly Review Of Computing machinery and intelligence*, 59(236), pp. 433–460.

Waddell, D. (1998) 'Resistance : a constructive tool for change management', *Management Decision*, 36(8), pp. 543–548.

Webb, N. (2018) 'Notes from the AI frontier : AI adoption advances , but foundational barriers remain', (November).

Yin, R. K. (2001) *Qualitative Research from Start to Finish*. New York: The Guilford Press.

APPENDIX I

Definition of AI in the context of my research:

A branch of computer science dealing with the simulation of intelligent behavior in computers. The capability of a machine to imitate intelligent human behavior, such as learn and make decisions.

1. Background

Q1: Tell me about yourself and your experiences in the company?

Q2: What kind of AI background do you have? Here or elsewhere?

2. AI as part of Strategy

Q3: What kind of AI Roadmap was used or sketched out before the projects started? Why your company was interested in AI?

Q4: Who made the decision to buy/make? At what level?

Q5: What kind of development culture / history there is? Have you for example had many different development projects to try out different new technologies?

Q6: Was there internal concerns or discussions about Artificial Intelligence?

3. Added value

Q7: What specific problems AI was implemented to solve? What was the business case?

Q8: How the problem was selected? Was AI the only possible solution? Was others considered?

Q9: Did you find other possible problems after understanding rose?

Q10: Was the data readily available?

4. Project mechanics
Q11: What kind of project team was present?
Q12: What kinds of steps the project followed?
Q13: What kinds of challenges there were?
Q14: What kind of successes there were?
Q15: How was the final product rolled to production? How was it received and published?
Q16: Was there external barriers or regulations?
Q17: Are you planning to continue developing your AI related processes and services also in the future? How is your confidence on the technology after the initial trials?

Table 5. Interview guide