DEGREE PROJECT IN MECHANICAL ENGINEERING,
SECOND CYCLE, 30 CREDITS
STOCKHOLM, SWEDEN 2019

AI - an Untapped Opportunity for Innovation

Developing a screening tool for AI and Innovation

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Master of Science Thesis TRITA-ITM-EX 2019:64
Industrial Engineering and Management
KTH Royal Institute of Technology, Sweden

Industrial Engineering and Management	**Master of Science Thesis TRITA-ITM-EX 2019:64** **AI – an Untapped Opportunity for Innovation** *Developing a screening tool for AI and Innovation* Stefanos Aktas Thomas Wennhall	
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Abstract

It is known that innovation enables companies to penetrate new markets and achieve higher margins and that technology can contribute to achieving a competitive advantage and growth for organizations. A technology that has as of recently grown to become relevant for organizations is Artificial Intelligence (AI). Even so, previous studies have expressed the difficulty of implementing AI, which motivated this study.

The main purpose of this study was to develop and test a screening tool that will work as a support in increasing an organization's utilization of AI and innovation capability. During the course of the study, a great amount of focus was also put into conducting a preliminary analysis in preparation for a larger study that will be dependent on gathering large amounts of quantitative data.

The research took on a three-phase-process. The first phase focused on gaining basic knowledge in regards to AI, innovation, technology management and model development. The findings in the first phase helped to formulate proper research questions that were applicable to the study.

After that, the study moved on to the second phase which focused on a more in-depth literature study. This then led on to the development of an appropriate questionnaire for investigating factors that are relevant for AI and innovation, and an assessment model that would be connected to the questionnaire. The questionnaire was used for gathering responses that would be beneficial for the preliminary analysis in the form of a pilot study. The questionnaire and the assessment model together form a screening tool that gives a visual output of an organization's position in regards to AI and innovation.

The third and final phase included testing of the created screening tool, analyzing the findings from the pilot study and drawing conclusions from both the developed

screening tool, and the results from the pilot study.

The result from the literature study was the screening tool which takes five dimensions into consideration that shows relevance to AI and innovation. These dimensions are *Structures, Resources, Methods, Action and Business*, each containing areas that exist in organizations that can be adjusted for the sake of the implementation of AI and improvement of innovation management. The screening tool was tested on two separate organizations and managed to reflect these organizations' AI progress through the assessment model. The screening tool was also applied to the pilot study which resulted in giving indications of what to expect when conducting a larger quantitative study.

Despite the results gained from this study, it showed that further tests and studies need to be made in order to obtain more viable results. This study will act as a guideline for future studies to attain those results.

Industriell teknik och management

Examensarbete
TRITA-ITM-EX 2019:64

AI – en outnyttjad möjlighet för Innovation

Utveckling av ett genomlysningsverktyg för AI och Innovation

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Sammanfattning

Det är känt att innovation gör det möjligt för företag att tränga in på nya marknader och uppnå högre marginaler. Det är även känt att teknik kan bidra till att uppnå en konkurrensfördel och tillväxt för företag. En teknik som nyligen har vuxit till att bli relevant för företag är Artificiell Intelligens (AI). Trots det så har tidigare studier uttryckt svårigheten med att implementera AI, vilket motiverade denna studie.

Huvudsyftet med denna studie var att utveckla och testa ett genomlysningsverktyg som kommer att fungera som ett stöd för att öka en organisations utnyttjande av AI och innovationsförmåga. Under studiens gång lades en stor del av fokuset också på att konstruera en preliminär analys i förberedning för en större studie som kommer att vara beroende av att samla stora mängder kvantitativ data.

Forskningen utfördes genom en process uppdelad i tre faser. Den första fasen fokuserade på att få grundläggande kunskaper med avseende på AI, innovation, teknikhantering och modellutveckling. Resultaten i den första fasen bidrog till att formulera lämpliga forskningsfrågor som var applicerbara för studien.

Efter det så gick studien vidare till den andra fasen som fokuserade på en fördjupad litteraturstudie. Detta ledde senare till utvecklingen av ett lämpligt frågeformulär som undersöker faktorer som är relevanta för både AI och innovation, och även en bedömningsmodell som är kopplad till frågeformuläret. Frågeformuläret användes för att samla svar som bidrog till den preliminära analysen i form av en pilotstudie. Frågeformuläret och bedömningsmodellen bildade tillsammans ett genomlysningsverktyg som ger en visuell redovisning av en organisations position med avseende på AI och innovation.

Den tredje och sista fasen inkluderade tester av det skapade genomlysningsverktyget, analys av resultaten från pilotstudien och formuleringen av slutsatser gällande både

genomlysningsverktyget och resultaten från pilotstudien.

Resultatet från litteraturstudien var genomlysningsverktyget som tar hänsyn till fem dimensioner som anses vara relevanta för AI och innovation. Dessa dimensioner är *Strukturer, Resurser, Metoder, Handling och Affärer*, varav varje innehåller områden som existerar i organisationen och kan anpassas för att förbättra AI-implementering och innovationshantering. Genomlysningsverktyget testades på två separata organisationer och lyckades reflektera dessa organisationers AI framsteg genom bedömningsmodellen. Genomlysningsverktyget applicerades också på pilotstudien som resulterade i et antal indikationer av vad som kan förvätas i en större kvantitativ studie.

Trots resultaten från denna studie visade det sig att ytterligare tester och studier måste göras för att uppnå mer pålitliga resultat. Denna studie kommer att fungera som riktlinje för framtida studier för att uppnå dessa resultat.

Foreword

This thesis was conducted in 2018 and is part of the master's track Innovation Management and Product Development at the Royal Institute of Technology.

This master's thesis is part of a larger study that is being conducted at the Royal Institute of Technology in collaboration with the consulting agency Seavus. The role of the thesis in relation to the larger study is to act as a pilot study of sorts.

Here we take a moment to extend our gratitude to some important people who made this thesis possible to finalize.

To our supervisor Jenny Janhager Stier, researcher at the Royal Institute of Technology, thank you for guiding us and always being available to provide invaluable feedback when it was needed.

To our contact person at Seavus, Reijo Silander, thank you for meeting us every week and giving us an insight into the world of AI that would have been difficult to reach without you.

To all of our close friends and family who have offered us their support in all kinds of ways during our time writing this thesis, we are both very thankful.

Stefanos Aktas
Thomas Wennhall

Stockholm, November 2018

Nomenclature

AI	Artificial Intelligence
CS	Computer Science
GDPR	General Data Protection Regulation
AIIM	AI Innovation Maturity
ICMM	Innovation Capability Maturity Model
ISM	Innovation Strategy Model
BMI	Business Model Innovation
GPT	General Purpose Technology

Contents

1 Introduction

It is stated that technology can greatly contribute to achieving a competitive advantage and growth for companies, but efficiently integrating it into the business processes is very complex and requires considerations in different perspectives including the technical, the marketing, the finance and the human resources perspective (Cetindamar et al., 2010). Technology enables a business to quickly adapt to changing customer demands and enables access and development of new market opportunities, if combined with highly motivated and properly trained people.

Looking at the past, the computer revolution became possible by introducing new ways to to make arithmetic inexpensive (Agrawal et al., 2017). Before computers, humans were employed to do arithmetic problems. Since then, computers have become widespread and used for other tasks, such as to communicate, play games and music, design buildings, and even produce art. The computer has over the years been recognized as a General Purpose Technology (GPT), meaning that it has the potential to affect the entire economic system and can even lead to social changes such as working hours and constraints on family life (Helpman, 1998).

Another technological evolution shortly after the computer was the Internet (Naughton, 2016). The Internet, like the computer, has become widely known to be regarded as a GPT with its several areas of use.

Brynjolfsson et al. (2018) believe that AI has the potential to be the GPT of our era. This will however require numerous complementary innovations within products, services, work flow processes, and even business models. But ultimately, it is believed that AI will have an important effect on the economy and public welfare.

The expectations for Artificial Intelligence (AI) are immense (Ransbotham et al., 2017). Firms are gradually realizing that AI has the potential of becoming a valuable asset in their organization. Even so, AI is not a simple plug and play solution (Gerbert et al., 2017). Although elements of AI are available in the market, managing the interplay between data, processes, and technologies is hard work that is done within the organization.

Despite the admiration it has received, there is currently a great gap between the ambition and execution of AI initiatives for companies (Ransbotham et al., 2017). A study performed by MIT Sloan Management Review along with The Boston Consulting Group showed that about 85% of the participants in the study believe AI will allow their companies to obtain or sustain a competitive advantage, but only less than 39% of the companies have a business strategy in place that involves AI. Even though a large amount believe that AI is necessary for the survival of the organization, less than half of the companies in the study are prepared for it. According to the Principal Digital Technology of GE Oil & Gas in a study made by Capgemini (2017), *"Organizations are now convinced of the benefits that AI can bring. They are now asking themselves where and how they should invest"*.

Innovation enables companies to penetrate new markets and achieve higher margins (Shilling, 2013). However, it is also a competitive race of which speed, skill and precision are key. It is therefore not enough for companies to only be innovative, but they need to innovate more than their competitors.

According to a study conducted by Gerbert et al. (2017), which was a cooperation between BCG and MIT Sloan Management Review, AI will have a major impact in all industries within upcoming years. The question however is how can companies make use of AI to spur their innovation capabilities?

1.1 Purpose

As previously stated, people are aware of advantages that can emerge from applying AI to their current organizations, but are uncertain of how to realize the task of introducing the technologies.

The introduction of AI can be supported by consultancy firms that specialize in assisting organizations with increasing their AI performance. This requires identifying where in the organization there is a need to make adjustments to create a better environment for AI-adoption.

The main purpose of this study is to develop and test a screening tool that can help with analyzing several areas within an organization and give an output of the organization's level of "maturity" when it comes to AI and innovation in the respective areas. This tool can then be used by consultancy firms to analyze specific areas within organizations that are in need for support in order to streamline the implementation process and eventually make the AI implementation a reality. The tool will also focus on identifying factors relevant to the organization's innovation work that can be improved to ensure that the organization's AI will continuously improve and remain sustainable.

Another reason for including innovation related factors in the tool is to find if there is a correlation between AI-maturity and innovation capability maturity. If a correlation is found, it can lead to a more effective implementation of AI while simultaneously supporting innovation. The second purpose of this study is, therefore, to prepare for a larger study that will be dependent on gathering large amounts of quantitative data. This is to investigate the following:

- How AI is used in Sweden.
- Possible relations between AI and Innovation.

The preparation for the larger study will be done through a pilot study, which requires a smaller amount of quantitative data.

1.2 Delimitations

The literature study will not focus on any specific AI-technologies or any sub-areas of AI, nor will it focus on any specific type of innovation. Both major areas covered in the literature study will be researched as broadly as possible, hence not looking at specific areas within AI or innovation.

This study focuses specifically on respondents that have an insight in both the innovation section, and the AI section of their respective organization.

For this study, the quantitative data gathering will be done in Swedish.

Due to the timespan and lack of resources, this study will act as a pilot study to give an indication of what to expect from a larger study.

2 Background

As mentioned earlier, the expectations for AI are great and its value is starting to get recognized by various types of firms. Organizations know that AI has the potential to change how current industries do business but do not know how to implement it in their business. Recent studies have shown that AI will be crucial for organizations to implement in the future to survive (Ransbotham et al., 2017). While it is suggested that AI will be important in the future, it has been stated that innovation is essential for companies to survive and remain competitive in the present (Shilling, 2013). This study investigates if proficiency in the use of AI has any connection to an organization's ability to innovate.

This section covers areas such as Artificial Intelligence, Innovation, Technology management and Model development.

2.1 Artificial Intelligence

This section is divided into two due to its vastness. The *Definition and origin* section focuses on the interpretation of AI and how it was coined while *The progress of AI* explains the journey AI has gone through up until now.

2.1.1 Definition and origin

The concept of AI has several interpretations of what it is. According to Bostrom (2014), AI can today be perceived in three different ways. The first is that AI is something that might answer all your questions, with an increasing degree of accuracy, like an "Oracle". The second is that it could do anything it is commanded to do, such as a "Genie". The third interpretation is that it might act autonomously to pursue a certain long-term goal, like a "Sovereign".

According to Webster's dictionary, AI is the capability of a machine to imitate intelligent human behavior (Merriam-Webster, 2018). There are different types of intelligence when it comes to AI and they can be divided into three levels (Annergård and Zetterberg, 2017):

- Artificial Narrow Intelligence which is a machine intelligence solely intended to perform a specific task
- Artificial General Intelligence which possesses intelligence corresponding to a human being and can therefore be used for problems that are solvable by humans.
- Artificial Super Intelligence which is a level that exceeds the best human experts within one or several areas such as science, creativity, social behavior, common knowledge etc.

The term Artificial Intelligence was brought up as early as in 1956, where John McCarthy and a group of experts came together for a two month workshop to discuss the topic of intelligence simulation (Corea, 2017). It can even be traced back to a couple years earlier when the late Alan Turing published a paper in which he proposes for the first time, the idea of a thinking machine and the more popular Turing test to review whether such a machine, in fact, shows any form of intelligence.

Many confuse AI with the term machine learning, which is an application of AI. Machine learning is based around the idea to give machines access to data and let them learn for themselves (Marr, 2016). AI is a broader concept. Tecuci (2012) defines AI as a field in computer science that exhibits the qualities that are associated with human intelligence, they are: perception, natural language processing, problem solving, planning, learning, adaptation and acting on its environment, and this definition is used in this work.

2.1.2 The progress of AI

Since it was first defined, AI has had its ups and downs in progress. In the early days, successful AI seemed to be easily reachable (Corea, 2017). It later became clear that that was not the case.

Several AI-related projects were initiated between the fifties and sixties (Corea, 2017). McCarthy initiated a high-level AI programming language by the name Lisp which became the dominant AI programming language, and published a paper in which he described a hypothetical program that went by the name Advice Taker, which can be seen as the first complete AI system. Early work on neural networks was also starting to make progress. AI researchers were very optimistic in regards of the progress AI would make in the near future (Russel and Norvig, 2010).

It did not take long until the difficulty of successfully creating AI became clear. In the late sixties and early seventies issues arose when trying to apply AI. The problem was a lack of knowledge in scaling up the AI to complex real-world problems (Tecuci, 2012). Difficulties such as AI programs not knowing of the subject matter, being unable to solve complex issues and the fundamental limitations on the basic structures of the AI resulted in funding being reduced to nearly nothing (Russel and Norvig, 2010). Thus began “the AI winter”.

It was not until the eighties that AI received fundings again due to the introduction of “expert systems” which essentially were AI systems narrowed down to specific functions, or artificial narrow intelligence (Corea, 2017). It did not last long until AI hit another bump on the road. In 1987, personal computers started advancing to the point of being more powerful than the Lisp Machine, which was the product of years of research within AI, it initiated the coming of the second “AI winter”. This period ended in 1993 when the MIT Cog project was initiated to build a humanoid robot and other progresses being made for AI.

Since then, AI had been researched but was only recognized as a paradigm shift (Corea, 2017). Although in 2012, a group of researchers made substantial progress in improving the classification algorithm and set the use of neural networks as fundamental for artificial intelligence. According to Corea (2017), this acted as the trigger for the popularity of AI.

According to AI Index which is an open, not-for-profit project to track activity and progress in AI, the numbers of AI papers produced each year has increased by more than nine times between 1996-2015 in the Scopus database (Shoham et al., 2017). It also shows that the number of active startups in the US has increased 14 times between 2000-2015.

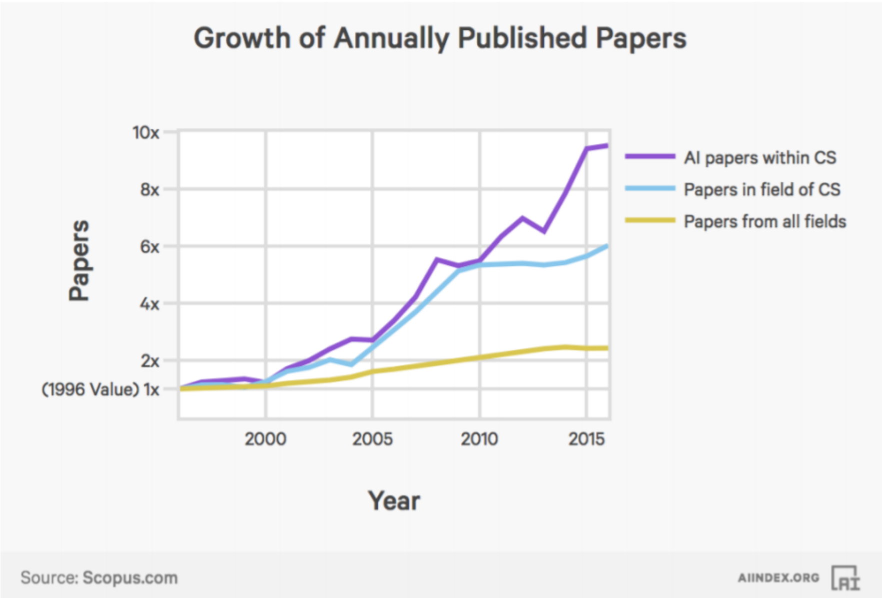

Figure 1: Illustration of the growth in numbers of published papers within Computer Science (CS) (Shoham et al., 2017)

AI is continuously growing and improving, but there have been many concerns that AI might be about to reach its peak yet again (Dhar, 2016). Corea (2017) believes that there are three reasons for why this will not occur. The first is the technological progress, meaning that technologies have become both better and cheaper since the past. The second is due to the resources democratization and efficient allocation introduced in business models belonging to companies such as Uber and AirBnb. The third reason is the increased availability of bulks of data that is needed to feed the algorithms. According to the cofounder of the machine-learning company Vicarious, at least 80 percent of the recent advances in AI can be attributed to the availability of more computer power (Hof, 2013).

Today, AI has become a global race between countries (Dutton, 2018). Countries such as China, France, India, Italy, Japan, South Korea, Sweden etc have all released their own strategies to promote and develop AI in their respective nation. These strategies involve policies regarding scientific research, talent development, skills and education, public and private sector adoption, ethics and inclusion, standards and regulations, and data and digital infrastructure.

The government of Sweden has released a document stating that Sweden is going to be the best in the world when it comes to utilizing AI (Regeringskansliet, 2018). This includes adapting areas such as within education, research, innovation and the infrastructure in Sweden to get the most out of what AI has to offer. For this to be possible organizations need to be innovative.

2.2 Definition of Innovation

This study aims to find how companies adopting AI can do so with the best effect on their ability to innovate. To measure how well an organization innovates and to communicate it in this study, first a definition of innovation is needed.

There is no doubt that it is imperative for organizations to successfully innovate to stay competitive in today's market (Corsi and Neau, 2015; Domínguez-Escrig et al., 2018; Edison et al., 2013; Lee and Trimi, 2018; Tidd et al., 2005). Corsi and Neau (2015) call innovation "*the driving arm for evolving organizations*" and stress that innovation is more than an approach, a process or a set of results, it is a way of thinking evolution.

While there are several factors to fulfill to achieve success in the marketplace, the ability to employ knowledge, skills and experience to create and deliver new products and services (to innovate) is an increasingly dominant way to achieve competitive advantages (Tidd et al., 2005). Lee and Trimi (2018) argue that the ultimate goal of innovation is to create a better future which implies that it is indeed essential, but what is it?

In the literature, plenty of different definitions of innovation are presented. Edison et al. (2013) conducted a thorough literature review to define innovation and found that there are different aspects of innovation from which it can be categorized. Based on the impact of innovation they defined four categories; *incremental innovation, market breakthroughs, technological breakthroughs and radical innovation*; based on four **types of innovation**; *product-, process-, market- and organization innovation.* Lee and Trimi (2018) chose to use only four categories of innovation: *incremental-, radical-, ambidextrous- and disruptive innovation* in their study "*innovation for creating a smarter future*". The *incremental-, radical-, and ambidextrous innovation* categories are explained more in depth here. These categories are chosen because they describe innovation in a way that does not exclude any type of innovation.

Incremental innovation is improvement of what is already known. It is minor changes in technology based on existing platforms which results in minor benefits for the customer or user (Bessant et al., 2014; Edison et al., 2013; Lee and Trimi, 2018).

Radical innovation is in contrast to incremental innovation something that comes from the previously unknown and introduces new values to users and new profits to the organization (Lee and Trimi, 2018). Edison et al. (2013) refer to radical innovation as **disruptive innovation** and and explain that it introduces first time features or extraordinary performance. It uses completely new technology at a cost that has the potential to change (disrupt) the current market or create a new one (Edison et al., 2013; Lee and Trimi, 2018).

Ambidextrous innovation refers to the development of the dynamic capabilities that are needed to simultaneously create both incremental- and radical innovation (Lee and Trimi, 2018; Tushman and O'Reilly, 1996). The notion of ambidexterity also applies to the ability to create the different **types of innovation** presented by Edison et al. (2013) simultaneously (Lavie and Tushman, 2010).

After their extensive literature review and the input from interviews, Edison et al. (2013) decided to recommend this definition of innovation by Crossan and Apaydin (2010):

"Innovation is: production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and establishment of new management systems. It is both a process and an outcome."

This definition is chosen for this study and special consideration will be put on ambidextrous innovation.

2.3 Technology Management

Technological changes are continuously creating new challenges and opportunities for new product, service, process and organizational development and also for industrial expansion (Cetindamar et al., 2010). It has been the driving force in the 20th century and it will continue to hold the same if not even greater importance in the 21st century. Organizations that are greatly capable of managing the creation, development and application of technology are considered to be successful and in the forefront of technological innovation. (Antoniou and Ansoff, 2004)

Technology management develops and exploits technological capabilities that are changing continuously (Shilling, 2013). It is not considered to be the same as innovation management, as innovation management applies to the development and exploitation of several types of capabilities, not only the technological capabilities. Technological innovation is considered the most important driver for competitive success in many industries.

According to Antoniou and Ansoff (2004), it is essential for general managers to have the mindset and skills to interpret the direction the technology is taking in today's turbulent environment. To assure future success for an organization, their strategic direction should be determined by anticipating the future needs of the environment (Tichy and Sherman, 1993). Managers that tend to be myopic do not support technological developments that would serve to be most successful for their firm's future. (Antoniou and Ansoff, 2004).

2.4 Model Development

Organizations always want to improve and to do so the first step should be to understand where they are currently at. That is why there is a lot of literature about assessing, evaluating or measuring different organizational processes and methods (Edison et al., 2013; Metrics, 2009). Innovation capability measurement has evolved but there is still a lack of metrics for it. Edison et al. (2013) explain that one of the reasons for this is that there is still not a common understanding of what innovation is and that therefore, organizations only measure innovation performance for which there is no standard.

There are a number of studies to be found in the current work of literature about innovation capability measurement but according to Edison et al. (2013) the only validated innovation measurement model is the technological innovation audit by Chiesa et al. (1996). The most well-developed tools found during this study were the Innovation Capability Maturity Model (ICMM) by Corsi and Neau (2015), the ICMM by Essmann and du Preez (2009), and the Innovation Strategy Model (ISM) as presented and used by Fruhling and Siau (1996).

The book in which Corsi and Neau (2015) presents the ICMM, a thorough foundation and reasoning for the model's structure is also presented. The model is designed to support organizations in finding what needs to be done next on their journey to become successful innovators. They describe the model as "*a maturity model for organizations to track themselves on their ability to act on innovation*". They found that similar "*structural phases*" laid the foundation for innovation success regardless of industry and corporate culture. These phases were named "*maturity levels regarding the issue of innovation and regardless of field of operations*". Each maturity level was defined based on a set of 12 questions. The maturity levels span from level 0 - no need to innovate - to level 5 - dynamic, total and sustainable innovation. Each level is explained in depth and examples on actions are included.

Essmann and du Preez (2009) developed the ICMM as part of a PhD thesis. Similar to Corsi and Neau (2015), Essmann and du Preez (2009) present a detailed explanation of how the ICMM was developed. The ICMM consists of three areas in which the components of the model are categorized, these are:

- a framework which provides the structure of the model
- the core requirements for innovation capability representing the primary content of the model
- the organizational roles required for innovation.

The abovementioned framework contains 3 dimensions: an Innovation Capability Construct, an Organizational Construct and Capability Maturity. The capability maturity dimension is divided into five levels that can be described as:

Level 1 - Ad Hoc Innovation. This level is characterized by maximising short-term revenue and reducing cost.

Level 2 - Defined innovation. A basic understanding of the different factors that affect innovation has been established.

Level 3 - supported innovation. Innovation is supported and managed with relevant practices, methods and tools.

Level 4 - Aligned innovation. A deep understanding of the in-house innovation model and its relationship with business requirements has been established.

Level 5 - Synergized innovation. Synergy is achieved through the alignment of innovation strategy and business and the synchronization of relevant actions.

To complement the ICMM, Essmann and du Preez (2009) developed an Innovation Capability Questionnaire. This questionnaire can be used to relate an organization's situation to the framework and in particular, the five levels of Capability maturity to determine its innovation Capability Maturity.

The ISM has successfully been put to use to asses organizations' innovation capability (Fruhling and Siau, 1996). The ISM has arguably the most pedagogic and easily interpretable presentation of its results. Fruhling and Siau (1996) describe the ISM as "*... a systematic framework and a useful tool for analyzing an organization's competencies and abilities to create and move ideas into practice*". The ISM is not only an evaluation model, but it can also be used to identify flaws in an organizations innovation capabilities to then allow distinct actions to be taken. The use of the ISM has been summarized as: "*It enables an organization to take an innovation snapshot of the entire organization*".

The ISM consists of 10 dimensions of innovation capability. The ratings received for the dimensions are based on several questions specific for each individual dimension. The ratings are then presented on a radar chart (see figure 2) where the individual ratings make up a whole.

Apart from its primary use for assessing an organization's innovation capability, Fruhling and Siau (1996) recommend the ten dimensions of the ISM as a good start for organizations to analyze how prepared they are for implementing new IT. Fruhling and Siau (1996) used the ISM to analyze two different organizations' innovation capabilities with special regards to their recent push into IT.

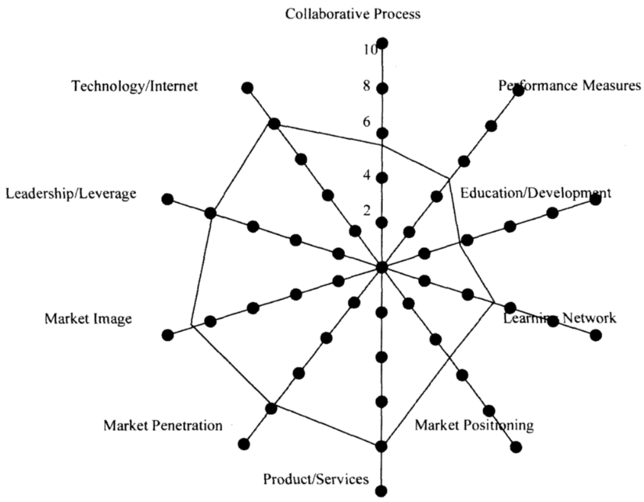

Figure 2: The ISM radar chart presenting results from a case study (Fruhling and Siau, 1996)

Literature on AI-maturity measurement are profoundly scarcer because of the field being relatively new. Also finding literature on AI-maturity from a management and organizational perspective is very challenging. However, literature concerning these topics were found. A report from Corporation (2018) and one by Groopman (2018) give an insight into the current state of the literature on the subject as they both write about AI readiness. Corporation (2018) presents some important factors for organizations to take into consideration when implementing AI and categorize them as foundational, operational, and transformational. Groopman (2018) identify and present five areas of AI readiness, namely: *strategy*, *people*, *data*, *infrastructure*, and *ethics*.

When developing the ICMM Essmann and du Preez (2009) made an attempt of defining maturity. Their attempt resulted in the following definition which was described as generic in nature and excluding of the system's purpose, "*A system assessed to be optimally fit for its purpose, as described by its designer*". This definition is used in this thesis and should be able to cover the terms, innovation maturity and AI-maturity.

3 Research questions

An ambition for this thesis is to help organizations understand how to build better environments for AI adoption and how it relates to an organization's innovation work. The thesis will consider different factors for managing, implementing and organizing for AI to increase the chances of becoming successful in that field. The approach for meeting this task will be based on two research questions that were formulated for this study.

There are several articles regarding the measurement of innovation capability maturity, but as of now, attempts of measuring AI-maturity have not been found. To create a tool for the sake of simplifying the introduction of AI into organizations, it is important to know what factors are essential for AI-maturity. Therefore, the question "what is AI-maturity?" covers what factors are important. This led to the definition of the first research question:

> *RQ1: What is AI-maturity, and how can it be measured?*

In this study a tool for measuring the AI-maturity, as well as the innovation capability of an organization is being developed. This presents an opportunity to find possible common factors that are applicable for both areas in organizations. If these factors are identified it will hopefully introduce positive effects on both AI development and innovation capabilities. This introduced the definition for the second research question:

> *RQ2: What similar characteristics and capabilities are beneficial for both AI development and innovation capabilities?*

4 Method

In this chapter the methods used for the study are presented. First the general approach is presented followed by more detailed explanations of the literature study and the development of the questionnaire.

4.1 Research Approach

The research took on a three-phase-process; the first phase spans from beginning to formulated research questions as suggested by Payne (2013). The second phase involves the deeper literature study which would provide the required support for the development of the model as mentioned by Turner (2018), and also the questionnaire. The third and final phase includes tests, analysis and conclusions.

Phase one included learning about the project and getting familiar with the area of the study. The process was straightforward: find and collect literature about AI and innovation, and read about these (see figure 3). Because of the newness of AI in literature, most of the initial literature study went to searching for relevant literature about AI and managing AI. This resulted in the background of the study which in turn led to formulating the research questions on which the rest of the study would be based.

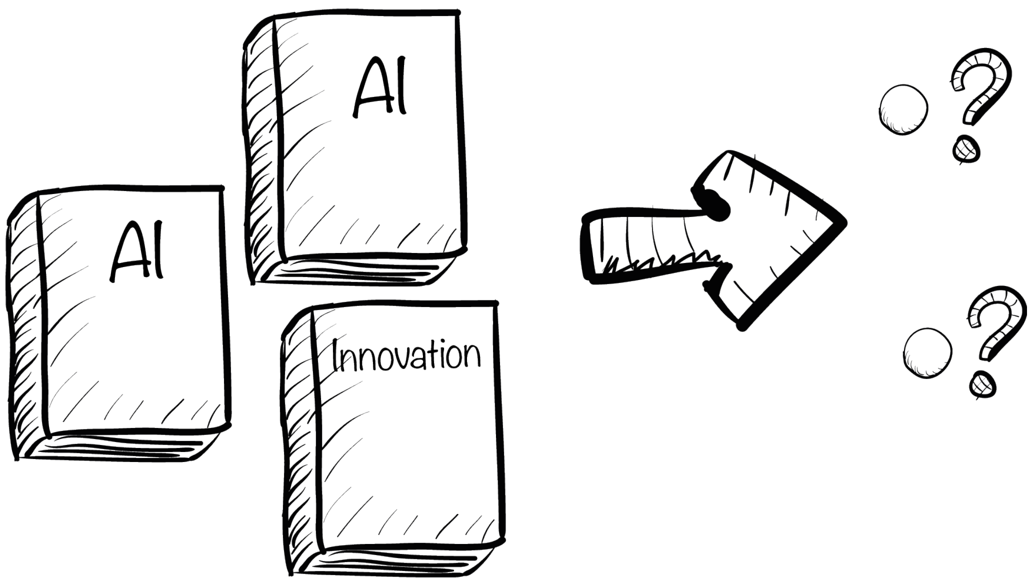

Figure 3: The first phase of the method resulted in two research questions based on literature

Phase two, the main part of the study followed an approach inspired by scrum methodology (Gonçalves, 2018). Using scrum in a research environment is not common but can be justified by describing a research project as an unstable and complex process that needs to stay agile, ie. able to change over the course of the project (Marchesi et al., 2007).

During this part of the process, meetings were held with an AI-expert at a consultancy firm on a weekly basis, similar to sprints used in scrum methods. The sprints were one-week-long boxes (Popli and Chauhan, 2011). A sprint started by having a meeting with the AI-expert where the team presented results from the previous week and then decided together with the AI-expert which requirements were needed to be fulfilled until the next session.

The iterations confined within the sprints involved studying literature and building the questionnaire and assessment model (see figure 4). Assessment is "*the process of considering all the information about a situation and making a judgement*", the assessment model uses the data from the questionnaire to help make a judgement of an organization's AI-maturity and innovation capability (Cambridge Dictionary, 2019). New literature findings led to input in the questionnaire and assessment model which are intertwined. Modification of the questionnaire and assessment model then identified new goals for the literature study. Input from the AI-expert and occasionally also from innovation researchers completed an iteration. Using an agile approach to this study allowed for this iterative process to flow smoothly.

Five dimensions were created to categorize the literature and all questions and statements that were identified for the questionnaire. These dimensions changed along the way to adapt to the content of the assessment model. With a growing understanding of the whole concept that was being created with the assessment model, and a larger amount of literature and subsequently questions and statements as well, a number of areas in which the questions could be categorized were identified.

This phase of the study resulted in a complete literature study, a questionnaire and an assessment model which were both ready for testing.

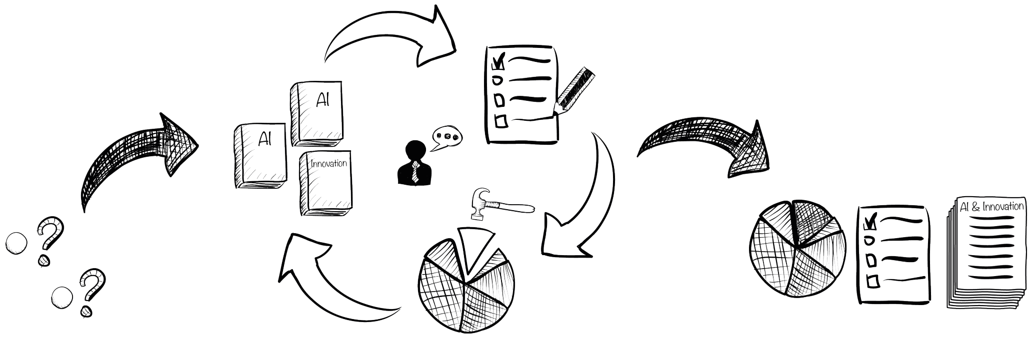

Figure 4: The iterative work in phase 2 was based on the research questions and resulted in a literature study, a questionnaire and an assessment model

Phase three involved synthesizing the literature, testing both the questionnaire and assessment model, collecting questionnaire data and analyzing the collected data to finally draw conclusions for the study. This final part took on a more traditional step-by-step process (see figure 5).

The synthesizing of the literature took into consideration all similarities that were found for the two main fields of study (AI and innovation) respectively and presented them together. The questionnaire was distributed to a number of people at a number of organizations in order to test its functionality, usability and usefulness (Chiesa et al., 1996). This initial test helped detect flaws in the questionnaire and the assessment model. Flaws of various nature were discussed and corrected. The last part of the study resulted in an assessment model ready for beta-testing.

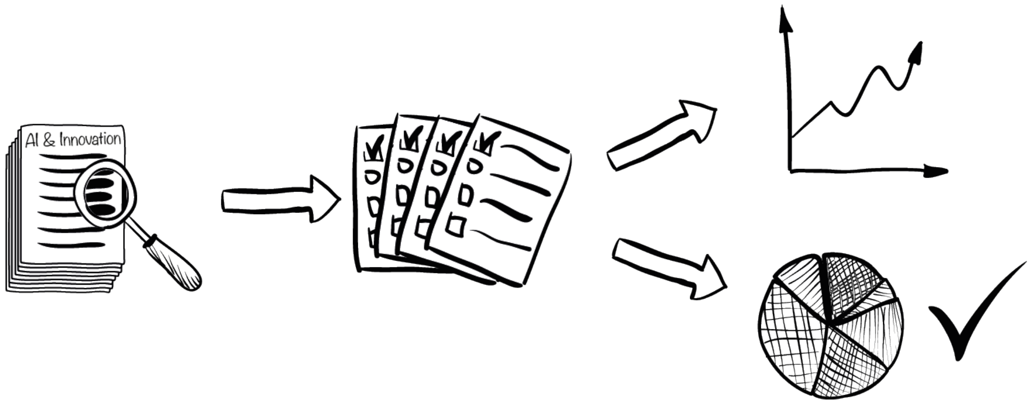

Figure 5: The third phase included synthesizing the literature and collecting questionnaire responses which resulted in tests of both the questionnaire and the assessment model respectively

4.2 Literature study

The literature study was conducted in two phases; initial study and main study. During the initial study the focus was mainly on learning about AI from an innovation, management and organizational perspective, and to build a basis within technology management and model development. The goal of the initial study was to be able to formulate the research questions. The main literature study followed an iterative process in conjunction with the rest of the project. The goal of the main study was to find theory to build an assessment model and a questionnaire to identify different aspects that are important for sizing up the AI application work at various organizations, and evaluate their innovation work. The assessment model and questionnaire were later combined to create a tool.

The first step was creating a map of keywords concerning the two subjects (see Appendix A). The different words were combined in different ways and used to search for literature, mainly through the search engines Google Scholar and the KTH Library, but also in various scientific journals. A lot of the most useful literature was found using backwards reference search in already selected literature (Levy and Ellis, 2006). The first selection phase was based on the relevance found in the title and abstract of each article. During the second selection phase the articles were read through to find relevant data.

Searching for literature in the various fields proved to be different from each other. Innovation-related literature which is plentiful was easily found in many books, different types of articles and so on. The challenge here was to find the most relevant information among all the literature. Searching for AI-related literature on the other hand, was as anticipated, not very easy. Here, the challenge was to find any relevant literature since the subject is so fast-growing and still changing a lot. The information is difficult to find when searching for literature on AI from a managerial and organizational point of view. Most AI literature was found through new studies conducted at universities and research institutes.

The last part of the main literature study took place after all relevant literature from both innovation and AI had been collected. To find possible similarities between the two fields, a synthesization of the literature was conducted. The synthesization involved comparing and contrasting the two different perspectives on the topic. (Leedy and Ormrod, 2005)

4.3 Questionnaire

The method used for analyzing organizations' AI-maturity and innovation capability was through a questionnaire. From this questionnaire, both data for analyzing the research questions and data for evaluation through the assessment model can be gathered (Essmann and du Preez, 2009). The tool (the combination of assessment model and questionnaire) was designed to be used to evaluate different types of organizations. The questionnaire was designed to be answered by people who possess a certain insight within both the AI and innovation capabilities of their respective organization.

The questionnaire was tested twice to determine if it would work as a reliable data collecter for the tool and for analysis concerning the second research question. Both tests included pinpointing problems that the respondents identified, which would result in determining if the questions are easily interpretable, ensuring that the respondents are not influenced by the order of questions and, generally put, to reduce the respondents' burden.

The first test was done internally in iterations with the assistance of an AI-expert at a consultancy firm, the innovation researchers at KTH and other acquaintances to adjust the questionnaire according to the feedback received.

For the second test, the questionnaire was used to perform a preliminary analysis which took form as a pilot study. There are two reasons for performing a pilot study. The first is due to its ability to allow a pre-testing of a particular research instrument (Baker, 1994), and the second reason is for making a small scale version of a study in in preparation for a larger study (Polit et al., 2001). According to Ruel et al. (2016), pilot studies prove to be beneficial as they usually show whether the project is feasible, realistic, and rational from start to finish, which may not guarantee success in the main study, but does however increase the likelihood. A rule of thumb for a pilot study is to include around 30 to 100 participants, but can vary depending on the number of respondents in the included sample. The data which was collected in the pilot study helped with assessing and subsequently identifying flaws related to the questionnaire, such as what questions or parts of the questionnaire respondents found difficult to understand (similar to the first, internal test). The data from the pilot study also provided an indication of what results to expect if the questionnaire is used in a larger study. Gathering respondents for the questionnaire was made through connections provided by the AI-expert at the consultancy firm, the students and also by contacting various knowledgeable people through LinkedIn and by email.

The data collected in the pilot study was used to test the assessment model to see if it would work as a good way of visually presenting the length of AI-adaptation in different organizations. A sustainable method for translating the questionnaire results to the visualization in the assessment model was not developed. What was used in this case is a method where the different responses from the questionnaire are compared to each other in an Excel document and manually calculated and put into the assessment model in Adobe Illustrator.

To formulate one question or statement, specific theory was translated into something that could be answered on a Likert scale. Most questions and statements in the tool were formed to use the Likert scale, which has multiple options from which respondents choose based on their opinions, attitudes or feelings in regards to the issue. The advantages of using Likert-scale surveys are; that the data can be gathered relatively quickly from a large amount of potential respondents, they can provide highly reliable person estimates, the validity of the interpretations that is made from the provided data can be made through different ways, and the data acquired from the survey can be used to compare or even combine with qualitative data-gathering techniques (Nemoto and Beglar, 2014).

A typical Likert scale statement would give the respondents 7 options to answer from, gradually going from 1: "Strongly disagree" to 7: "Strongly agree", with an additional option: "Don't know".

An important note when creating a questionnaire is the length of it and the duration it would take for a participant go over the entire survey. Longer questionnaires result in greater respondent burden and may lead to lower response rates and diminished quality of response (Hugick and Best, 2011). Hugick and Best (2011) suggest that this is true when an online survey exceeds 20 minutes. Not exceeding 20 minutes is common for online questionnaires as Crawford et al. (2001) showed in a study: that online questionnaires that took longer than 20 minutes to go over had a significantly high non-response rate. This is relevant when using the questionnaire for the sake of gathering information from several organizations for a quantitative study, but not as critical when the questionnaire is used as a screening tool within organizations.

5 Literature study

In this section the results of the literature study are presented. The topics involving AI and innovation are presented separately. When going over the literature involving AI, a few topics came to mind which were used to structure the theory on AI. These topics are *The potential of AI*, *Challenges toward AI*, and *The need for data*. The innovation literature is divided into two topics: *Organization & Culture*, and *Idea management*.

5.1 Potential of AI

Today, expectations for AI run high across industries, company sizes, and geography (Ransbotham et al., 2017). A global study made by MIT Sloan Management Review involving over 3000 executives shows that even though most of them have not seen any greater effects from AI yet, they expect to do so within the next five years, especially within the areas involving information technology, operations and manufacturing, supply chain management, and customer-facing activities (Ransbotham et al., 2017). Another study, made by Microsoft, consisting of 277 AI leaders' participation from 15 European countries shows that 81% of them believe that AI will have a high or significant impact on their industry within the next five years (Microsoft, 2018). It also shows that only 65% of those people believe AI will help in transforming products and services. While if looking solely at the respondents from Sweden, 90% expect AI to transform products and services. Companies that are seen as very R&D-heavy consider AI and advanced analytics as contributors to speed up the product innovation and discovery process.

Figure 6 shows the most popular reasons to why organizations decide to adopt AI according to the study by (Ransbotham et al., 2017). One of the greater reasons for getting into the AI business is to stay relevant in the market while a reason such as cost reduction is less attractive to organizations that are interested in AI. This quote from Assa Abloy, found in Microsoft's 2018 report, summarizes the expectations of AI:

"It is fairly easy to see that we will be able to do more automation and we will have better optimized flows around business. But the key is that we will be able to create new revenue generating services that we were not thinking about before"

A common usage for AI within organizations is automation of repetitive tasks, for example hunting for data to put together in reports (Ransbotham et al., 2017). However, according to Agrawal et al. (2017), the value in AI lies in its ability to use prediction. Prediction is not the same as automation, as prediction is an input in automation. Using prediction, AI can be used to solve problems that previously were not prediction oriented. This property becomes more valuable when data is more accessible and widely available. The computer revolution has enabled huge increases in both the amount and variety of data. As the availability of data expands, so do the possibilities in using prediction for a wider variety of tasks.

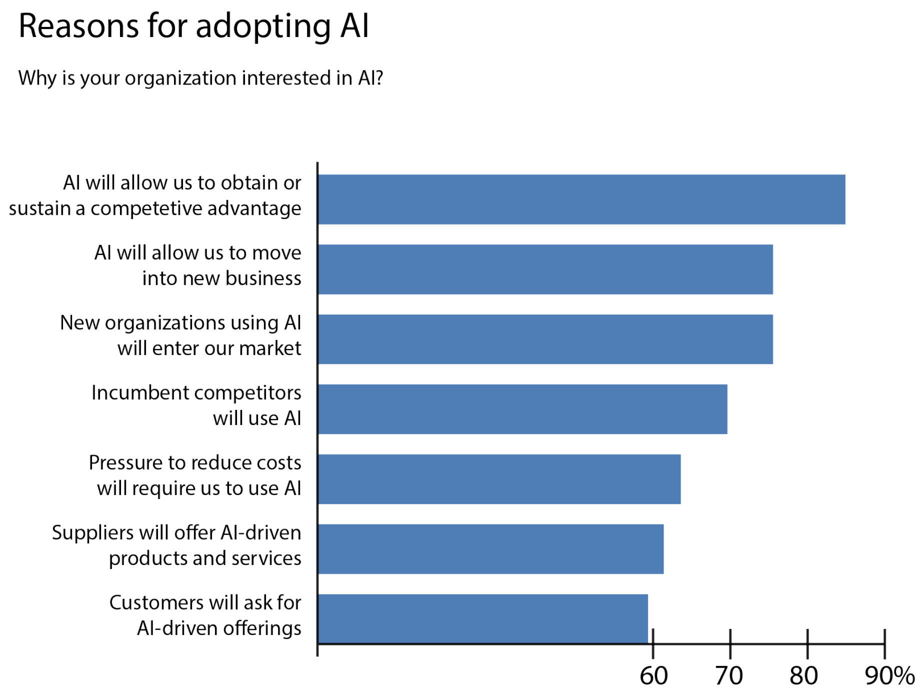

Figure 6: A bar chart showing the most popular reasons for adopting AI (Ransbotham et al., 2017)

Aside from potentially using AI for the purpose of prediction, AI capabilities such as pattern recognition, classification (e.g. pairing animal trackings to their respective species), image recognition, speech to text, cognitive search (e.g. offering personalized recommendations in online shopping), natural language interaction (e.g. having a software application generate a report on sales revenue predictions) and natural language intersection (e.g. getting summaries from a large collection of documents), are some of the other capabilities that can also be used in a business context (SAS, 2018). These can be used either independently or combined for various creating AI applications.

5.2 Challenges towards AI

As mentioned earlier, AI is not simply a plug and play solution. When it comes to adopting AI at an organizational scale, several factors that may act as barriers to adopting AI may occur within most organizations. A main cultural issue is employees concern about AI's impact on jobs (Capgemini, 2017). This makes employees anxious about working with machines or AI applications due to the risk of potential job losses and encourages resistance to change. It is therefore important to establish a clear focus and work plan for AI initiatives (Ransbotham et al., 2017). This means starting an AI program in the organization that includes regular communication, education, and training.

Despite the excitement that revolves around AI, many company leaders are not sure what to expect from it or how it will fit into their business model (Ransbotham et al., 2017). Another acting barrier is due to the state of where AI is currently at regulation-wise. Company leaders worry about investing in solutions when the rule book is still being written. A study made by Microsoft showed that over half of companies partaking in the study are concerned regarding regulatory requirements of using AI (Microsoft, 2018).

An important demand is that data and algorithms that are relevant for AI are not only accurate and high in performance, but also that they satisfy privacy concerns and meet the regulatory requirements. On the 25th of May 2018 the EU initiated the General Data Protection Regulation (GDPR) which ensures a high standard of personal data protection, including the principles of data protection by design and by default (Commission, 2018). An important reason for GDPR is to create a building trust which will in the long term be of great importance for people and companies.

AI presents many of the same issues and challenges as other digital technologies, which leads to the belief that companies can utilize a strategy similar to their digital strategy (Ransbotham et al., 2017; Gerbert et al., 2017). However, AI also presents some important nuances. Even so, both AI and digital capabilities share similarities when it comes to respecting and safeguarding customers personal data to ensure their trust (Ransbotham et al., 2017). AI also shares similarities with digital technologies when it comes to performing health checks to gain a clear view of their starting position regarding technology infrastructure, organizational skills, setup, and flexibility. It is also crucial to understand the organization's amount of access to both internal and external data. To prepare for the disruption that AI can cause in the market, it is important for companies to adopt a scenario-based planning to think more expansively about their businesses, build connecting future scenarios, and test their situation in such possible scenarios.

AI, as of now, has a way of creating a sense of unease, since even knowledgeable experts have difficulties in specifying how far AI will lead. Employing and educating people who combine both business and technical skills will be of critical matter, as will the ability to deploy cross-functional teams, which requires flexibility on both an individual and organizational level (Ransbotham et al., 2017). While data scientists, software engineers, and even data architects can be recruited externally, training employees from the line of business and adding AI skills will nurture a hybrid profile which is essential for identifying relevant use-cases in the business with possible AI solutions (Microsoft, 2018).

Another important factor is the commitment of the leaders within organizations. According to the study by Microsoft (2018), companies more advanced in AI tend to have stronger involvement of the C-level and the Board of Directors than the rest. They focus less on the technology itself and more on the business problems that AI can address. Davenport and Foutty (2018) state that it is necessary that leaders are familiar with AI and set clear business objectives for its usage. This involves preparing the employees as well by developing training programs, recruiting for new skills when necessary, and integrating continuous learning into their models.

It is essential to take an experimental agile approach towards AI, which proves beneficial for most R&D functions as they are already prepared for that initiative (Microsoft, 2018). Employing agile methods along with having a collective leadership among C-level executives will not only lead to progress in AI, but will also communicate throughout the organization that a new way of working and managing is being adopted (Davenport and Foutty, 2018). For Sweden in particular, this will prove to be beneficial as, according to the Microsoft (2018) study, they had the highest number of respondents (60%) that report that AI is an important topic, not only for the management level, but also for the non-managerial level.

Microsoft identified the eight most recognized capabilities for organizations to create value from AI successfully. These capabilities are presented below (Microsoft, 2018):

1. ***Advanced Analytics:*** *Obtaining and deploying specialized data science skills to work with AI by recruiting talented people and working with external parties.*

2. ***Data Management:*** *Capturing, storing, structuring, labeling, accessing and understanding data to build the foundation and infrastructure to work with AI technologies.*

3. ***AI Leadership:*** *The ability to lead a transformation that leverages AI technology to set defined goals, capture business value and achieve broadly based internal and external buy-in by the organization.*

4. ***Open Culture:*** *Creating an open culture in which people embrace change, work to break down silos, and collaborate across the organization and with external parties.*

5. ***Emerging Tech:*** *The organizational-wide capability to continuously discover, explore and materialize value from new solutions, applications, and data platforms.*

6. ***Agile Development:*** *An experimental approach in which collaborative, cross-functional teams work in short project cycles and iterative processes to effectively advance AI solutions.*

7. ***External Alliances:*** *Entering into partnerships and alliances with third party solution providers, technical specialists, and business advisers to access technical capabilities, best practices and talent.*

8. ***Emotional Intelligence:*** *Applying behavioral science capabilities to understand and mimic human behavior, address human needs, and enable ways to interact with technology and develop more human-like applications.*

Among these eight capabilities, AI Leadership was the most important capability in Sweden (Microsoft, 2018).

5.3 The need for data

As new techniques are developed, tools that enhance these techniques appear quickly. For AI, the scarce resource is the data, not the algorithms (Ransbotham, 2017). No matter how sophisticated an algorithm is, it will not overcome a lack of data (Ransbotham et al., 2017). It can, on the other hand, overcome limited data if its quality is high enough (Capgemini, 2017). According to a researcher at the MIT Sloan School's Initiative on the Digital Economy when participating in the study made by Capgemini (2017), most companies that utilize AI well have a policy and process around the data governance and treat the data as an asset.

The availability of greater volumes and sources of data is, for the first time, enabling capabilities in AI and machine learning that remained dormant for decades due to lack of data availability, limited sample sizes, and an inability to analyze massive amounts of data in milliseconds (Bean, 2017). To possess data for use in training and testing AI systems is critically important (Ransbotham et al., 2017). AI can help make sense through huge quantities of data, but setting up AI and learning to use it effectively requires feeding the technology the right data and working out what is useful versus what is noise (Microsoft, 2018). According to Ransbotham et al. (2017), having insufficient or irrelevant data can have a negative effect on the accuracy of AI applications, which can make them unreliable or unusable. Aside from having data that is used to train the system in what should be followed, there is also a need for so called negative data which allows the system to learn what is wrong (Reshaping). The negative data is almost never published, but it is necessary for building an unbiased database.

An obstacle to rolling out broader AI initiatives is due to the data and data infrastructure, where companies have separate projects which aim at improving the structure of existing data, collection of new data, and data access in general (Microsoft, 2018).

To collect and prepare the data for usage are typically the most time-consuming parts in developing an AI-based application, much more than selecting and adjusting a model to be used (Ransbotham et al., 2017). This implies that relevant data assets need to be easily attainable. According to Ransbotham et al. (2017), the success within AI is dependent on the amount of access to data sources, whether it is for the existing internal or external data or by investing in a data infrastructure. Many organizations will need to work on improving their internal data quality and integration before it can be put to use in their AI projects, while others will instead be in need of turning to data from an external source to augment their internal sources (Davenport and Foutty, 2018). Some companies state that they are increasingly looking to entering into data partnerships where they can either buy or exchange data with other parties (Microsoft, 2018).

5.4 Innovation

The findings from the literature study regarding innovation is divided into *Organization & Culture* and *Idea Management*.

5.4.1 Organization & Culture

An innovation is a successfully commercialized invention (Tidd et al., 2005). An innovation process is the commercialization of an invention which may also include the steps from nothing to an idea and from idea to invention. Different organizations have different innovation processes depending on different requirements. For example, a large company might have a more structured process compared to a smaller firm that can allow a more informal process. In all cases though, there needs to be a somewhat structured innovation process in place.

Simon et al. (2003) identified that for organizations to be able to produce radical innovations, a number of things need to be in place. One is the involvement and support of senior management in the innovation work, allowing a clear communication of the organizations' strategies. Steiber (2014), in her study of Google, also found the importance of senior management's involvement for innovation. Secondly, radical innovation should not be treated in the same manner as incremental innovation in regards to project management and project evaluation. Simon et al. (2003) suggest that radical innovation project portfolios be evaluated, rather than individual projects and to evaluate people's performance using different metrics from the ones used for incremental innovation.

The selection of ideas for radical innovation and incremental innovation ideas need to be based on different criteria. It may be the case today, that radical ideas are disregarded not because they are bad but because they do not fulfill the criteria for incremental innovation (Bessant et al., 2014; Rice et al., 1998; Sandström and Björk, 2010). It may also be beneficial, or even necessary, for some radical projects to be run completely separated from the main organization to avoid any restrictions that it may cause the project (Tidd et al., 2005; Simon et al., 2003).

Simon et al. (2003) recommend that organizations seek beyond their own walls to find other organizations to partner with for gathering new resources and ideas and to spread the risks of radical innovation. Steiber (2014) argues that it is essential for organizations to become more open to collaborations to be able to survive in the future. When the advancement of technology accelerates, companies are more dependent on seeking to other organizations to complete their resources and competencies (Perez, 2002; Steiber, 2014). There are a number of reasons for a company to collaborate with others. According to Tidd et al. (2005) collaborations concerning innovation are typically initiated to achieve a reduction of cost, time or risk of access to new or unfamiliar technologies or markets. Having a clear strategy for what to achieve from a collaboration is important to make it successful (Lee and Trimi, 2018). This is especially difficult for incumbent firms since they, in addition to building a new network, need to break down their current (outdated) network Bessant et al. (2014).

Although radical innovation is important it is, as mentioned, best to have a balance between incremental and radical changes to meet the needs of existing customers and to be ready to meet the needs of the customers in the future (Magnusson and Martini, 2008). Tushman and O'Reilly (1996) called this balance ambidexterity. The term ambidexterity also includes the balance between innovation and developing internal processes (Lavie and Tushman, 2010). Although Gibson and Birkinshaw (2004) describe a different type of ambidexterity (contextual organizational ambidexterity) their research shows that a higher level of ambidexterity within a business unit leads to a higher level of performance. Despite that the notion of ambidexterity has been looked at as a trade-off between, in this case, incremental and radical innovation, researchers have pretty much reached a consensus that modern companies need to become ambidextrous to be able to stay competitive (Andreassen and Gertsen, 2008; Lavie and Tushman, 2010; Magnusson and Martini, 2008; Tidd et al., 2005).

In a fast-paced business environment, more important than product-, service- and process innovation is business model innovation (BMI) (Lindgardt et al., 2013). BMI is when at least two dimensions of an existing business model are improved, which is difficult for competition to imitate which, according to Lindgardt et al. (2013) in turn is a reason for organizations to focus more on BMI. They further suggest BMI as a way to tackle new technological shifts. As Tidd et al. (2005) put it, "*having the technological means is no guarantee of business success*".

Making mistakes or not succeeding with some innovation projects or initiatives is a sign of good innovation capabilities (Steiber, 2014). Organizations that do not fail do not take any risks while the ones who learn from their failures have good innovation capabilities. Sarder (2016) emphasises the importance of that managers consider mistakes an essential part of learning. To manage innovation in an unstable, evolving environment, organizations need to not only learn but become agile and flexible (Tidd et al., 2005). Corsi and Neau (2015) make this clear by stating that reaching the highest level of innovation capability according to their ICMM involves having mastered agility. In the theme of agility and flexibility, organizations should seek to create an environment that allows people from different business units to work together. It is crucial to save any information that could be of help in the future and to keep it accessible for the ones who might need it (Steiber, 2014). Tidd et al. (2005) recommend that the innovation process includes an ending stage of reflection and review of the finished project to learn and improve the process.

Organizations that have understood the strategic importance of being able to change and adapt to current surroundings are far more likely to be successful in change-oriented initiatives (eg. education) than more conservative organizations (Reeves and Deimler, 2013). It is essential for companies to learn to be able to adapt to the ever changing business environment of today (Edmondson, 2008; McGrath, 2001). Sarder (2016) explains what a learning organization is and how to build one. Sarder mentions that training for specific tasks and educating for the future are two essential things. Letting employees build on their education does not only increase their knowledge but also if they use their new learnings they are more likely to stay at the organization.

Building on the importance of adaptability, Tidd et al. (2005) provide an interesting example of successfully changing one's business: the one time biggest mobile phone producers in the world, Nokia, started out with a product range including toilet paper. Some organizations have, evidentially, made dramatic changes to stay in business.

Edison et al. (2013) stress the importance of measuring innovation ability. A part of learning and improvement is knowing what and how to improve. Finding ways to measure innovation, would then support improving one's innovative capabilities.

5.4.2 Idea management

An innovation starts with an idea, hence an innovative company needs to be able to come up with and gather creative ideas that lead to successful innovations. Ideas appear pretty much everywhere in close vicinity of a firm and it is important for the firm to find, select and develop the best ones (Bessant et al., 2014; Sandström and Björk, 2010). Christensen (1997) found that most of the ideas that led to new groundbreaking technologies (or radical innovation) came from employees at incumbent companies. Steiber (2014) found that to be innovative an organization needs to put emphasis on the individuals in the organization. Organizations need to create an environment which allows individuals to be creative. It is important to let individuals work on tasks they are passionate about and to find others who have the same passion to keep them motivated at work. Individuals should be given the freedom to suggest and develop their own ideas and to find others to develop their ideas together with. This requires that management is engaged in the development of innovation. It has been found that companies that allow more freedom to the individuals of the organization are more innovative. Also, companies that have a common and strong vision, are more innovative.

Steiber (2014) suggests that new innovations are created in a setting somewhere in between control and chaos. It is a challenge for managers to decide what is to be controlled and what should be left to the individual workers to figure out on their own. There needs to exist a freedom to improvise which requires a learning culture with easily accessible relevant information. An innovative company has managers who effectively communicate the company's vision to the workers but let them decide how they work on their specific tasks. An innovative company allows conflicts and debates to arise and gives individuals a lot of freedom in problem solving.

6 Results and analysis

This section presents the results of the study and is divided into three subsections. The first focuses on presenting the similarities in managing both innovation and AI that were found in the literature study. The second subsection presents the screening tool which resulted from the performed literature study. The third subsection shows the findings from the quantitative pilot study which involved investigating various organizations using the screening tool.

6.1 Synthesizing the literature

The theoretical framework presented managerial theories on how to succeed with AI and innovation, respectively. This section focuses on the literature that highlights qualities that benefit both of these fields. These identified factors are compared with what is presented in another recent study within this field. The study that is used for comparison was performed by Microsoft and it included AI leaders in 277 companies, across 15 countries in Europe. This was done to increase the reliability of the findings. The synthesis of the literature is done to contribute to answering the second research question. Presented below are the seven common factors that were found in the literature.

6.1.1 Clear Vision

Having a clear AI vision is key to achieving enthusiasm and motivating exploration of AI-applications with uncertain outcomes (Microsoft, 2018; Reshaping). Steiber (2014) says the same for innovation, a clear vision helps show the long-term goals and helps motivate people. Reid et al. (2015) underlined the importance of having a vision for new technology to succeed with radical innovation, saying that concentrating on long-term goals inspires people to look past their own self-interests to reach the vision. Sarder (2016) argues that a clear vision is essential when building a learning organization. Microsoft (2018) realized that companies found it important to involve employees and to make it exciting for them to work with new technologies, in particular AI.

6.1.2 Learning organization

Microsoft (2018) predict that projects will become more explorative and have less certain outcomes, which will require leaders to be ready to change the overall direction of the organization more frequently. Building an agile, learning organization falls in to line with building an AI-ready organization. The innovation literature is unanimous in that being adaptable to changes is essential for organizations in today's dynamic market. Microsoft (2018) mention that one big challenge when adopting AI is that of training employees to work together with AI. The innovation literature clearly states that organizations that are prone to change and adaptation, through eg. training and education, are likelier to succeed. Organizations that are used to training for change in general will surely be more likely to successfully train for change with AI.

6.1.3 Engaged management

Simon et al. (2003) and Steiber (2014) explained the importance of involvement from senior management for radical innovation. According to Microsoft (2018) the same applies for AI-initiatives, as it is shown in their study that the organizations with more advanced AI usage had more involvement from management and the board of directors.

6.1.4 Business focus

The Microsoft (2018) report showed that organizations that were more advanced in their AI implementation were more focused on the business problems that AI can help solve, rather than the technology itself. This goes in line with the suggestion from innovation literature, that the most successful innovators are the ones focused on BMI.

6.1.5 Open Culture

Open culture is, according to Microsoft (2018), to establish projects that allow collaboration and learning across functions which is important for development of AI. While it is often presented more broadly, an open culture is presented in innovation literature as one of the most important factors for radical innovation success. Steiber (2014) found that the culture at Google is an essential factor for the company's success with innovation.

6.1.6 Agile development

Agile development is cut from the same cloth as an open culture. Agile development supports engagement of people between functions, triggering collaboration, and bringing together tech and business (Microsoft, 2018; Ransbotham et al., 2017). The importance of good communication and collaboration ability within the organization, across different functions, is brought up in innovation literature as important, as well. According to Microsoft (2018), agility is key to successfully adopt AI. Coincidentally, having an agile approach to innovation work shows to foster innovation success. Many business leaders today are concerned with investing in AI when laws and regulations are not yet decided (Microsoft, 2018). The challenge for investments in AI seem similar to figuring out what radical innovation initiatives to invest in.

6.1.7 External alliances

External alliances can be considered an extension of an open culture. According to innovation literature, there are many reasons to why organizations need to focus on establishing collaboration with other organizations. One reason is that it enables for tapping into a significantly larger pool of capabilities and talent. Reasons for outer-organizational collaborations are also found in AI literature, one example presented by Microsoft (2018) is that organizations seek partnerships to solve the challenge of finding enough high quality data for AI development. Lastly, collaborations with universities are increasingly attractive for both innovation and AI.

6.2 The AI and Innovation Maturity Model

Using the literature, a framework was developed that covered important aspects that are relevant for both the AI and the innovation work of an organization respectively. The framework helped in creating an interpretation of AI-maturity. An attempt of formulating a definition for AI-maturity was made based on the definition of maturity. Organizational AI-maturity became defined as "An organization assessed to be optimally fit for using AI". This definition includes the assessment of an organization's progress within AI and how well adapted it's environment is to adopting AI effectively. This along with an organization's innovation capability maturity is the measurable output from the tool.

The framework resulted in the assessment model which was named the AIIM (AI and Innovation Maturity) model, and is presented below (see figure 7). The assessment model consists of five dimensions: *structures*, *resources*, *methods*, *action* and *business*. These dimensions categorize a number of areas that are associated with AI- and innovation capability maturity. Radar charts are used to visually present the measurement of each area in every dimension (see figure 8). Every area has an axis that displays a rating from zero to seven, zero being the worst rating and seven being the best rating.

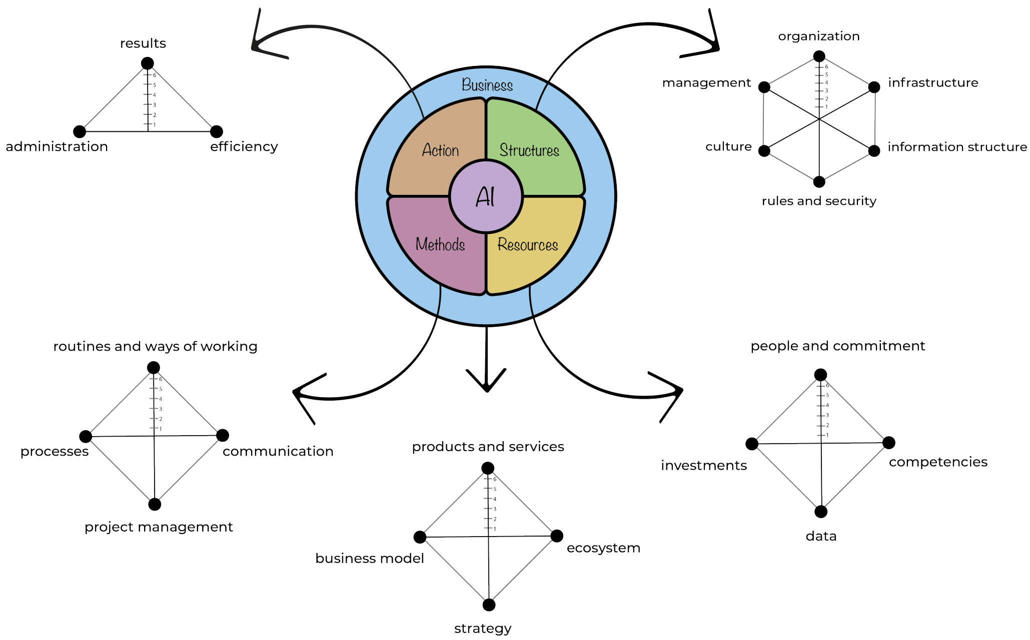

Figure 7: The AI and Innovation Maturity model

It is important that the assessment model translates the answers from the questionnaire to easily interpretable results, for the respondents to understand their situation regarding AI and innovation. Presenting only a single maturity rating is not helpful to the organization, it is necessary to be able to present the results at different levels of aggregation (Essmann and du Preez, 2009). To achieve this, the AIIM model can be viewed at four levels of aggregation; (1) An overall maturity rating (to give a benchmark that can quickly be compared with other organizations), (2) an overall rating for each of the six dimensions (to show the big picture of where the organization needs to improve), (3) an individual rating for the different areas within the dimensions (to give a clear view of what to improve), and (4) the results from each question and statement of the questionnaire can be viewed if there is an interest to learn the specific reasons for an area having a specific rating.

Each dimension of the AIIM model and their respective areas are explained in detail below.

6.2.1 Structures

The *structures dimension* considers how structural factors like organization, how people work together and what kind of an infrastructure is in place. The *structures dimension* is divided into 6 areas.

Organization refers to how and how well the organization arrange the people within it. A high rating in organization indicates; that a clear and engaging vision of how the organization will evolve is in place, that there is a clear leadership of the innovation work, and that innovation work is usually conducted in collaboration between functions. Moreover, AI-projects are run separate from the rest of the organization, by highly capable people.

Infrastructure includes digital and physical tools that support organization and communication to improve working. A high rating for infrastructure indicates that AI is implemented to a moderate or high degree in the organization. It also indicates that the surveyed organization has been required to make organizational changes for AI, and that it is easy for employees to find relevant people within the organization for collaboration.

Information structure is infrastructure for information. It includes how important information is protected and shared. A high rating for information structure indicates; that it is easy for employees to access relevant data for AI, and like for infrastructure it also indicates that the surveyed organization has been required to make organizational changes for AI.

Rules and security measures how well the organization knows and works with laws on security. A high rating for rules and security indicates; that the organization has full understanding of laws and regulations regarding storage and use of data, that there are strict rules in place for how data may be used, and that data security is a priority for the organization.

Culture includes norms and values, common for the whole organization, that are hard or even impossible for others to copy. A high rating for culture indicates that the organization encourages employees to take initiative and make their own decisions in day-to-day work, employees are encouraged to suggest ideas for innovation and they are given the means to develop them. It indicates that the organization allows for projects with uncertain outcomes to be followed through and that people within the organization question what is believed to be true.

Management includes all manager levels. The area takes into account how supportive and involved the managers are in innovation and development of AI and its applications. A high rating for management is achieved if top management is very involved in the work with AI. A high rating indicates a large interest for AI at management level, and that AI is communicated a lot from top management.

6.2.2 Resources

The *resources dimension* presents how well the organizations' resources are in line with what is recommended to succeed with AI. This ranges from data, to the right competencies and the right people. The resources dimension is divided into 4 areas.

People and Commitment covers employees interest and loyalty to the organization. A high rating for people and commitment indicates that people are interested in and excited about AI and its potential implementation at the organization.

Competencies are the individual's ability to apply their knowledge for specific tasks. A high rating for competencies indicates that the organization already possesses specific AI competencies and a sufficient amount of employees working with data. It indicates that the organization understands how existing knowledge and competencies need to change and focuses on training and educating employees to achieve it.

Data is the information the organization owns and has access to. The amount and quality are considered. A high rating for data means that the organization has a good understanding of the importance of data, their need for it, the amount that is required and where it comes from. Also, that the organization understands the different types of data that AI requires, and that there is a sufficient amount of data that the organization can access.

Investments includes the strategy of selecting what initiatives to invest in. A high rating for investments is achieved if there have been significant investments in AI-related initiatives.

6.2.3 Methods

The dimension considering methods covers how the organizations use their resources, what processes there are and how projects are run, if the communication is effective and what routines are in place. It describes the overall way of working within the organization. The methods dimension is divided into 4 areas.

Processes are defined series of methods used for specific tasks. A high rating for processes indicates that there is a systematic process for the innovation work, and that there are established ways to work with generation, development and prioritizing ideas for innovation. A high rating further indicates that the organization has a part in their projects dedicated to documenting learnings and that the established processes and ways of working are dynamic to allow for change.

Routines and ways of working refers to the typical ways tasks are done, they are similar to processes but less defined. A high rating for this area indicates that the organization has routines for generating different types of data and for preparing specific datasets. It also means that it has been put in to routine to measure the effects of AI applications.

Project management explains how projects are selected and how resources are allocated between them. A high rating for project management is achieved if the projects have a clear connection to the organization's business model. It also indicates that uncertain projects are allowed and that AI-projects are not handled the same way as other projects in the project portfolio.

Communication refers to how people talk about AI and how easy it is to find relevant people within the organization. Communication receives a high rating if AI is communicated at different levels of the organization and when there is an open culture where employees can easily get in contact with the right people when necessary.

6.2.4 Action

In the *action dimension* the assessment model presents what the usage of AI has led to in the organization, what effects it has had on day-to-day activities and the usability of automating work. The action dimension is divided into 3 areas.

Results of implementing and using AI within the organization. A high rating for results indicates that AI has been implemented in the organization, that the AI applications that have been developed have had the expected effects, and that the organization's innovation work has involved new digital technology during recent years.

Administration includes how much the implementation of AI has affected administrative tasks. A high rating for administration is achieved if AI has helped simplify some tasks in the organization and if AI has reduced the amount of repetitive tasks.

Effectivization looks into how much the implementation of AI focuses on making processes more effective. A high rating for effectivization indicates that AI has contributed to making the organization's work more effective, and if there are plans for it. It also indicates that AI has helped simplify some tasks and if the organization's innovation work predominantly results in effectivization of internal processes.

6.2.5 Business

The business dimension deals with how the usage of AI has affected the organizations business. This dimension includes any effects of AI on other stakeholders. The business dimension is divided into 4 areas.

Products and services covers how AI is used to improve and develop new products and services. A high rating for products and services indicates that AI has and will continue to contribute to new offerings for the customers and that AI-offerings have already been well received by customers. It also indicates that the organizations innovation work predominantly results in new offerings for their customers.

Ecosystem refers to how well the organization knows its strategic position within their market and all stakeholders affected by their decisions. A high rating for ecosystem indicates that the organization has an understanding of their own customers needs and how AI can affect their industry. A high rating is achieved if the organization has a clear strategy for external collaborations regarding both AI and innovation respectively.

Strategy questions if there is a strategy in place for implementing AI in the organization or its products or services. Strategy receives a high rating if existing strategies have been modified because of AI and if there is a strategy for data management and one for AI management.

Business model considers how the business model is affected by implementing AI. A high rating for business model indicates that AI has had or will have a big impact on the existing business model.

The choice of using radar charts to visually present the performance (at level three) in the AIIM model was due to its usage in benchmarking in the private and public sectors, and for being a well established management tool (Mosley and Mayer, 1999). There are two important contributions that radar charts make to benchmarking. The first is that it provides a simplified presentation of multiple performance indicators, which is suitable for widespread use in organizations. The second contribution is that its surface can be used as an overall indicator of the level of goals that may be measured in different dimensions, instead of separate indicators for each goal. A second reason is that it was effectively used in the Innovation Strategy Model (ISM) by (Fruhling and Siau, 1996).

The assessment model has a relatively low level of detail. This is to remain generic, in other words applicable for different organizations in different industries and of different sizes (Essmann and du Preez, 2009). Despite the lack of detail, the assessment model covers a wide area of factors that, according to the literature, have an effect on innovation or AI within an organization. This focus on a big number of factors helps identify areas of strengths and weaknesses for many different organizations. The assessment model focuses on measuring the conditions (organizational, managerial, physical etc.) for innovation (rather than the current innovation success).

The model also focuses on measuring the conditions for successful AI-application.

The tool does not include specific solutions for improving areas that receive low ratings but is simply an instrument that helps the organization and its people aware of their situation regarding AI. Suggestions for what needs to be achieved can be derived from the assessment model and questionnaire but methods to get there are not provided. Like Essmann and du Preez's 2009 Innovation Capability Maturity Model (ICMM), the AIIM-tool defines the "what" of AI and innovation maturity and not the "how".

Since the authors and the participants of the study want to protect the material, the fully content of the tool are not attached to this report.

6.3 Test of tool & Pilot study

Gathering respondents for the survey was made through connections provided by the AI-expert at the consultancy firm, the students and also by contacting various knowledgeable people through LinkedIn and by email.

6.3.1 Test of tool

The study involved approximately 80 individuals from various industries. Out of these, 31 replied for the study and among them, 14 answered all of the questions in the questionnaire of which 12 revealed their business status and industry of which they work within. Of those who shared their organization's line of business, about half of them worked within IT and telecom, and the other half consisted of participants working in various lines of businesses. Most people surveyed worked at large organizations.

The responses that were collected involved people in organizations with various levels of AI-maturity. Displayed below (see figure 8) are two different cases of AI-maturity found among the responses. The first case is considered to be an organization with a high level of AI-maturity and the second is considered to be an organization with a lower level of AI-maturity. The data that is presented with help of the assessment model was transferred manually from the questionnaire. The ratings for each area is the mean value of all the responses within that area.

The two cases displayed in figure 8 are at different levels of AI-maturity. The first (red) is a company renowned for its work with AI solutions and is considered to be at the front end of applying AI. The second (green) is a Swedish state-owned company that according to themselves are currently early in the process of adopting AI.

The visualization from the tool in figure 8 shows what is expected. The red company covers a larger area in every single chart diagram, which indicates that according to the tool, the red company has a higher level of maturity. Since it is known that the red company has come a long way with AI compared to the green company, this indicates that the AIIM-tool could be used for evaluating a company's prospects for applying AI.

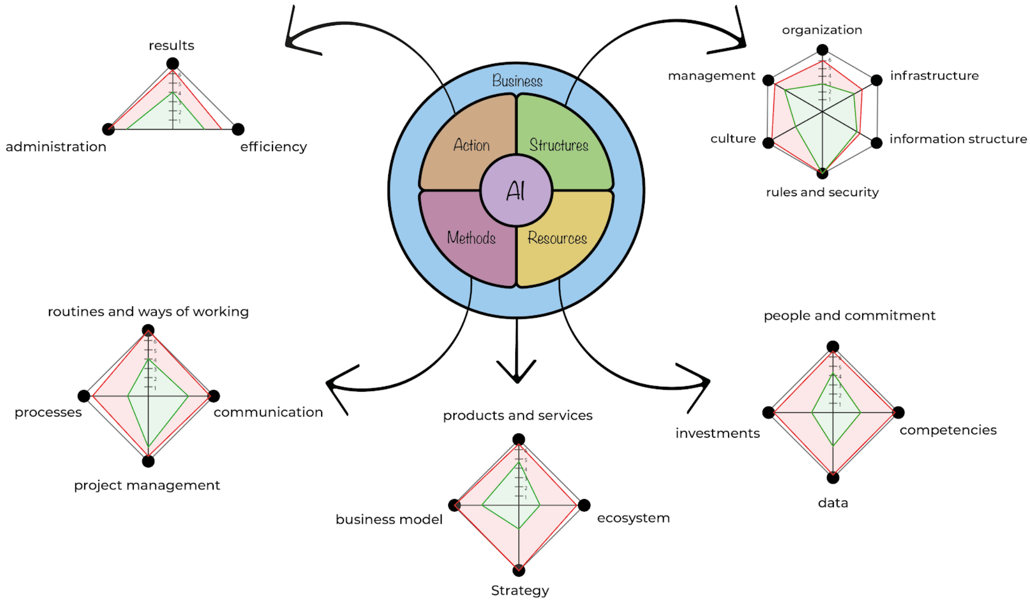

Figure 8: The AI-maturity and innovation capability rating of two organization using the AIIM-tool

Although most of the radar charts look like expected, some things are surprising. In the *structures* chart it is evident that the two companies received similar ratings (3-4) for the area *infrastructure* and the area *information structure*. Looking closer into the questions within these areas, it is revealed that the questions are not as clearly stated as they would have to be. For instance, one question reads: *"To what extent is AI already applied in the business?"*, and the available answer is a rating between 1-7 labeled as: *"not at all"* and *"a great amount"*. What is missing here is something to compare the rating to, a reference. Presented like this, the questions is too subjective and the response depends on the respondents interpretation. Moments like this show that the tool needs some more testing to be applicable at a larger scale.

6.3.2 Pilot study

Apart from the main use of the questionnaire in the AIIM-tool, it has also been developed to be able to serve as a collector of quantitative data in order to study AI and innovation. As the initial test of the tool collected data from all kinds of organizations in Sweden, a pilot study using the questionnaire could be delivered. This pilot study includes an undetailed evaluations of Sweden's AI-maturity and innovation capability, and indications of what a larger study using this questionnaire would result in. Based on the responses received, Sweden's rating according to the AIIM-tool is presented below (see figure 9).

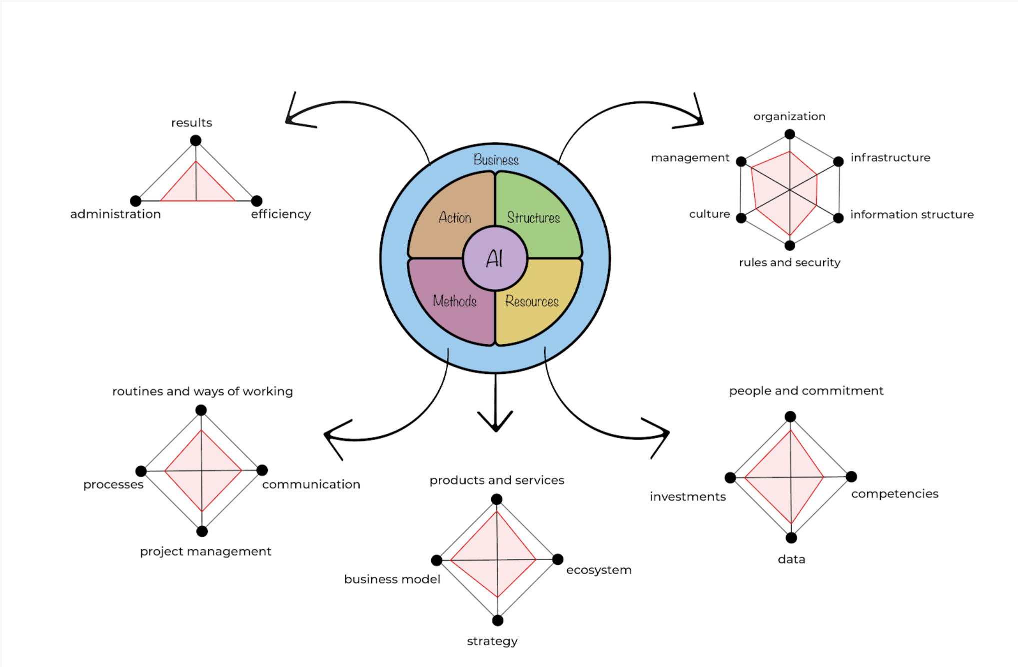

Figure 9: Sweden's AI-maturity and innovation capability rating presented in the AIIM-tool

Taking a closer look at the pilot study presents some results. One result was the increase between the current effect of AI within organizations and the expected effect within five years (see figure 10). It shows a significant increase in the effect AI will have in both the way of working within the organization and the output that the organization will produce. People seem to expect AI to have growing effects in the near future. This can be related to the high expectancy of AI by executives in previous studies (Ransbotham et al., 2017; Capgemini, 2017; Microsoft, 2018). Ransbotham et al. (2017) claims that managers are expecting to see substantial effects from AI within the next five years, similarly to the results presented here. In the study made by Microsoft (2018), 81% of the participants surveyed believe that AI will either have a high or significant impact on their industry within the next five years.

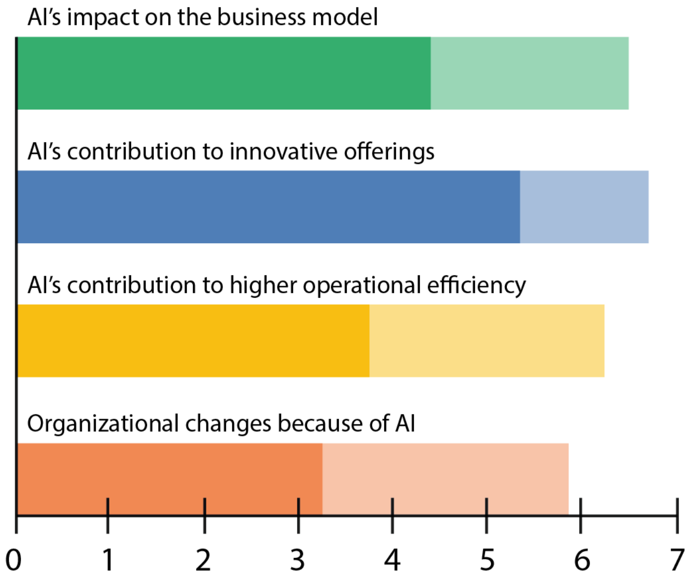

Figure 10: The current effects (darker colour) and expectations (lighter colour) of AI within five years. The numbers 0-7 represent the Likert scale used in the questionnaire from little to large impact

Another result from the pilot study is the score for having individual workers who are responsible for AI initiatives. Although the management alternative was higher, having individuals responsible for AI initiatives was equally popular as having an independent working group that responds to AI issues, while introducing new roles for this subject was, as expected, at a lower level (see figure 11)

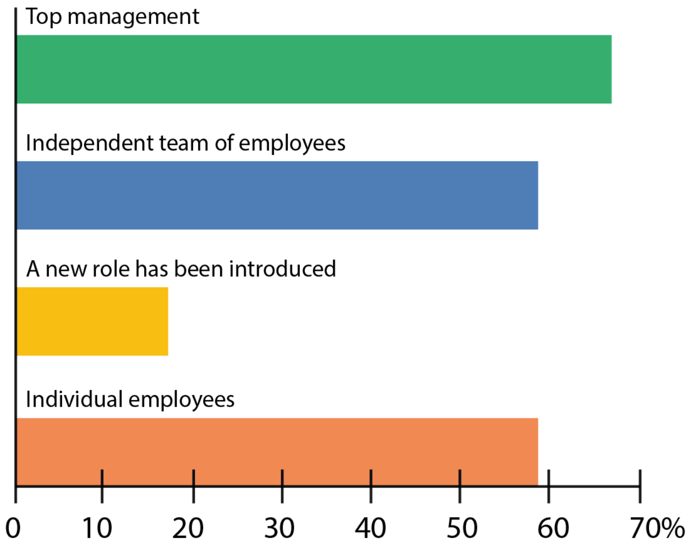

Figure 11: How Swedish organizations handle AI initiatives.

When asking about the organizations' understanding regarding certain AI related topics, the highest score was given to the topic of the laws and regulations regarding data management (see figure 12). Moreover, on another question most respondents agreed that data security is highly prioritized for their organization. This suggests that organizations in Sweden are well adapted to handling one of the most crucial parts of AI; rules and security.

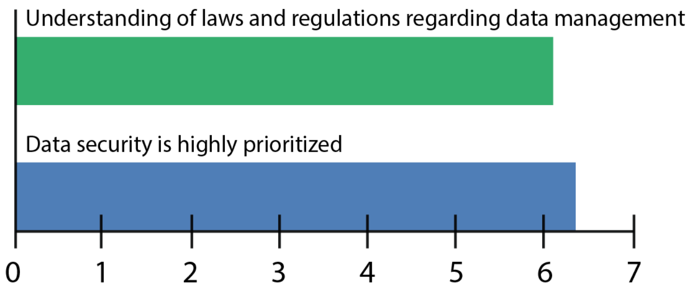

Figure 12: The understanding of rules and regulations for AI data security is highly prioritized.

According to the questionnaire results, most respondents had a good understanding of the need of reference data that the AI needs to follow. Even so, when asked about the understanding of the need for negative data, most respondents either understood it completely or seemed to be unaware of the term negative data and answered that they did not know (see figure 13). Another observation is of the score regarding identifying important data sources, which was lower than the other scores involving the need of data, indicating that the need for data is understood but not fulfilled.

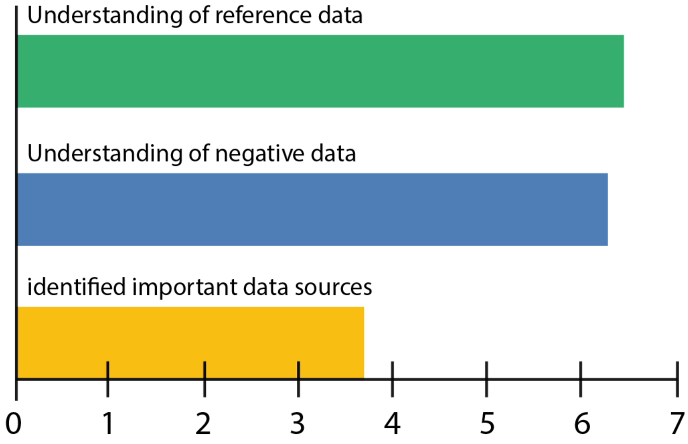

Figure 13: Reference and negative data along with data sources

When talking about the necessities for operating AI, most respondents were confident in their organization's possession of AI competencies (see figure 14). Also when asked about the organization's focus in training of employees within AI, most respondents leaned towards a lower score

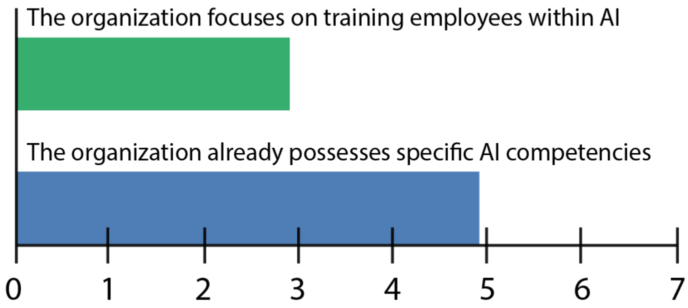

Figure 14: Results regarding education and possession of competence

7 Discussion

This sections includes a discussion of the study which first goes over general topics and is then divided into the subsections *Pilot Study* and *The AIIM-tool*.

The initial approach for RQ2 was a classic deductive research approach. It would include hypotheses based on the literature study (see Appendix B) and then these hypotheses would be answered with help from analyzing qualitative data gathered from interviews and quantitative data gathered from the questionnaire. The qualitative data was chosen not to go through with at this stage of the research. The amount of quantitative data fell short of what was required for the data to be representable for the selected population. So, the conclusions for RQ2 cannot be considered to be statistically accurate but are indications of what to expect from future work.

In their surveying of companies adopting AI, Microsoft (2018) found that 90% of the Swedish companies surveyed, *"expect AI to transform products and services"* (compared to 65% of European companies), which goes to show that Sweden is a good place to conduct this study. More specifically, companies within more R&D-focused industries see AI as a concrete tool for making the innovation process faster which could potentially give rise to entirely new business models.

A large part of the theoretical framework involves the Microsoft (2018) report on AI-maturity in Europe. This report was released while this study was being concluded and while there was time to implement some new insights from the Microsoft report into this study, a lot of it confirmed what had already been written in this study.

One of the most common uses of AI is to automate activities, which at least 85% of the companies surveyed in the Microsoft (2018) study, deem relevant to their business. Automation will most definitely have a positive effect on the innovation process, freeing up time and energy for people to put on more creative tasks. This is one reason to embrace AI to allow it to boost innovation.

7.1 Pilot study

As mentioned earlier, the questionnaire was introduced to approximately 80 potential respondents of which 12 responded to every single question, resulting in a response rate of 15%. The low response rate can be due to various factors. One of them being that the questionnaire is quite "heavy" and contains several questions covering areas of interest in both AI and innovation. Both of which contain questions that can be difficult to answer, despite requesting that they answer each question according to their point of view. This could be the cause for why several potential respondents discontinued the questionnaire midway. The questionnaire structure was mainly divided into an AI-section and an innovation section, the AI-section being the first one to appear when doing the questionnaire. The online questionnaire tool showed that most respondents that discontinued the questionnaire did it in the section that covers AI related questions. This means that most participants who cleared the AI-section also went through the rest of the survey. This also indicates that there is a certain difficulty in answering AI-related questions, or that people were simply uncomfortable with answering those types of questions.

All information indicates that Sweden is a good place to perform this study since it seems to have come a long way in adopting AI. This study was conducted in Swedish though, which revealed itself to be a barrier for collecting enough data. When this was realized the questionnaire was translated to English but it was so late in the process that none of that data could be used. Many advanced organizations work in a global network and it is common that there are non-Swedish speaking employees in Sweden, which was the case with several of the companies surveyed in this study.

Some of the respondents were unsure of what they were allowed to share in the questionnaire due to the secrecy regarding AI and therefore skipped questions regarding their AI usage. Because of the fact that AI is new to most organizations, all rules have not yet been set which means people cannot be sure of what they are allowed to share. Even though it was made clear in the questionnaire that all data gathered was handled confidentially, it resulted in many of unfinished questionnaire responses.

As to preemptively avoid the risk of forfeiting participants due to the questionnaire being too large, the survey was made to take about 15 minutes to complete. The participants were informed beforehand of the approximate duration of the questionnaire study and were given a progress bar to follow up on their position in the questionnaire. Even so, several participants that went on with the questionnaire discontinued midway. Feedback was also received from one participant that they finished about half of the questionnaire and did not go further because they experienced it to be too large.

It is clear that changes need to be made surrounding the questionnaire to be able to collect enough data for making statistically sound conclusions in a quantitative study. In this study changes that were made were made to the structure of the questionnaire. It was decided that AI and innovation were to be separated in two parts in the questionnaire instead of the initial structure where the questions were structured more according to the dimensions in the assessment model. This was decided to avoid forcing the respondents to change focus between AI and innovation during the completion of the questionnaire. The size of the questionnaire was always a concern and before the pilot study the questionnaire was shortened by three minutes. The least relevant questions related to areas that had several questions already were deleted.

The initial questionnaire structure included short explanatory texts throughout to avoid any confusion but after the initial tests these were all deleted as they were deemed unnecessary and only made it take longer for respondents to finish the questionnaire. The initial questionnaire also included the function that did not let respondents finish the survey without answering all questions, this was deleted to avoid frustration if a respondent might accidentally miss a question.

Using different types of questions in the questionnaire was considered to make it more fun and interactive. However, this caused confusion for the respondents. A few questions had ranked options, but these were changed to Likert scale because it only caused confusion. The questionnaire initially included a few free answer questions which were deleted to make it easier for the respondents. So, in the end the questionnaire only included Likert scale questions and multiple answer questions, to keep it simple.

Using online surveys is a great way to reach out to people but it is easy to disregard doing them. Based on a meta study made by Manfreda et al. (2008) which included examining the differences in the response rate between web surveys and other survey modes in 45 studies, it is estimated that response rates on online surveys are on average 11% lower than any other survey modes. Unlike other data collection methods, doing a questionnaire over the internet is impersonal which could make people feel less obligated to respond to the questionnaire.

When attempting to contact potential respondents in an organization, it was unclear to people in the organization who was in charge of AI initiatives and they could therefore not help find the most relevant person. This would either lead to a dead end when seeking participants in that particular organization, or require to be forwarded to several people within that organization until finally being redirected to someone with insight regarding the topic. In other words, there did not seem to be a defined position for the management of AI initiatives within most organizations.

Looking at other studies made within the fields of AI, it seems that they managed to gather a great amount of participants with the assistance of consulting firms. An example of this is when The journal MIT Sloan Management Review did a collaboration with the Boston Consulting Group in order to conduct their global study regarding AI for organizations, or when Microsoft collaborated with Ernst Young in their study regarding AI in Europe. The resources of both partners allowed for the studies to give fruitful results. Using the resources of a consulting firm would greatly benefit this study as it would make it easier to gather a large sample of people from the desired population.

It appears that the majority of participants in the study understand the laws and regulations that are centered around AI. There are several articles that highlight the uncertainty of if today's society is adjusted to AI. A report from Accenture (2018) which focuses on the future growth of AI shows that Sweden, among other countries in Europe, shows promising growth in the AI section. However the report argues that there is a need for updating and creating adaptive, self-improving laws to close the gap between the pace of technological change and the pace of regulatory response.

The study showed that there is a possible gap when it comes to progress within

AI. Even though there seemed to be a mutual understanding of the importance of reference data, there was a difference in the understandings of negative data. Organizations within Telecommunications or IT are most likely ahead in AI utilization and therefore understood the term of having negative data and its importance, while other organizations that had not made as much progress were most likely the ones unfamiliar with the term.

The lowest score for the data related questions was the identification of important data sources, which indicates that most organizations are experiencing a scarcity in terms of data sources, whether they are internal or external. This is understandable as AI requires large amounts of data which is not easily accessible for most organizations, aside from large and established organizations like Google or Microsoft for example.

As of now, it seems that AI has not yet influenced new positions within most organizations in the study. However, several studies such as the one made made by Capgemini (2017) argue that AI will lead to new jobs, of which most of these new jobs will be at a senior level. In a study made by Gartner (2017) they predict that the amount of jobs eliminated by 2020 will accumulate to 1.8 million, but will at the same time create 2.3 million new jobs.

According to Ransbotham et al. (2017) it will be critical for organizations to attract and develop people that posses both business and technical skills which is why an AI program that includes education and training is important in order to grow AI-wise. It was expected that the organizations surveyed would be leaning more towards education and recognizing that their current competencies are as of now insufficient as several sources stresses the importance of educating employees for AI utilization and acquiring competence that applies to AI.

The collected results from Sweden presented in the AIIM-tool shows no irregularities or significant differences between the axes in the *Methods* and *Action dimensions* respectively. This may indicate that the average of organizations are steadily working towards implementing AI into their ways of working and its utilization internally.

The other dimensions however display differences between the axes in their respective dimension. The *Resources dimension* shows that there is a great focus within the area *people and commitment*, and *data* in the organizations, while new *competencies* for the sake of AI is not as prioritized. Going over the *business dimension*, there appears to be a focus towards AI's effect on organization's *products and services* and business model, more than how AI will affect the organization's surroundings (*ecosystem*).

The radar charts show the mean value of all questions in the survey within the same respective areas. When looking at the radar chart for the *structures dimension* (see figure 15) it seems evident that the areas *infrastructure* and *information structure* are where organizations are lacking today when it comes to structures, which does conform with the Microsoft (2018) paper. Although, as explained in *6.3 Test of tool & Pilot study* these results may come down to the phrasing of the questions. These are arguably the most important factors for successful AI and according to Microsoft (2018) the *information structure* is one of the first things to prioritize when implementing AI. It makes sense that if there is no structure in place to handle the data, there is no one using the data. On the other hand, organizations seem well prepared when it comes to the areas *management* and *rules and security*. *Rules and security* takes into account an organizations understanding of and priority for regulations regarding data. A great understanding for security issues is paramount for any organization handling large amounts of data. This shows how diverse the AIIM-tool aims to be, as this area does not say anything about an organization's ability to use AI but does take into account factors surrounding it.

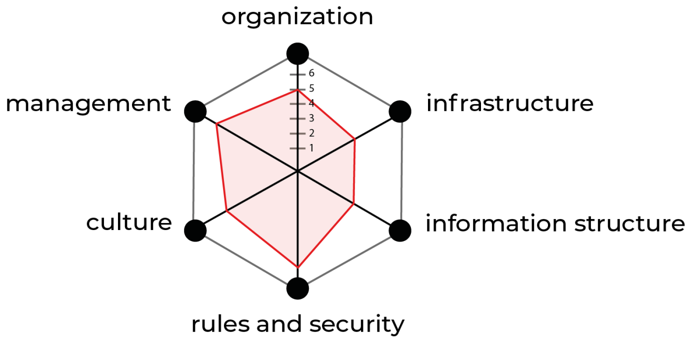

Figure 15: The structures radar chart

The radar chart for *resources* shows clearly how it works well to at a glance get an idea of areas for improvement from this way of presenting the results from the questionnaire (see figure 16). It is apparent that *resources* gets an overall high score, and a closer look shows that two areas are well covered and two are not. That the area *competencies* received a low score was expected because such a fast-growing phenomenon as AI in organizations would surely lack people who understand it. However, Looking even closer at the rating for *competencies* reveals that the actual reason it is low is that organizations do not prioritize education for AI internally while the rating for already having the right competencies was high. The assessment model rates these questions equally which may cause an issue when evaluating organizations. It might be the case that if there are enough competencies, there is less need for education and vice versa. To solve this, weighting might be added to one of the questions so to make it more important than the other. As recognized when analyzing the radar chart for *structures*, this problem may be solved by phrasing the questions more carefully. That the rating for *investments* is relatively low is not surprising, big investments in AI initiatives is not yet common.

The *business dimension's* radar chart presents a couple of interesting things (see figure 17). *Products and services* is expected to be the first area where AI is used successfully and there are already products on the market today that use AI. Generally, organizations have not developed a strategy for AI yet, given that it is fast-growing and relatively new to many organizations this was expected. *Business model* re-

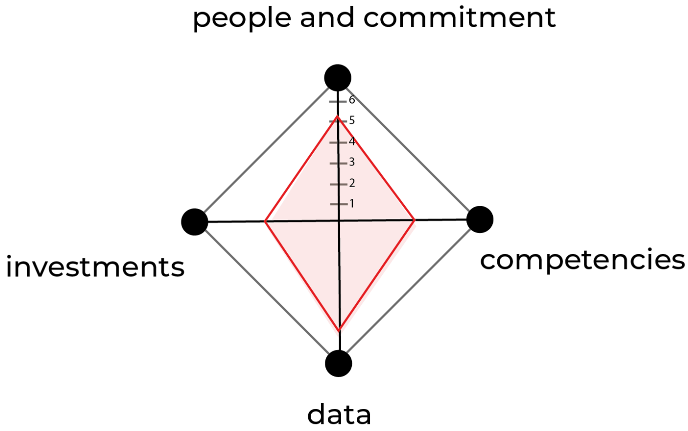

Figure 16: The resources radar chart

ceived a surprisingly high of rating of 5,46. Having a closer look at why shows that AI's effects on current business models received a more modest rating of 4,42 and that the expectations of AI's effects on business models received a high rating of 6,50. This suggests that the assessment model needs an adjustment here, to give a fair and helpful evaluation. It also shows a case where going all the way to the highest level of aggregation in the assessment model is necessary to get an understanding of the results.

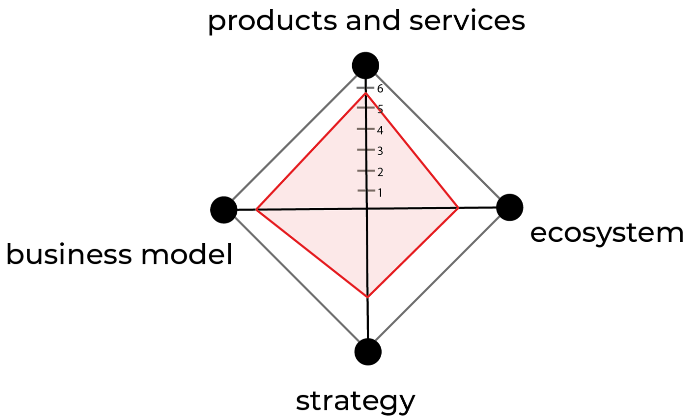

Figure 17: The business radar chart

In this study, the state of the art according to literature is presented. What is missing is the state of the art in practice. For this to be achieved the questionnaire needs to be answered by a large number of people in different organizations, the exact numbers depends on the selected population to study. The number and diversity of the respondents also depends on if a generic assessment model is desired. As many sources for AI, especially the ones including case studies, are focused on one organization or industry, the collected data needs to be diverse to have the assessment model be generic.

7.2 The AIIM-tool

The data collected through the questionnaire would contribute to improving the AIIM-tool as it would identify what the most important factors for AI and innovation are according to the people using and trying to implement it in practice. A large amount of data would be needed to statistically validate the concept of the AIIM-tool and to draw conclusions for the hypotheses (see appendix B and research questions.

One unreached ambition for this study was to test the tool at one or several organizations proven to have successfully implemented AI. This would, together with the diverse amount of data, probably be enough to fully validate the AIIM-tool. Firstly, this would show the most important factors at successful AI organizations. Secondly, establishing a best practice would mean establishing a benchmark for evaluated organizations to strive for.

As the best practice changes, the AIIM-tool will have to change with the industry to always be relevant and helpful to organizations seeking to become innovative with help from the use of AI. The iterative development of the AIIM-tool will continue as long as the industry and way to use AI changes, as it sure will.

The introduction of the AIIM-tool at an organization that intends to use it should be done in a workshop setting. Essmann and du Preez (2009) say that this increases individuals' understanding of the situation in which the organization is in.

To build on the intended use of the AIIM-tool, it could be used several times over a period of time at one organization to see if specific initiatives for AI has had an effect on the organization. For instance, if an organization wants to track the effects of a large investment in AI, the AIIM-tool could be used before the investment as a reference and then after a while to see its effects over time.

The AIIM-tool combines factors that relate to both innovation and AI sections of the organizations and therefore gives an output that is relevant for both of them. This can make it difficult to review specific components in the tool solely based on AI or vice versa. Furthermore, it may cause confusion for organizations that seek to become more competitive in only one of these fields by using this tool. Having the option to distinguish these fields from each other may be more revealing for organizations when seeking to make adjustments more according to their need.

Over the course of the study it became clear that not all questions were appropriate for every organization. Depending on their progress within AI, certain questions or answers could in some contexts be easily misinterpreted. Questions that were appropriate for early or late majority organizations could be irrelevant for early adopters. For instance, organizations that are not previously experienced with carrying through AI-related projects would logically treat that project differently in comparison with their other projects. But for AI-experienced organizations that have made substantial progress within that field, it would be expected that they treat their AI-related projects like any other. In this case the "correct" answer depends on the level of AI-maturity that the organization possesses. It can therefore be argued that there is a need for having multiple levels in the tool for different cases, depending on the level of AI-maturity. Much like the ICMM by Corsi and Neau (2015) incorporate five levels of maturity, a suggestion would be to further develop the tool in order to adjust it to three different levels. These levels could be presented as such:

- Beginner level for those that are new to AI and have little to no experience within that field.
- Intermediate level for those that have commenced an AI initiative but need further improvement.
- Advanced level for those that have come a long way in their AI development but could improve certain areas in their organization.

As of now, the tool has been adapted to be convenient for all types of organizations, no matter how much progress has been made within AI. Dividing it into levels would allow for having more advanced questions in regards to the organization's field in AI for further identification and analyzing.

Organizations that want to introduce AI to their business typically look towards successful utilizers of AI, like Google, and try to imitate their processes which most often leads to failure due to their organization's lack of foundation in terms of AI. Implementing AI takes time and effort and cannot be rushed through implementation of processes that are relevant to already successful AI utilizers. The purpose of the tool is to assist in this task and enable gradual improvement for reaching the preferred level of AI in organizations that want to either get started with AI or strengthen qualities related to the subject.

The tool is today a concept to be further developed. With the AIIM-tool using a generic assessment model it could act as a foundation for other, eg. more specific, AI related assessment models to be developed upon. With enough data collected, the AIIM-tool could involve a feature that describes different common levels of maturity and suggest what is most important to focus on for improvement at these specific levels of maturity.

Inspired by the concept of introducing different levels of maturity in the tool is the concept of more specific assessment models for organizations based on other differences. For instance, maybe it is found that most small organizations have some factors in common compared to larger organizations, this could be a reason to develop a version of the tool intended for small organizations.

A future step could be to create a platform from the tool by, for instance, making an app of it that can be accessible for everyone in the organization. This would make it easier for different levels of management to access the assessment model for a real-time visual representation of the assessment model to quickly locate areas of improvements in specific sectors. The tool would also be able to receive updates through the platform which will be necessary as AI is making progress at a daily basis as more information around that subject is yet to be discovered. Also, the tool in the form of an app, could present ongoing and finished AI initiatives and operate as a source for all AI-related matters for that specific organization. By doing so, it enables the higher ups to easily mediate current AI-agendas to everyone within the entire organization.

8 Conclusions

Here, the most important outcomes and learnings from the study are presented. The conclusions are presented based on each research question.

RQ1: What is AI-maturity, and how can it be measured?

The most important factors for organizing for AI, managing AI, and achieving effective implementation of AI were extracted from the literature. These factors formed the definition for AI-maturity which is embedded in the AIIM-tool. More generically the definition is “An organization assessed to be optimally fit for using AI”. These factors combined with important factors for innovation capability found in literature were used to develop a conceptual screening tool, called the AIIM-tool, which presents an organization’s AI-maturity with special regard to innovation.

The AIIM-tool consists of a questionnaire and an assessment model. The questionnaire consists of all the above-mentioned important factors for AI-maturity and innovation capabilities translated to questions and statements that can be rated on a scale from 1 to 7. The assessment model categorizes all the content of the questionnaire into five dimensions: *Structures*, *Resources*, *Methods*, *Action*, and *Business*. The assessment model presents the dimensions and accompanying radar charts to give an easily interpretable result. The results of the study strongly indicate that the model can actually present a somewhat reliable assessment of an organization’s AI-maturity and innovation capability.

RQ2: What similar characteristics and capabilities are beneficial for both AI and Innovation?

Aside from the synthesization it is not possible to conclude anything in regards to a relation between AI and Innovation from the result from the questionnaire. This is due to having a too low response rate for the designated population which will therefore leaves the second research question unanswered.

According to the theory, there are several factors in organizations’ ways of working that are beneficial for the utilization of AI and innovation capability. The synthesis of the literature presented all the common factors between organizing for AI and for innovation found in this study and are:

- Clear vision
- Learning organization
- Engaged management
- Business focus
- Open culture
- Agile development

- External alliances

9 Future work

The purpose of this study was divided into two parts. The first was to develop a tool that measures both the AI-maturity and the innovation capabilities of an organization. The second purpose was to conduct a pilot study with the developed questionnaire for evaluation in preparation for a larger study. This will increase the probability of success for the larger study through guidelines and recommendations.

Most important for the future development of the AIIM-tool is to perform at least one case study, to test it in the context of its actual use. This could be done at a best practice for several reasons. First, performing it in a workshop setting would spur a discussion with people who have experience and knowledge of AI which could result in a lot of valuable information. Secondly, it could test the relevance of the factors taken into account in the assessment model as of now. Thirdly, as AI is an unexplored territory for most organizations, it can lay down a foundation on what results should be sought out by organizations for each area in the assessment model. In other words, it would establish a benchmark that other organizations can strive for. Right about here, the importance of more case studies comes in. The organizations for which the tool is being developed to help might be too far behind a best practice to see that as a realistic goal. Therefore, conducting case studies at different organizations in different industries and at different levels of AI-maturity is crucial. These could then lead to the different versions of the AIIM-model which would be especially useful for organizations at specific maturity levels.

The AIIM-tool should not be considered to be a final version. AI is a field that is constantly evolving, which is why the tool needs to be constantly updated and adjusted based on newer findings within the field. It is therefore necessary to remain updated on the latest within AI and apply new findings to the tool in order for it to constantly contribute organizations with their AI progress. As AI progresses, the tool also progresses.

An alternative approach for gathering respondents is through collaboration with consulting firms, like MIT Sloan Management Review did with BCG for instance. Using the resources of a consulting firm makes it easier to perform studies that requires a large sample due to their access to people that work in various organizations. Additionally it will secure the reliability of the respondents that participated in the study.

There have been several studies that have investigated factors that affect response rates for surveys. Among these factors is the use of incentives to attract potential respondents. The studies have shown different results on different occasions. In some cases it shows no effect, while in others it leads to an increase in the response rate. It is therefore advised to use incentives for the purpose of increasing the number of respondents in the study. These incentives can either be tangible or they can be a motivation for the benefits of participating in the study. In this case it is that the respondents get to see an overview of their organization and investigate different areas through the tool. Either way, the subject should be brought up beforehand to potentially increase the number of respondents.

One concrete suggestion for further quantitative studies is to delimit the study further to force the required size of the questionnaire to its minimum. Because at its current size it is proven to be hard to collect responses.

When going ahead with performing a study using the questionnaire, it is recommended to take a look at the pilot study that is presented in this paper to gain inspiration for future analysis.

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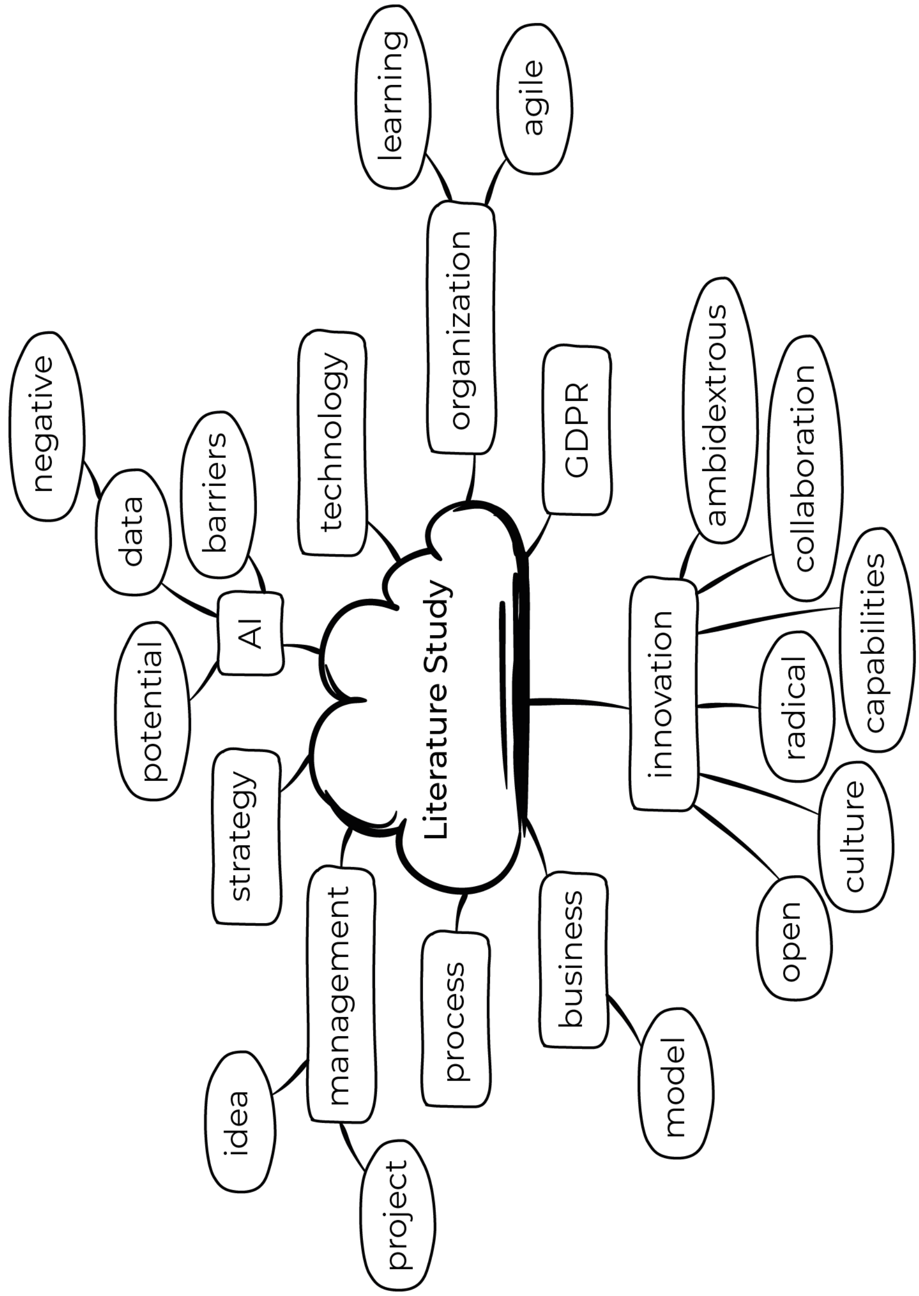
APPENDIX A

Keywords for the literature study



APPENDIX B

Hypotheses for AI and innovation adoption

- Few companies use AI to develop innovative solutions for their customers.
- Most companies using AI do it for rationalizing and saving costs in their business.
- Most organizations that use AI start by using it in their after-sales process instead of understanding customer needs or identifying new solutions or ideas.
- Companies experiencing medium-high pressure from stakeholders use AI to a greater extent than those with very high or very low pressure.
- The organizations that have been successful in using AI to develop innovative solutions for their customers have a higher degree of systematic processes in their innovation work.
- The organizations that have been successful in using AI to develop innovative solutions for their customers have experience of using other digital technologies in their products and services.
- Large companies with an inveterate culture and an organization focusing on efficiency and cost minimization have it difficult to implement AI.
- Flexible organizations are more likely to succeed in implementing AI.
- Companies with good data storage and information structure (centralized data and good data availability) have a better chance of developing and benefiting from AI.
- Organizations that own a large amount of quality data (including negative data) have a better chance of developing and benefiting from AI.
- Companies with greater in-house skills regarding AI have a better chance of developing and benefiting from AI, unlike those that outsource development of AI.

- Managers who have a thorough understanding of AI manage better with the use of AI.
- Companies do not implement AI because they do not consider it to be profitable. Because of lack of knowledge in the field of use.
- Companies that use open innovation to a large extent can benefit from it in the development of AI.
- Large organizations have it difficult to access their data compared to smaller organizations.
- It benefits the company's AI if they use both internal and external data.
- Companies with more focus on innovation of business and management models are more likely to be competitive in the long term.
- Companies with a clear culture focusing on innovation have a greater chance of being competitive in the long run.

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