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Developing services based on Artificial Intelligence

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Sincerely,
Marcus Karlsson
Karlstad Universitet
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Abstract

This thesis explores the development process of services based on artificial intelligence (AI) technology within an industrial setting. There has been a renewed interest in the technology and leading technology companies as well as many start-ups has integrated it into their market offerings. The technology´s general application potential for enhancing products and services along with the task automation possibility for improved operational excellence makes it a valuable asset for companies. However, the implementation rate of AI services is still low for many industrial actors. The research in the area has been technically dominated with little contribution from other disciplines. Therefore, the purpose of this thesis is to identify development challenges of AI services and drawing on service development- and value-theory to propose a process framework promoting implementation. The work will have two main contributions. Firstly, to compare differences in theoretical and practical development challenges and secondly to combine AI with service development and value theory.

The empirical research is done through a single case study based on a systematic combining research approach. It moves iteratively between the theory and empirical findings to direct and support the thesis throughout the work process. The data was collected through semi-structured interviews with a purposive sample. It consisted of two groups of interview participants, one AI expert group and one case internal group. This was supported by participant observation of the case environment. The data analysis was done through flexible pattern matching. The results were divided into two sections, practical challenges and development aspect of AI service development. These were combined with the selected theories and a process framework was generated.

The study showed a current understudied area of business and organisational aspect regarding AI service development. Several such challenges were identified with limited theoretical research as support. For a wider industrial adoption of AI technology, more research is needed to understand the integration into the organisation. Further, sustainability and ethical aspect were found not to be a primary concern, only mention in one of the interviews. This, despite the plethora of theory and identified risks found in the literature. Lastly, the interdisciplinary research approach was found to be beneficial to the AI field to integrate the technology into an industrial setting. The developed framework could draw from existing service development models to help manage the identified challenges.

Keywords: *Artificial intelligence, AI, AI service development, AI development challenges, AI development process framework, Industrial AI services.*

Sammanfattning

Denna uppsats utforskar utvecklingsprocessen av tjänster baserade på artificiell intelligens (AI) i en industriell miljö. Tekniken har fått ett förnyat intresse vilket har lett till att allt fler ledande teknik företag och start-up:s har integrerat AI i deras marknads erbjudande. Teknikens generella applikations möjlighet för att kunna förbättra produkter och tjänster tillsammans med dess automatiserings möjlighet för ökad operationell effektivitet gör den till en värdefull tillgång för företag. Dock så är implementations graden fortfarande låg för majoriteten av industrins aktörer. Forskningen inom AI området har varit mycket teknik dominerat med lite bidrag från andra forskningsdiscipliner. Därför syftar denna uppsats att identifiera utvecklingsutmaningar med AI tjänster och genom att hämta delar från tjänsteutveckling- och värde teori generera ett processramverk som premierar implementation. Uppsatsen har två huvudsakliga forskningsbidrag. Först genom att jämföra skillnader mellan teoretiska och praktiska utvecklingsutmaningar, sedan bidra genom att kombinera AI med tjänsteutveckling- och värdeteori.

Den empiriska forskningen utfördes genom en fallstudie baserad på ett systematic combining tillvägagångsätt. På så sätt rör sig forskning iterativt mellan teori och empiri för att forma och stödja uppsatsen genom arbetet. Datat var insamlad genom semi strukturerade intervjuer med två separata, medvetet valda intervjugrupper där ena utgjorde en AI expert grupp och andra en intern grupp för fallstudien. Detta stöttades av deltagande observationer inom fallstudiens miljö. Dataanalysen utfördes med metoden flexible pattern matching. Resultatet var uppdelat i två olika sektioner, den första med praktiska utmaningar och den andra med utvecklingsaspekter av AI tjänsteutveckling. Dessa kombinerades med de utvalda teorierna för att skapa ett processramverk.

Uppsatsen visar ett under studerat område angående affär och organisation i relation till AI tjänsteutveckling. Ett flertal av sådana utmaningar identifierades med begränsat stöd i existerande forskningslitteratur. För en mer utbredd adoption av AI tekniken behövs mer forskning för att förstå hur AI ska integreras med organisationer. Vidare, hållbarhet och etiska aspekter var inte en primär aspekt i resultatet, endast bemött i en av intervjuerna trots samlingen av artiklar och identifierade risker i litteraturen. Till sist, det tvärvetenskapliga angreppsättet var givande för AI området för att bättre integrera tekniken till en industriell miljö. Det utvecklade processramverket kunde bygga på existerande tjänsteutvecklings modeller för att hantera de identifierade utmaningarna.

Nyckelord: *Artificiell intelligens, AI, AI tjänsteutveckling, AI utvecklingsutmaningar, AI utvecklingsprocess, Industriella AI tjänster*

Abbreviations

AI – Artificial intelligence
NSD – New service development
SOMA – Service orientated modelling and architecture
BSD – Business service design
SOA – Service oriented architecture

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1. Introduction

The field of AI, short for Artificial Intelligence, has been gaining much attention due to its ability to effectively analyse and act upon a vast amount of collected data (Bughin et al. 2017). The technology has been recently featured frequently both in media and in companies' public relations. However, as a research subject, it has been around since the 1950s, during which it has survived a few "winters" of deflated interest and is now experiencing a summer again (Ning & Yan 2010). This spike in interest is mostly due to the advances in the subfield of machine learning and supporting factors such as data storage and computational power (Quan & Sanderson 2018).

There is a high interest in the technology and different actors present numbers to communicate the high potential of AI, but it has proven hard to estimate the value of the technology. More generally, Davenport (2018) points out that AI systems can both enhance products & services or be used to optimise internal business processes. It can be used to automate specific tasks to increase efficiency or provide analytical insights to people with no programming or data-scientist education (Davenport & Ronaki 2018). AI systems then become a powerful tool to be applied and can lead to faster, more rational decisions and more efficient work. Therefore, substantial benefits are likely to be achieved as the technology further diffuse on both an organisational and a societal level (Brynjolfsson et al. 2017).

1.1. Problem background

Despite the field´s maturity as a research subject and its frequency in the media, it has only reached the implementation stage in a small segment of the overall industries (Lichtenthaler 2018). Mostly technology giants such as Facebook, Google, Amazon and Baidu have been researching and investing heavily in AI technology and also has implemented applications (Agrawal et al. 2017). Also, many start-ups have been founded around an AI idea (Statista 2019) and then often absorbed by larger companies to gain their competence and ideas (Pan 2016; Quan & Sanderson 2018). However, the rest of the industry actors still struggles to understand how to use the technology in their business and often only reaches the proof of concept phase with their AI initiatives (Bughin et al. 2017). Only a few initiatives reach beyond to implemented industrial applications (Davenport & Ronanki 2018).

Therefore, there is considerable uncertainty in how to take this technology from research to industry applications (Plastino & Purdy 2018). According to the survey Bughin et al. (2017) conducted, 20 % of the companies had adopted any AI technology and only 9 % were based on machine learning. Considering that machine learning is credited to the recent explosive development of AI, there is a significant gap between research and industry implementation. Similar numbers were found by Ransbotham et al. (2017) where the AI adoption was estimated to 23%, with only 5 % that had extensively incorporated the technology. Regarding this, the US National Science and Technology Council (2016) recommended the development of an implementation framework for AI R&D as a focus area in their report.

An argument for this lack of implementation could be that as before the last "AI winter" the technology suffers from hype and is inapplicable in a general industrial environment. However, there are some critical differences from the last time that contests this argument. The amount of data generated by today's society is on a completely different scale (Louridas & Ebert 2016), which is paramount for many AI applications. It has been observed that for instance, machine learning applications can perform terribly with 1000 examples, decent with 100 000 and on a human level with a million (Ng 2017). The data availability is also coupled with the exponential decrease in storage cost of that data and an exponential increase in processing speed to process the massive amount of data (Burgess 2018; Pan 2016). These factors create a better foundation for AI to perform and to be used to create value, which indicates that some other challenges are affecting the industrialisation of AI.

1.2. Empirical context

This master thesis is conducted in relation to the transportation industry, an emerging industry in the AI context. The industry has followed the digital trend and large amounts of data are generated as vehicles get more connected. Thus, creating a high-value potential and subsequently, a high interest in AI. For instance, predictive maintenance is an example of a high-interest area within the transportation industry as the market strives to offer uptime guarantees in their transport service (Prytz et al. 2015). That is by using data and advanced technologies to predict failures and therefore be able to plan maintenance to reduce downtime proactively. Therefore, a cost calculation has been done for the predictive maintenance case to be used as an example and support the thesis reasoning.

However, the industry has no digital background or experience in analytical driven organisations which can create a challenge in adopting this technology. Therefore, it can act as a functional unit of research to represent the part that is struggling with the business implementation of AI. Hofmann et al. (2017) highlight the opportunities for new or improved services with AI, which can provide higher customer value or better operational excellence in the transportation industry.

1.3. Problem discussion

More knowledge is needed in regards to the industrialisation of AI to reduce uncertainty and increase the implementation rate. It has been observed that the majority of current research has been focused on the technical aspect of AI and not much on the purpose of the technology (Russel et al. 2015). Due to this, there is ample research to understand how to utilise the technology's different methods and build them into applications. However, there is very little research on how to convert those applications into useful service offers as there have been limited research contributions to AI from other disciplines.

In industrial applications, the technical aspect is generally not enough for implementation, but business viability, customer´s desirability and organisational adaptability aspects must also be considered. To do so, it requires an interdisciplinary approach to the problem to understand and manage the existing challenges related to AI service development. These can then be translated into a process framework to manage them better and promote valuable and implementable industrial AI services.

1.4. Purpose, aim and research question

The purpose of this master thesis is, therefore, to explore the presented research gap of how to develop industrial AI based services and its inherent development challenges. It aims to adjust a process framework to the challenges that the technology poses on the development and the contextual challenges it incurs on the organisation.

The research question is, therefore:

What challenges does AI pose on the service development process, and how can they be accounted for in a process framework to develop valuable and implementable AI based services?

The thesis will explore and identify development challenges through a literary review and empirical research. Then combine the field of AI with service development- and value theory, drawing from three existing service development processes, New Service Development (NSD), Service-oriented modelling and architecture (SOMA) and Business service design (BSD).

These are general processes for service development, each selected to represent a different perspective. NSD to reflect the service perspective, SOMA the software development angle and BSD a business point of view. Value theory is incorporated to understand how to integrate value into the process to create implementable and valuable services. The thesis draws from these theories in order to generate a process framework for AI service development.

The research will have two main contributions. Firstly, it will explore and compare identified development challenges from theory and reality. Secondly, the identified challenges will be combined with service development theory and value theory to generate a process framework adjusted for AI service development. These contributions will contribute to the effort of a multi-disciplinary approach to understanding how to industrialise AI technology.

1.5. Thesis outline

The thesis consists of 7 sections and will be outlined in here.

The *Literary review* will introduce the AI-, service development- and value theory in that order. First, with an introduction to the AI technology and the development challenges that were found in the literature. Next, the service development theory is presented, where the process models of NSD, SOMA and BSD are outlined. The section closes with the value theory, presenting the service logic value perspective in regards to service development.

The *Theoretical framework* collects and summarises the main aspects of the literature review and relates their contribution to the research.

The *Method* section outlines the research design, adopted research perspective, the methodology, methods and trustworthiness of the thesis.

The *Empirical findings* section presents the results from the empirical research in two parts. The first presents the empirically driven development challenges of AI. Then the second part presents the development aspects considered beneficial to the AI service development process.

The *Analysis* section is where the AI service development process framework is generated. The generation is done by utilising the service development theory, value theory and empirical development aspects by matching them to the identified theoretical- and empirical development challenges.

The *Discussion* section reviews and deliberates on the result, focusing on the difference between the theoretical- and empirical development challenges, ethical and sustainability aspects of AI and the proposed process framework.

The *Conclusion* section outlines the main findings, managerial implications, limitations and suggestions for future research.

2. Literature review

The chapter outlines the relevant theories of AI, service development processes and value that are found in previous research.

2.1. Artificial intelligence

Currently, there does not exist a generally agreed upon definition for the term "Artificial Intelligence", mainly because there does not exist one for "intelligence" (Honavar 2016). Multiple definitions can create a challenge when discussing AI as people may have different views of what it means depending on their background. However, some clarity can still be gained by reviewing suggestions on definitions by prominent actors, here represented by John McCarty and an expert study panel.

The term "Artificial Intelligence" is said to be coined by professor John McCarty in 1955 and his definition is; "*the science and engineering of making intelligent machines*" (McCarthy 2007, p. 2). By "intelligent", he further specifies as the ability to achieve goals in the world.

The 17 AI expert study panel for the "one hundred year study on AI" (Stone et al. 2016, p. 12) is; "*Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.*"

The central part of both these definitions is that it refers to making machines or computers intelligent, whether that is referred to goal achievement, mimicking human intelligence or adapting to its environment. The definitions also imply action, to achieve goals or functions in an environment by not only performs a function like a calculation but also performing actions. The AI technologies can thus be seen as ways of enabling this "intelligent" behaviours in machines.

To do this, different methods can be used and combined into numerous application that solves specific tasks intelligently. Due to this possibility to compose different task-specific applications from a few methods, the AI technology has a general application property (Brynjolfsson et al. 2018; Cockburn et al. 2018; Klinger et al. 2018). It has been used across industries and value chains demonstrating this property (Bakshi & Bakashi 2018; Hofmann et al. 2017).

However, a highly relevant consideration regarding AI is that although the application potential is broad, it still requires a narrow, specific problem area (Honavar 2016). This property is referred to as "narrow AI" which includes all current AI application that only achieves adequate performance within a narrow domain.

The recent paradigm of methods has enabled a data-driven learning approach, fuelled by the advances in machine learning (Agrawal et al. 2017). By feeding data to a model, it can learn to estimate properties enabling higher automated and sophisticated behaviour to be achieved without explicitly program each function (Bakashi & Bakashi 2018). It essentially learns from the provided examples that the data represents, which is a central property in the development of AI and represents a different way of developing software solutions. The approach can be used to create monitoring- (Holst 2002), anomaly detection- (Angra & Ahuja 2017), recommendation- (Jannach et al. 2016), prediction- (Shah 2007) and classification applications.

Other methods include building ways for machines to store and utilise knowledge enabling logic-based reasoning and decision making within a limited domain (Mohammed et al. 2019). It can use what it knows or stored in its knowledge base to make inference and deduction within this domain. Further, AI methods can also be used for both planning and problem solving with applications to make dynamic applications such as route planning, scheduling and logistic planning. Lastly, advances in natural language processing methods, enabling man to machine communications that improve potential customer engagement (Hirschberg & Manning 2015). It is featured in the recent upswing of smart agents such as Siri, Alexa among others. It furthers provides access to a reservoir of unstructured data in text and audio to be utilised (Chowdhury 2013).

In summary, AI technology could be seen to represent a collection of methods to create intelligent and more automated solutions in numerous applications. Recent development has been highly data-driven, representing a different way of developing and solving problems. For further reading, Appendix I offers a more detailed view of the parts of an AI system and also in four different methods related to AI and their use. The application has, therefore, a high potential in service development but there are also comes with development challenges, which will be covered in the next section.

2.2. Development challenges

As with any new technology, the development process needs to be adjusted to fit the unique aspects of the technology. Both technical and business-related challenges have been identified and will be presented in this section.

Of note is that the literature review has been developed iteratively throughout the thesis process and along with the empirical research. The selected research design enabled this approach and is covered in chapter 4. Thereby, some challenges, the majority in the business-related challenges, have been introduced in the later stages of the research to support the empirical findings.

2.2.1. Technical associated challenges

For AI, several aspects need to be considered in the development within the technical sphere. Three main aspects have been identified; data, technology characteristics and IT architecture.

Data is a central part of AI services as many methods and applications are only as good as the data it feeds off (Quan & Sandersson 2018). The acquiring, management and quality of data are therefore important factors to enable functional and valuable AI services (Jenke 2018). How and what data that is acquired needs to be considered in the development as well as incorporating a continuance of data acquisition in the developed services (Gao et al. 2018). That way, the service can be continuously improved over time.

What data strategy the company has in storing and managing the acquired data is another complicated question. It concerns both the defensive aspect of protecting and governing the data and offensive aspects of utilising the data effectively (DalleMule & Davenport 2017). Data storage is often decentralized in large organisations which can make it complicated to get access to the data and that may delay the development process if not considered early on. Furthermore, real-world data usually are not well defined and needs to be cleaned and aggregated, requiring manual labour (Gao et al. 2018). That means it requires continuous work to make the data useable and effective for AI development.

The quality of the data needs to be considered to ensure the service can deliver as expected. Many companies claim to have an abundance of data but without considering the use of it (Hazen et al. 2014).

A consideration that has increased in importance is privacy concerns of user data concerning the European general data protection regulation law (GDPR) (Butterworth 2018).

Technology characteristics can be seen as "side-effects" from the data-driven process. Explainability, bias and validation are such effects that have implications of the development of AI services. Explainability has become an important research topic and refers to the "black box" property that some AI methods & applications possess. The problem is that it can be hard to explain why a model made a decision or action, which is central to liability and responsibility issues (Government Accountability Office [GAO] 2018). With the data-driven learning, the model uses patterns within the data not visible for humans and therefore can be hard to explain, which must be taken into consideration in services where explainability is an important property. For instance, if an AI-based loan officer service denies someone a loan, it would be essential to be able to provide a reason for the customer.

Bias is another critical topic in AI as it clashes with the perceived objectivity of analytics. Learning from data also means learning inherent bias that exists within the data set (Brynjolfsson & McAfee 2017). If the data is human-generated, the same human bias that may exist can be transferred and amplified in the AI service. This problem was discovered by Amazon that had built a recruitment tool that was discovered to discriminate against women hires and was consequently scrapped before implementation (Dastin 2018). The historical data used to learn from were male applicants dominated, which was reflected in the estimated model causing it to act with bias.

As a consequence of these two characteristics, a challenge in AI development is the validation of the selected model (Gao et al. 2018). As seen, AI consists of a wide variety of methods containing numerous sub-methods. Therefore, the developer must choose the appropriate method or combination of methods for the problem. Of those, several approaches, such as machine learning and knowledge representation build upon not explicitly state what the program should do. Therefore, the models must be validated thoroughly and monitored to ensure that it solves the problem and act as intended (Gao et al. 2018; Jenke 2018). Both bias and explainability create challenges in this effort.

IT architecture can be a challenge for the implementation of the developed AI service. The services must be made available to the internal or external user either through a device or a platform. The integration to existing or a new platform is vital to ensure the service can be scaled up and used (Davenport & Ronanki 2018). The methods & application used requires high computational power and data communications. Cloud-based infrastructure has been acting as an enabler to AI because of its scalable storage and analytics capabilities (Leitão et al. 2016). However, there were also identifiable risks regarding security, privacy and high network dependency. At the other end of the spectrum are edge systems that utilise the hardware in products like smartphones or embedded systems. This choice of platform creates other challenges related to available- computational power, storage and the heterogeneity of development environments of different devices (Stoica et al. 2017).

Different degrees of cloud-edge hybrid solutions exist in-between to achieve specific system characteristics suitable for the intended application. The evaluation of IT infrastructure, therefore, needs to be use-case based but considered early in the process. Through close collaboration with the IT department to ensure scalability and implementation (Davenport & Ronanki 2018). A specific set-up may be working in a proof of concept phase but may incur a to high cost in the upscaling phase or put high demands on internal systems and IT infrastructures (Stoica et al. 2017).

2.2.2. Business associated challenges

However, as important the technical aspects are to create a service, they become somewhat irrelevant in an industrial setting if the service is incompatible with the business of the company. The developed service must be able to be deployed and create benefit for the company or its customer (Gummerus 2013). For the business sphere, there are some business alignment and organisational challenges to consider. Top management support, team composition, project management and business linking was identified.

Top management support has been referred to as a challenge with AI development. The generality of AI makes the technology relevant for a wide variety of industries, but could also pose increased organisational challenges for companies with a "non-digital" past (Troilio et al. 2017). Low AI knowledge diffusion makes the governance harder for AI project as the top management are generally not "digitally savvy" in non-digital native firms (Weill et al. 2019).

In their survey, Weill et al. (2019) found that only 8 % of board members in the transportation industry can be considered to be "digital savvy". Therefore, the push for AI is often a bottom-up approach through engaged digital knowledgeable employees but in order to gain traction and scale, the top management support is often crucial (Plastino & Purdy 2018). Troilio et al. (2017) highlighted the need for a senior manager as a champion for data-intensive innovation. The champion's presence was found to reinforce the initiative and help remove emerging organisation obstacles.

Furthermore, this can create challenges to gain support, priority and investment in the AI initiatives to be able to work with the presented technical challenges. This challenge was also observed in the research presented by Davenport and Ronanki (2018) and in Ransbotham et al. (2017). For a wider organisational adoption and use, strategy formulation and change management were identified aspects related to the challenge (Lauterbach & Bonime-Blanc 2016; Ransbotham et al. 2017).

Team composition refers to the challenges of finding and creating the right team composition and collaboration as the solution requires an interdisciplinary approach (García & Pinzón 2017). The challenge is to find new ways of engaging business experts with technology (Ransbotham et al. 2017). Ross (2018) argues that recruiting data scientists is not the primary challenge but rather enabling the wider workforce to utilise the technology; in other words, a higher general AI competence.

Furthermore, incorporating domain experts have been identified as a crucial component along with the data scientist in AI development (Ross 2018). Understanding the specific business domain, customer need (Quan & Sanderson 2018) and also being able to understand the physical meaning of the data is fundamental for development (Lee et al. 2018). Ransbotham et al. (2017) promote three types of roles, the technical, business domain and project management to bring them together.

Project management was further brought up by García and Pinzón (2017) in their work. They researched success factors in business intelligence implementation, which is also a data-driven analytical field with similarities to AI. Thereby, the same challenges could be relevant to AI development. The project management entails the coordination of activities and people in order to reach the goals of the development. This challenge builds upon the team formulation challenge.

In other words, the challenge to organise in order to create the right condition to succeed with complicated and new technology development. Observed challenges regarding planning, data collection, control, quality and environment adoption were identified within the project deployment (García & Pinzón 2017). Interdepartmental cooperation was also brought up as a challenge in regards to AI development by Ransbotham et al. (2017). They identified project management skills to be considered an important dimension in AI development in order to bridge together the business and technical perspectives.

García and Pinzón(2017) also identified the *business linking* that they argued to be the starting point for the project to ensure it is providing benefit to the business. That requires to match the projects to the business strategy and how it can help the company in the journey towards its vision, missions and goals. Yeoh et al. (2007) stress the need for a strategic business vision to guide the development and implementation. The main concern was argued to understand the business and translate the requirements into the technical system (Yeoh et al. 2007). The linking presents a challenge due to the technology-driven approach to the AI technology and connects back to the top management low digital savviness and team formulation challenge. Leuterbach and Bonime-Blanc (2016) follow the same argument in their article of the need to formulate a business strategy for integrating AI and the challenge for traditional industries that do not fully understand the technology.

The business and organisational factors therefore also need to be considered, in addition to the technical one, in AI development. Otherwise, there is a risk of decoupling the governance, project management and service development professional for the process. Making the development disjoint from the overall organisation and not considering the business factors until late in the development. Existing theory within the service development field could, therefore, be used to help manage these challenges and will be presented in the next section.

2.3. Service development

The service development process in this thesis considers the entire process of creating, delivering and managing the new service (Goldstein et al. 2002; Xu & Wang 2011). There are numerous different development processes with different angles and benefits, but a full evaluation of these was not within the scope of this thesis. Therefore, the field was limited to three development process approaches, each selected to represent a dimension deemed relevant to AI service development.

New service development (NSD) by Yu and Sangiorgi (2018) represents the service science approach. The second is the service orientated- model and architecture (SOMA) that were developed by IBM:s in their service approach for software development (Arsanjani et al. 2008). Lastly, there is the business service design (BSD) developed by Johnsson and de Rouw (2017), which has a business-driven service development. The section will provide an overview of each of the different service development angles and then outline the different phases in each development process. These processes will form the theoretical baseline for the AI process framework.

2.3.1. New service development

The NSD field represents the service science approach in this thesis, which can aid the transformation of AI application to industrial services. The general NSD process was summarised to have four non-linear phases; design, analysis, development and full launch by Johnsson et al. (2000) (referred in Froehe & Roth 2007; Stevens & Dimitriadis 2005).

However, the NSD process has been criticised for having high failure rates from both Edvardsson et al. (2013) and Alam and Perry (2002). Edvardsson et al. (2013) focused on the service development strategy as a missing link to higher performance. They conclude that the service development strategy should align and coordinate the development, value proposition, internal capabilities and resources to the business context and overall business strategy (Edvardsson et al. 2013). Alam and Perry (2002) focused instead on the relative importance of different stages and the incorporation of customer input. Their findings showed that cross-functional teams, idea generation and screening were highly important along with the adoption of a customer-orientated approach.

An alternative NSD model was presented by Yu and Sangiorgi (2018), seen in Figure 1, where they introduced the concept of value co-creating and service design into the process.

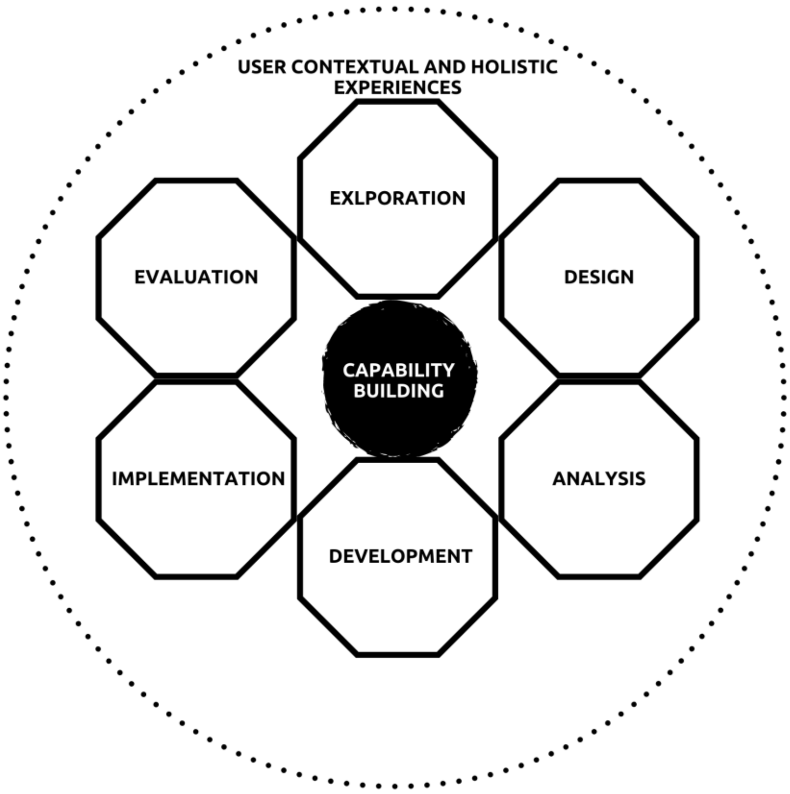

Figure 1: New service development process adapted from Yu & Sangiorgi (2018).

The authors added two additional steps, Exploration and Evaluation to the original four. The exploration phase is used to understand the user's needs and how they determine value. Thereby, the process assumes a user-centric perspective by using the customer need to be the guiding vision as well integrate the value creation in the process.

Then follows the design phase that aims to generate ideas and conceptualise the service to meet the identified user needs. These concepts are evaluated in the analysis phase where the business viability is determined, and a decision of project authorisation is made. The selected service is developed, and the accompanying service system is assembled in the development phase. The developed service is launched in the implementation phase and evaluated in the added evaluation phase. The evaluation was added to bridge the implementation and the development in order to ensure the process delivers value.

It further enables the continuous improvement to create value co-creating outputs and not only value-laden market offers. (Yu & Sangiorgi 2018). In doing so, the authors argued to enable the user-centric NSD and align the practices to create value for the customer. However, no formal strategy formulation activity is included in this model, as suggested by Edvardsson et al. (2013).

2.3.2. SOMA

In addition to the service aspect, AI service development still represents a complex software development. Therefore, influences from the SOMA process could assist in the development. It is a widely used process for designing and implementing service orientated architecture (SOA) solutions (Mohammadi & Mukhtar 2013). The SOA approach represents a paradigm shift in the field of software development towards a service orientated approach, as a new way of thinking about the IT process to creates value (Arsanjani et al. 2008; Demirkan et al. 2008). The process focuses on how to design for flexibility and reusability for rapid system, data and application implementations (Mohammadi & Mukhtar 2013). SOA approach has also been argued to narrow the gap between the business and IT department (Arsanjani 2004).

However, SOA is a general approach and not a process. For that, IBM has developed the SOMA process based on their market experience. It is therefore sprung from the industry, but IBM has been heavily researching service orientated technology and management service systems (Demirkan et al. 2008).

SOMA uses a fractal process model, which means that it does not follow a rigid sequence. It consists of 7 phases in the one presented in Arsanjani et al. (2008) and shown in figure 2.

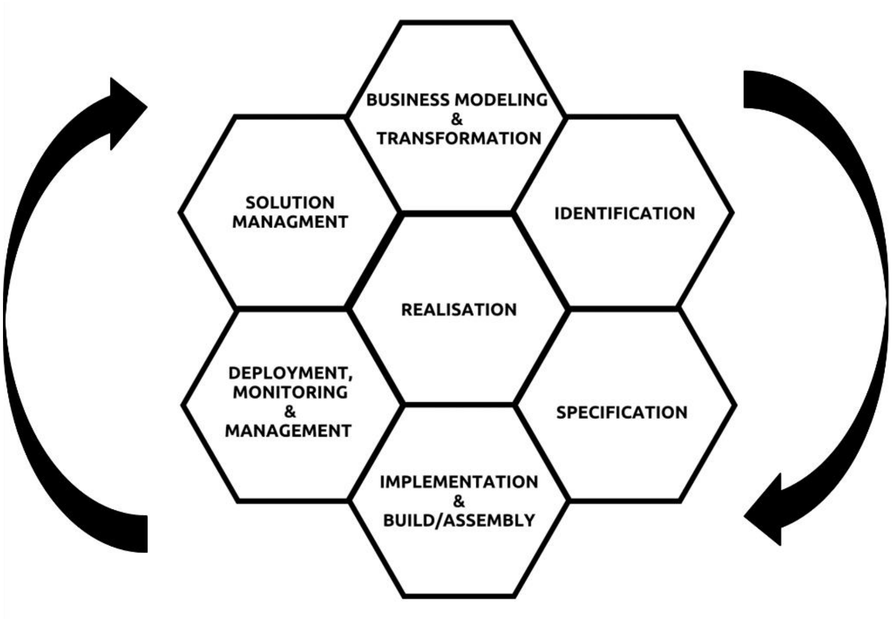

Figure 2: SOMA process adapted from Arsanjani et al. 2008.

Business modelling & transformation refers to the identification of what business model to use and what focus area the development targets. The phase sets the environment that the project shall be conducted in, which helps align it with the business.

Then *Solution management* is included to promote flexibility in service development, as it builds a repository of solution templates to use in new projects. It consists of a collection of methods that were used in specific case circumstances but are not part of the general SOMA method to help new projects.

The *Realization* phase is initially concerned with the sourcing option of software to realise a service (Arsanjani 2004). Sourcing is an important consideration as some services may not be profitable to develop internally. Then as the process progress, it will also cover the decisions regarding security, management and monitoring that would be needed. There should also be a validation of the decisions by prototyping to test technical feasibility and discover high-risk factors, preferably done early on.

The I*dentification* phase´s goal is to identify possible service candidates to develop further. Aranjani et al. (2008) suggest three different methods to use for the identification process, each based on different search angles.

Goal service modelling searches for business challenges or opportunities in relation to the corporate´s strategy and business goals. Then a top-down approach called domain decomposition works by breaking down the business domains into smaller parts to understand the underlying system. In doing so, candidates that can assist those systems can be identified. The third method is the asset analysis, that is a bottom-up analysis that explores the existing services that the business provides to identify candidates for improving or extending those.

The S*pecification* phase expands the identified candidates where the high-level design and major parts of the detailed design are completed in this phase. The work is done through a service specification in where the service design is modelled along with the mapping of dependencies of other services or components, flows and compositions of the candidates. Service operations are also included in the service model to realise and orchestrate the services into business functions.

The specification should create the support for a decision of what candidate to select and fit the new services with existing as well as leveraging existing assets to assist the development.

The *Implementation* phase consists of activities and tasks that build the service, components and flows and integrates it with potential existing assets in order to realise a service.

Lastly, is the *Deployment, monitoring and management* phase. The service is packaged, tested in a user environment and then deployed in the production environment in this phase. Then monitoring aspects are managed in this phase both in run-time, production and infrastructure.

Some considerations were put forward by Baghdadi (2013) in an evaluation of SOA methods. None of the methods perceived the customer to have an active role, which means that SOMA is a provider-centric method. The role of the manager was limited to mainly be concerned with the monitor of service quality. The SOA process is also more focused towards the commoditisation of hardware, software and business process. A service is more considered as a reusable object that leads to repeatable business activities (Demirkan et al. 2008).

2.3.3. Business service design

Lastly, as the thesis focuses on an industrial setting, a business aspect needs to be considered. Therefore, the business service design model presented in Johnson and de Rouw (2017) could provide helpful insights for AI development.

The focus of the model is getting the service requirements right in order to create the right IT-driven business services. The authors highlight the need to bring together the IT- and business department to work in an alliance, to understand and adapt to each other. The alliance is managed through a stakeholder focused approach to collect all requirement regarding the service in an early stage. Three areas of requirements are outlined in the model, which were business, user and operational. The business includes the objectives, strategies and vision of the company in order to make sure the business perspective is considered. The user requirement is the beacon to work towards and determines the goal, output and performance of the service. Operational requirements are the functional, system, external resources and technical constraints of the service offering.

The model is based on four main assumptions:

- The customer formulates the target
- A specified responsible owner of the project
- Exploration and design are done cross-functional
- A service is not only the design result but the result of the entire set of requirements.

Coordination with stakeholders is one of the main focus of BSD and are represented by a model of five stakeholder elements and four different domains seen in figure 3.

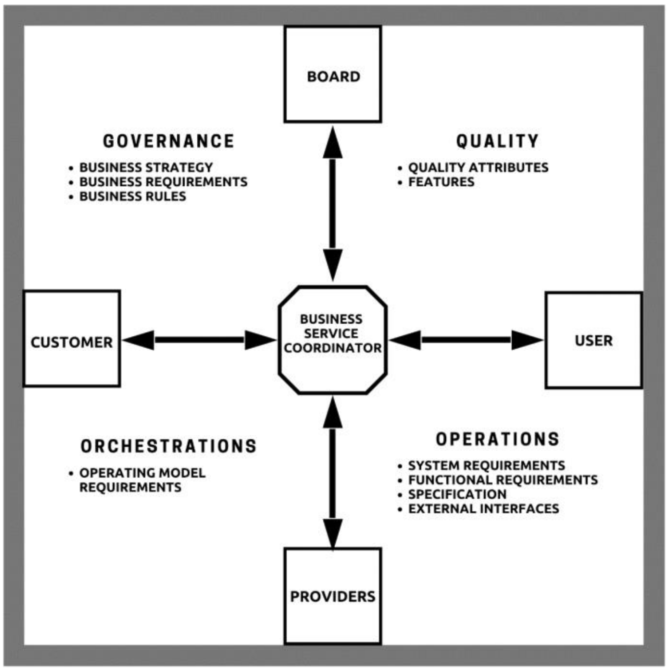

Figure 3: Business service design process adopted from Johnson & de Rouw (2017).

The stakeholder elements are the board, user, customers, providers and the business service coordinator, each with a separate role. The board sets the direction of the general business and ensures the services fall within that direction. BSD defines the user as a consumer of service and the customer as the internal recipient of the service, such as a business unit manager or the project executive. The customer is the one that pays for the service development on behalf of the user and the providers are the one that delivers that service to them. In the middle of this are the business service coordinator (BSC) that is the connection point for the different stakeholders and should manage the balance with their different wants and needs.

BSD consists of four general phases that are; preparations, service outcome definition, analysis & synthesis and service design statement. However, the presented stakeholder model is the driving force in each of the phases and a central component of the process. In the first phase, the need is identified, and a service owner is assigned. Then a joint outcome definition is set based on an exploration of the nature of the service. The third phase analyses each stakeholder's responsibility and need then synthesis into the requirements specification of the intended service offering. Once agreed upon the output is translated into a service design statement that summarises the previous work. The statement should include the service offering description, customer and user, delivery and the requirements along with market and risk management considerations.

However, the BSD model only considers the service design in the development process and leaves out the development and implementation. The model must, therefore, be complemented with additional models to cover the entire development process.

2.4. Value in service development

Generating value from the services and products is a fundamental factor in business and is one of the primary goals to attaining a competitive edge (Gummerus 2013). Therefore, integrating and ensuring value creation in service development is a central factor for all processes, including AI development. The value theory will be used to help understand how to develop valuable AI based services through the process framework. What is value and how can it be captured in the development process, therefore, is a relevant question for the thesis.

Value has a central position in service science but has shifted from the provider sphere to be firmly located within the customer sphere in the service logic perspective (Grönroos 2011). Value has traditionally been considered embedded in the products by the provider in order to be consumed and destroyed by the consumer (Vargo et al. 2008). This traditional perspective places the value creation in the production with the organisations as a sole creator. The service logic, however, uses the value-in-use perspective, that it is not until the product or service is used that value has been created (Grönroos & Gummerus 2014). Thereby, the company cannot deliver value, only be a value facilitator. The value is created and determined by the user (Grönroos 2011).

A key consideration of applying this perspective onto the development process is to enable this value creation. Acknowledging the value-in-use perspective highlights the centrality of gaining access to the customer sphere. In order to effectively facilitate value in the development process, commonly placed in the back-end organisational process, it must meet and satisfy the needs within the customer sphere. A customer focus is then not solely confined in the marketing department but instead needed to be pervaded through the organisation (Grönroos & Gummerus 2014). Thereby, enabling a customer knowledge flow or interaction becomes an integral part of enabling the development to facilitate value.

3. Theoretical framework

This section will summarise the presented theories from the literature review and outline their relation to the research context.

The introduction to the field of AI and related development challenges was derived through the literature review. Significant aspects of the AI technology are its generality potential but narrow application paradox (Honavar 2016). Thus, providing numerous opportunities but require in-depth knowledge to specify a viable problem definition. Secondly, the recent increase in data-driven AI with the learning from data approach represents an alternative way of work in development (Agrawal et al. 2017; Bakashi & Bakashi 2018). Lastly, is the broadness of the field, which provides multiple different tools to combine and incorporate into the service offering to create more "intelligent" services.

The identified challenges are related to both the technical and business sphere. Within an industrial environment, technical feasibility is not enough to implement a service but also must fit in with the business and effectively utilised by the organisation. Therefore, the development needs to maintain a business, data, service and technology perspective throughout the process to manage business-, user- and operational (technical) requirements (Johnson & de Rouw 2017).

The cost calculation also illustrates this for the predictive maintenance case that can be found in Appendix II. The technical feasibility of predicting faults and its accuracy has direct impacts on business viability. Furthermore, by implementing the technology, business models and service contracts need to be adjusted to make use of the technology as a service efficiently.

The technical challenges summarise the needed attributes for AI technology. Data and IT architecture are the fundamental aspect of AI development fuelling and facilitating the applications (Davenport & Ronanki 2018; Quan & Sandersson 2018). The technical characteristics are more effects of the methods that the AI system is built upon (Gao et al. 2018; Jenke 2018).

The business challenges are more indirectly related to AI technology but can create complications for an organisation. Low knowledge level of the technology and its data-driven way of work complicates support and collaboration within an organisation that needs to be managed (Lauterbach & Bonime-Blanc 2016; Ransbotham et al. 2017; Troilio et al. 2017).

Therefore, both business alignment and organisational management need to be considered in addition to technology.

Figure 4 summarises the development challenges covered in the literary review and were used as a guide to the empirical research in identifying relevant challenges to AI service development.

	AI related development challenges							
Technical related	**Data**	The acquiring, management and quality of data to power AI services	**Technology characteristics**	Bias, explainability and validation	**IT architecture**	The integration to new or existing platforms to be available to user		
Business related	**Top management support**	Gaining support and room to develop AI services in a non-"digital savvy" organisation	**Team composition**	Getting the right team composition and collaboration within a organisation	**Project management**	Coordination and planning of the AI development	**Business linking**	Aligning to the business strategy because of the technology driven tendency

Figure 4: Overview of the identified AI development challenges.

The three models were selected to include three different perspectives deemed relevant to the AI service development process. NSD to include the service perspective in the development, SOMA for software development aspects and lastly the BSD to extend to a business perspective. The inclusion of a value perspective aimed to extend the development to also feature value creation.

The NSD process model by Yu & Sangiorgi (2018) includes exploration and evaluation phases which integrate a user-centric perspective and continuous improvement to the process. The process can assist in re-orientate the AI development from a technology- towards a user value focus.

The SOMA process was designed for value creating software development that combines business, technology development and project management (Arsanjani et al. 2008). The phases of the process provide structure to the project management but also flexibility through the fractured process model. Thus, utilising IBM´s research in combining software-based technology and management in service systems (Demirkan et al. 2008) to join the technology and business of AI development.

The stakeholder approach of the BSD process can assist in understanding the multi-requirement nature of AI development. Identifying the core competencies as well as relevant stakeholders in the different phases of development could be highly beneficial to AI development.

Further, the broad view on the requirements and its assumptions can provide valuable guidance to the AI service development.

The value perspective of Grönroos (2011) further supports the user-centric development with the value-in-use perspective. That provides insight into the value creation of services and highlights the need to gain access to the customer sphere.

Figure 5 summarises the contributions from the service development- and value theory into a framework. This framework acts as the base for the constructed AI service development framework to manage the identified challenges.

NSD		**SOMA**		**BSD**		**Value in service**	
User centric process and value creation		**Software development aspects**		**Interdisciplinary requirement collection**		**Value creation process**	
Exploration	Identify user need and value perception	*Business modeling & Transformation*	Focus area and business model selected	*Preparations*	Identified need and assign service owner	*User centric perspective*	Development based in a existing or latent user need
Design	Idea generation and conceptualization	*Solution management*	Project management template collection	*Service outcome definition*	Joint service definition	*Value-in-use*	Value is created when the service is used by the user
Analysis	Business viability analysis and authorization	*Realisation*	Implementation aspects and prototyping	*Analysis & synthesis*	Stakeholder requirement analysis and requirement specification	*Knowledge transfer from market to development*	Need to gain access to the customer sphere to enable user centric development
Development	Service developed and service system assembled	*Identification*	Service candidate identification	*Service design statement*	Fully outlines the intended service offering		
Implementation	Launched	*Specification*	Detailed service design in a service specification				
Evaluation	Evaluate value created and bridge to explore	*Implementation & Build/assembly*	Develop service and integrate with existing assets				
		Deployment, monitoring and management	Service is tested, launched and monitored				

Figure 5: An overview of the covered service development processes and the theories contributions.

4. Method

The method section outlines how the research was performed to answer the proposed research question. It consists of four sections; research design, data collection, data analysis and trustworthiness.

4.1. Research design

The purpose of this thesis was to explore AI based services development in order to understand how to increase the success rate in industrial implementations. The focus was to understand the inherent development challenges that the AI technology poses as well as understanding the surrounding contextual challenges that it affects. The research design was based on a qualitative single case study within an organisational setting to meet this purpose.

The case organisation is part of a larger corporation group in the transportation industry and is responsible for developing and managing connected services. The larger organisation has strong roots in the product-centric perspective but the case organisation more towards services. It only works with off-board solutions, thus mainly software dependent.

Because of the surge in connected assets that generate high amounts of data and the industry has invested heavily in AI (Bughin et al. 2017), and the case organisation, therefore, explores the possibilities. Therefore it is a suitable case for this thesis to understand the relevant challenges hindering a wider implementation of AI services. A deeper understanding of the contextual factors could be gained by collecting data in the case environment.

Process research in organisations has been argued to be challenging because it is complex and is often entangled in various social factors such as relationships, thoughts and interpretations (Langley 1999). Therefore, a case study was deemed suitable as it does not separate the contemporary phenomenon from its context, as experimental approaches do (Yin 1981). Figure 6 illustrates the research design used in the master thesis.

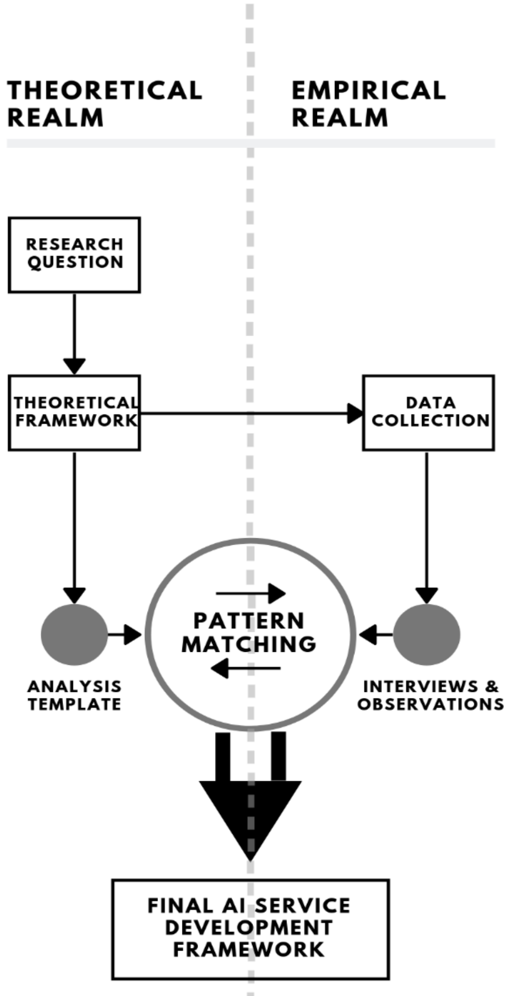

Figure 6: Research design.

Further, the systematic combining approach proposed by Dubois & Gadde (2002; 2014; 2017) was considered beneficial to the research environment. The approach fits the analysis of interdependent factors in a complex structure (Dubois & Gadde 2002). This because it is continuously matching theory and the real world with the focus of creating depth within a context. This approach was in line with the presented purpose and research environment of this thesis. The systematic combination approach advocates a nonlinear and non-positivistic research structure of a more in-depth case (Dubois & Gadde 2002).

It adopts the interpretivist paradigm´s ontology and epistemology view of a constructed social reality with multiple coexisting perspectives. Therefore, it needs to be explained by understanding subjective meanings and details of the situation (Wahyuni 2012). The cornerstone is the iterative approach of moving between theoretical- and empirical findings to generate a final framework.

The methodology is therefore dependent on an abductive approach of using and extending existing theory with empirical findings to generate new theory (Shank 2008).

Figure 7 illustrates the systematic combining path that the thesis followed to reach the final result, starting in the upper right corner. The initial approach aimed to understand the service components of an AI service. However, based on the initial literature review and observation highlighted the development aspect as more relevant. From the expert sample interviews, both the process angle and combination of technical and business challenges emerged. Further literary review supported the inclusion of business and organisational related aspects even though sources were scarce. Therefore, an internal sample group was included and a final research focus was established.

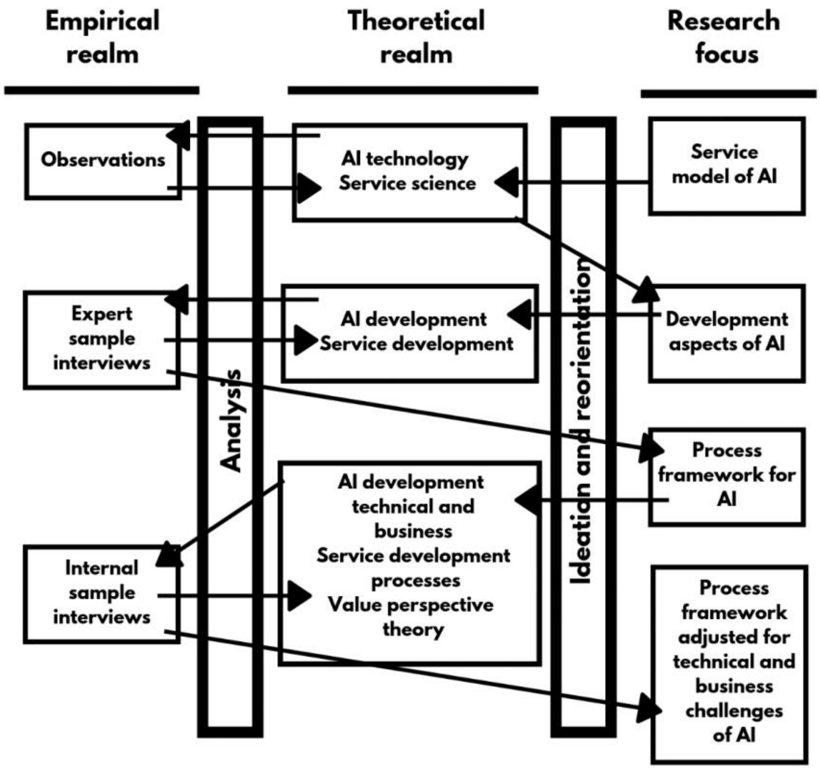

Figure 7: The systematic combining process of the master thesis, model adopted from Huhtala et al. (2014).

4.2. Data collection

The data was collected through the use of interviews and participant observation. The interview was the primary data collection methods and the observations were used as a supportive data source.

The interview method was selected because of its strength in deriving interpretations and to understand the meaning (Warren 2011). It was used to understand the different challenges and how to potentially manage those in order to develop valuable and implementable AI services. Participant observation was used to increase the reliability of the data collection through triangulation. It further allowed observation of behaviour that may not be addressed in an interview format. The observations was done by participating in context relevant daily activities such as meetings, projects and dialogues along with attending conferences within the field. The work was mainly in proximity with the analytics and data scientist team. The data was collected through the use of a research journal and field notes.

A semi-structured interview approach was used as it is a frequently used method for in-depth interviews (Guest et al. 2017) as it allows for the possibility to use probes to gain further information. Purposive samples were used in the interview study to get information-rich answers to gain depth in the case study while addressing the limited time factor.

The sample was divided into two sample groups, the first included "experts" that were judged to possess both technical AI and business knowledge either from research or practical experience. These were case-external actors and the purpose was to understand their challenges, experiences and best practices within the research field. The second group was context related and consisted of the internal stakeholders for AI service development, representing the different departments within the case organisation. The purpose of this group was to understand the different perspectives, needs and challenges that create the contextual complexities. The interview samples can be seen in Table 1 with a description of their background or position and length of interviews.

Table 1 A table over interview participants of each sample and a description of their experience along with the duration of the interview.

Reference no. and sample group	**Description of experience**	**Duration of the interview [min]**
Interview 1 – Expert sample	Business advisor in a large analytic solution provider company	[77.18]
Interview 2 - Expert sample	Top management member with a background in product development.	[58.34]
Interview 3 – Expert sample	A researcher with broad experience in AI and worked different research projects in the industry sector and part of various AI projects.	[47.36]
Interview 4 – Expert sample	Technical expert on a software company working with deep learning. Also oversaw the building of the AI effort.	[56.46]
Interview 5 – Internal sample	Manager	[27.27]
Interview 6 – Internal sample	Manager	[21.54]
Interview 7 – Internal sample	Manager	[34.04]
Interview 8 – Internal sample	Manager	[23.25]

An interview guide was created for each of the two sample groups to increase the consistency in the data collection, which can be found in Appendix III and IV. The guide was made by using the four steps suggested by Smith (1995). The research question was broken down to four major themes, the introduction, technology, service development process and value. Those were arranged in the presented order to form a logical sequence.

The introduction theme was added to help build report with the respondent as well as letting them adjust to the interview scenario (Smith 1995). For the expert sample, the focus was on AI technology and its effect on service development and value while the service development and value were the focus for the internal sample. The question was adopted to their level of knowledge in AI.

Then interview questions were generated in each theme drawn from the proposed theoretical framework. These were formulated as open-ended to enable the respondent to provide detailed and data-rich answers (Roulston 2010; Smith 1995). Caution was also taken to formulate the question without inherent jargon or to be leading. Lastly, potential probes and prompts were added to each question to support during the interview. The interview was conducted in person and to the best extent in a place where the respondent was comfortable. For the expert sample, the interview generally lasted around 60 minutes and for the internal sample, it lasted around 30 minutes instead. Each interview was recorded through an audio recorder with the consent of the interviewee and transcribed in order to be analysed.

4.3. Data analysis

The analysis of the collected data, both from the interviews and observations, was done based on the "within case analysis" approach discussed in the paper by Yin (1981). This thesis used the analysis method of flexible pattern matching explained in the paper of Sinkovics (2019) as it was thought to be in line with research design. The logic of flexible pattern matching is to link the predicted theory-driven patterns found in the literature review to the observable empirical patterns (Sinkovics 2019). The central part of figure 6 illustrates the process used to conduct flexible pattern matching. An analysis template was derived from the theoretical framework that predicted relevant challenges of the AI service development process. The template was then used to match with the underlying patterns within the collected data where empirical findings either supported, rejected or provided an alternative explanation. New patterns that arose from the analysis were collected and subjected to a focused literature search in order to evaluate its relevance. That way, theory and empirics could be iteratively combined and new challenges or aspects could be identified. Thereby iteratively forming the literature review and theoretical framework sections of the thesis. The use of an analysis template followed the abductive reasoning of guiding the analysis by the use of previous knowledge (Shank 2008). Therefore, the analysis method was deemed to be suitable and to strengthen the thesis research design of systematic combining and the abductive approach used.

4.4. Trustworthiness

The evaluation criteria suggested by Murphy and Yielder (2009) was used to judge the trustworthiness of the research. By trustworthiness, they specify to be that the meaning of participants is reflected as closely as possible. Four different aspects were used to assess the thesis trustworthiness; confirmability, transferability, dependability and credibility.

4.4.1. Confirmability

Confirmability reflects how well the findings and interpretations are founded on the collected data and not on preconceived notions of the researcher (Given & Saumure 2012). Full transcriptions were used in the analysis to reduce researcher bias and translated quotes were included to promote confirmability. The transcript of the interview was also sent to the respondent to confirm it reflected their accounts correctly. The iterative effect on the work was recorded and presented in figure 7 to allow the reader to follow the work path to the presented result. Showing the work path was deemed extra necessary due to the abductive approach adopted in the thesis. In line with systematic combining, the aim was to combine theory and reality to strengthen both and not to twist one to the other. Therefore, the complete cross interview analysis was included in the result section. Since a single researcher conducted the research, some researcher bias may nonetheless be present.

4.4.2. Transferability

Transferability accounts for the uniqueness of each case and is more concerned with the inference possibilities (Shenton 2004). The main point is to determine how well the findings could be applied to an alternative context (Given & Saumure 2012) and strengthen that property. The purposive sampling method was used to account for multiple perspectives in order to gain a more holistic view. The use of context-independent experts was used to broaden the understanding of less context-specific attributes. The semi-structured interview was also selected in order to generate rich and thick descriptions to understand the contextual setting. By understanding the context, a better determination of transferability can be done.

4.4.3. Dependability

Dependability was promoted by the inclusion of the method section that described the research design, methods and analysis used as well as the assumption and perspective adopted (Shenton 2004). This is not about being able to recreate the exact result in a different context but rather being able to produce similar results in a similar context (Given & Saumure 2012). Therefore, detailed knowledge of the research procedure was included.

4.4.4. Credibility

Lastly, the credibility that represents the plausibility of the findings and that it represents the data accurately regarding the research question. Open, unbiased and non-leading questions were formulated to avoid affecting the interviewee. Data triangulation was used to support the findings through both interviews and observations. The systematic combining approach further benefited the credibility as the findings were supported by relevant literature linking the reality to theory.

4.4.5. Ethical research

The study aimed to be conducted ethically to reassure and respect the interview and observation participants. Confidentiality and anonymity were ensured for the participants where only generic descriptions were used as a reference. Information was sent out before the interview outlining voluntary participation. It included; termination of the interview at any given time, the answer to each question is voluntary, withdrawal of participation in the thesis at any given time and confidentiality. A consent form was used before each interview to verify that the respondent understood and contained permission to record the conversation during the interview. The use of the interview transcripts was confined to this thesis unless otherwise agreed upon with the participant. The collected data was handled in accordance with the privacy law GDPR and the recording was deleted directly after being transcribed.

5. Empirical findings

The section will present the result of the data analysis of the collected data from the interviews and the participant observations within the case context.

Based on the conducted empirical research, the findings are divided into two sections. The first section presents the identified challenges with AI development. The second section presents the identified development aspect considered beneficial to the AI development process. Quotes and observations are used to support and strengthen the findings.

5.1. Development challenges

	Development challenges				
Theoretical and empirical pattern match	**Data availability**	**Data management**	**Technical characteristics**	**IT- architecture**	**Top management support**
New empirical patterns	**System adoption consideration**	**Identifying relevant problem definitions**	**High Uncertainty**	**Technology adoption**	**Work structure**

Figure 8: The empirical findings related to the development challenges of AI-based services.

Figure 8 summarises the identified challenges. The resulting analysis template is shown in Figure 9 at the end of this section for a more detail view of the findings.

The challenges regarding the technical aspects of data, technical characteristics and system architecture that was identified in theory were also identified in the empirical findings. All three were present across interviews with emphasis on data as a key resource and as a foundation to the development. Gaining top management support was also identified as a theoretical driven challenge with support in the findings. One of the participants had experience from both having and not having the support and emphasised the organisational challenges they faced without it. An internal actor referred to a "champion" within the organisation that can push the initiative forward. AI development has some particular needs with the data and system architecture that can be overlooked or down prioritised without a more in-dept understanding from top management. Illustrated by the following quote:

"*It is easy to say no to an AI initiative as they are complex and expensive. It is therefore beneficial to have insight and support from a high level early on until the organisation has adapted. It became a lot harder to have our specific needs heard without it.*"

Then there were empirical patterns that emerged in the data analysis of development challenges. The system adoption challenge of AI was emphasised the most by one expert but was present in all the expert interviews. It refers to the challenge of integrating the AI component to the surrounding service offering and service system. Too much focus can be placed onto the technical aspect but when the service is to be assembled and launched, it fails to satisfy the requirements and constraints needed to supply the service. Examples of these were an internet connection, latency in communication, coordination of other service parts, data transfer, business modelling, user interaction and service uptime. The following quotes summarise this challenge:

"Designing for the infrastructure and ecosystem is an important aspect as it is not only about your product but rather your product within an ecosystem."

"I think you need a wider perspective; it is not only about the product or the concept but how it is connected to the other things."

Identifying relevant problem definition is a challenge in two regards, both due to the general-application nature of AI and the technical focus tendencies. The technology has a wide application potential around a company and a challenge is to understand how to use it within their context. At the same time, it requires narrowly defined problems but can get good results within that frame. Thereby, the focus cannot be on the technology but instead on the problem. A common trap in AI development that was brought up in the interviews was having the goal of using AI, not to solve problems. That creates a risk of building an overly complex solution without solving an actual need.

The high uncertainty and explorative nature of AI development were also frequently brought up across the interviews. There is a lot of trial and error in the development as the feasibility is hard to determine. The same challenge was also observed in the participant observation, where both value estimation and technical feasibility was hard to determine in an initial phase. The uncertainty creates a challenge in planning, securing initial investment and communication. An interesting effect of this was discussed in one of the interviews regarding the tendency of only reaching the proof of concept phase in AI development.

"If you are not accustomed to handling uncertainty and in this, it will be a greater degree of uncertainty, then it becomes easier for a corporate or product management to do a proof of concept."

Two other challenges were identified concerning the organisational aspects of AI development. These were primarily found across the internal interviews. The technology adoption focuses on the challenge of effectively utilising the technology within the current organisation. It is not only about attaining the AI competences but also integrating it into the business processes of the organisation. One of the interviewees summarised it as:

"I think that things should be done in the context and then it is about getting all those that work within to use the AI technology. You cannot have a separate organisation to only work with AI as you need to understand the context, you could have a special set-up as a centre of excellence to start with, but it must be integrated into the teams otherwise it will not scale."

Another response to this supported the integration but highlighted the challenge of reaching that point:

"I think it needs to be the ones that develop the services today that need to drive and the AI group jacks into. But in order to do that to happen the AI group must help them to understand what capabilities we have and what can be done with it."

This lead to the second challenge of finding efficient work structures for the development. The challenge is to finding compositions and team formulations within the existing organisation structure. Where to place the AI competence and how to enable collaboration and knowledge exchange from the different stakeholders. Exemplified by the two quotes:

"Need to find a solution where the technology and delivery teams work together, with an immature area I think the AI persons need to be centrally located and work close but with tight communication and collaboration with the service development organisations."

"More about the forms of collaboration and how we find ways to connect to each other. That the teams know the centre exists and turns to it with an identified potential or vice versa where the centre finds potential to take to the stakeholder."

Another point of interest in the empirical findings was that the ethical and sustainability aspects of AI were only brought up in one interview as a challenge and an important aspect in AI development. It covered ethical guidelines to promote trustworthy AI and to use the technology to benefit for humans. These were questions the interviewee actively worked with and had the perspective that these softer questions would be more important going forward.

Development challenges	Theoretical pattern	Empirical pattern contribution			
Expert sample		I1	I2	I3	I4
Data as a key resource	Central part of AI services - (quan&sanderesson 2018)	Access to data is fundamental enabler that you must have	Need good data around the intended service	Many popular methods today is highly data driven which means more and better data = better results	Data is the most important degree of liberty in the work, need to work actively with the data
Data management	Acquiring, management and quality of data is major concerns - (Jenke 2018;Dallemule & Davenport 2017;Gao et al. 2017)	Continuous strive in both the quantitative and qualitative aspects of data	Work to structure data to be used, essential but not there	Often need data from several different parts of organisation, often major challenge to get access	Need to take control over your own data in order to create a product, need to invest money in the data and in the supporting infrastructure
Technical characteristics	Black box - (GAO report 2018) Bias - (Brynjolfsson & Mcfee 2017)	Transparency of application must be considered -		That data does not reflect reality or that it does but we don't want is to - bias	Need to ensure validation as you cant use black box code in something you care about, especially in safety critical aspects
IT architecture	High demands on IT system and infrastructure - (Stoica et al.2017)		Need to consider where the computation is done, is there enough computational capacity in our product or do we have the data rate to use cloud computing	Solution architecture design for synchronisation and coordination, Must work with the system and meet the requirements and constraints of entire system	Challenge to meet the computing requirement on edge/embedded devices
Top management support	Top management support are crucial- (García&Pinzón 2017; Plastino & Purdy 2018; Leauterbach&Bonime-blanc 2016); Top management low digital savviness - (MIT CISR)	Most potential in areas where top-management understand and drives opportunities	Important to be able to clearly communicate the value to the management to get their support, they don't have the time to understand everything of the new technology	Important to solve real problem to get support from the entire organisation as you will need different parts of the organisation in the development	Early commitment from top management helps a lot, became harder to get approval for special requirements without it
System adoption consideration		Often huge abyss between discover and deploy, needs to be considered early on	Need people that understand the integration to the larger system in the team	Not realise that AI part is a pretty small part of the system development; Design infrastructure and ecosystem where the important aspect is not your product but how it fits within the system	Functions and components creates many dependencies on a system level -I4
Identifying relevant problem definitions		Need to understand what possibilities there are within our domain	Can not start with how to solve everything with AI, need to understand what to solve for our customer	Classical problem is to decide to use AI, not solve problems. Need to be very clear of what to solve and within those boundaries can get adequate results	AI could be used to many different things around the company, it is good to consider where to work
High Uncertainty		A lot of research and exploration with no set plan, trial and error		There is a degree of uncertainty in it and will not be a deterministic process	Difficult to roll out a master plan, instead need to start early and test, gain fast feedback and fail early
Internal sample		I5	I6	I7	I8
Technology adoption		Need a small team of AI competence to drive, support and working with groups accelerate the progress	To integrate in the business it is important to help create understanding of the capabilities and potentials	Need to have a critical mass with a number of persons around the area, cant be dependent on 1-2 only	Can´t have a specific, separate organization that only focuses on AI, needs to be runned in the context and then its more about getting those to use the technology
Work structure		Needs to work actively with the teams team that develop services	More focus on to find ways to work and to set up collaboration structures, to connect the different capabilities	Find ways for the technology and delivery department to work together	Needs to be done out in the teams that develops within the context, otherwise it will not scale

Figure 9: The final analysis template for the development challenges of AI services.

5.2. Development aspects

Development aspects						
Business focus areas	Customer centric perspective	Interdisciplinary team composition	Domain knowledge	Agile approach to development	Continous improvment	Piloting

Figure 10: The identified development aspects in relation to AI service development.

Figure 10 shows the seven development aspects that were identified to be beneficial to AI development. Again, the resulting analysis template can be seen in figure 11 at the end of the section.

All the interviews brought up the perspective that the technology should target current business-related problems the company experiences, viewing it more as a tool. A firm business and strategic alignment were argued and to target certain identified business areas. A participant with an extensive background in product development talked about the relation between the business development and product development. Stated as:

"Sometimes, the business- and product development is run in parallel instead of determining the business development and develop products that fit into that. It then becomes a big question and can cause a bad atmosphere when trying to bring the two together. "

Another explained that they early on decided on what to do and where to work within while an acquaintance took a broad approach, explained here:

"AI could be used in numerous different things around the organisation; we decided early on that this is what we will do. It is a lot more challenging for my friend to try and satisfy everyone at once. It is probably very good to consider where to work. "

Adopting a user- or customer-centric perspective was highlighted across both the expert and internal interviews as an important development aspect for AI. The aspect was related to the uncertainty- and problem definition challenges that were identified. Identifying and clearly formulating the customer value can ensure that relevant problems are targeted. It can also work as an initial justification before a more certain value estimation can be done.

Interdisciplinary team compositions were deemed as an essential aspect for AI development. As the identified development challenges are coming from many different organisational functions, the team needs to have a wider perspective.

The team should include the technical, data and business capabilities and work closely to gain speed. The need for close cooperation was also observed as an important factor within the case context. Sporadic collaboration between actors led to misunderstanding and assumptions which further increases the uncertainty and slowed down the process.

An additional aspect related to the interdisciplinary approach is the need of including domain knowledge with AI service development. It was considered an essential part of the team in order to understand what to solve and if the developed service accomplishes that. Factors such as business translation, customer need and to measure the impact of the development were referred to. As stated:

"It is rather about combining the domain expertise with some form of technical expertise and that is when you get an effect. Only AI technical competence is not enough, and only domain competence is not enough either. Also, in many cases, only one type of competence is not enough, especially in regards to services where there are user interaction, back-end and the holistic aspect to consider."

Two experts referred directly to the agile project management as beneficial for the development. However, the other two referred instead to the incremental, iterative work process with sprints that are consistent with the agile way of work. It was deemed beneficial in order to manage the uncertainty and trial and error characteristic of AI development. The need for agility was also related to the data dependency, where the data dictated a lot of what could be done and not, which is hard to determine initially.

Continuous improvement was also something that pervaded through the interviews. It is connected to the agile approach but also focused on factors after the launch of the service. The work should continue to improve and develop the service after launch by adjusting and including additional features. A participant referred to the analytical lifecycle, to work iteratively over the discovery phase and the deployment phase. New ideas emerge from the deployment to be developed and then included. Another viewed the launch as a beta version that unlike the stepwise improvement of product needs to be faster updates. A perpetual beta to be continuously improved and that therefore a lot of progress was in web-based services where the update is easier was also discussed.

Piloting was the last empirical driven factor where the testing of the concept in a real environment and an integration test. This is related to the system adoption challenge to identify real world and adoption issues with the service in an early stage. That way, scaling issues could potentially be solved, or if not, the project could be terminated at a lower cost. Summarised in the following quote:

"We offered great services that were showcased on a laptop with a great internet connection but when we deployed it, the work environment had not as good connection and the servers went down from time to time causing the customer trouble."

Development aspects	Theoretical pattern	Empirical pattern contribution			
Expert sample		**I1**	**I2**	**I3**	**I4**
Business focus areas	Identify what business model and focus area - (Arsanjani et al 2008); Business linking and matching with the business strategy - (Garcia & Pinzón 2017)	Start with what do we want to do, how do we do it today. Either core activities to improve or as stepping toward a new business model	Should decide where to develop the business and then develop products that fits that business, think about our business strategies and decompose it to segments and areas to drive a project in.	Should look at what real problem do we have today that we don´t know how to solve and where we think this technology can help us	AI could be used to a lot of thing in a company, we decided early what to focus on and it will be a lot more challenging to try satisfy everyone at once
Customer centric perspective	Needs to understand business domain and customer need - (Quan & Sanderson 2018; Ransbotham et al. 2017); customer focus to facilitate value - (Grönroos 2011)		need to understand market, customer use and how we could expand current offers Clear formulated customer value		The main focus will be on problem that the customer needs to solve, and I think it is important to be near in our case our internal customer
Interdisciplinary team composition	Team composition and inter disciplinary collaboration - (Garcia & Pinzón 2017); Cross-functional teams, customer oriented approach - Alam & Perry (2002)	Need data/ IT-, Analytics and business people working in the same team, also often works with a management consultant that can drive the change management; Nothing happens when only 40 data scientists explores within a data lake	Cross-functional approach & customer understanding is key to create "unique selling points"; Core is analytics, data and domain knowledge	Often not enough to have only one domain competence but need several	Domain knowledge, new technology knowledge, statistic knowledge, computer science and software engineering are some key resources
Domain knowledge	Domain experts as a key competence in the team - (Ross 2018)	Require someone to translate the technology into business with deep industry knowledge	Domain knowledge is key, understanding customer business and need	Need to combine technical and domain expertise, then you will get traction. It is not enough with them separately	Good to have someone with domain knowledge that understand the problem and past problems to understand the effect of the work
Continuous improvement		Continuous improvement of discover and deploy	Launch a beta version and continue update is important, not done in the launch step	Implementation never done, perpetual beta	We want to as soon as possible test on the embedded device to measure and continuously improve
Agile approach to development	Project deployment and management most important sucess factor - (Garcia & Pinzón 2017)	More explorative process, needs to be fast incremental step with a clear direction with trial and error Time dictates, what can be accomplished on 12 weeks	work in small dedicated team in an agile way; fast iteration and fast real test in a limited market, avoid handoffs	Design and implementation should be iterative, hard to work sequential	Start early, iterate and grow over time - get feedback early and fail fast in that case; Agile project managment approach
Piloting		Analytical lifecycle where the process iterates over the discover and deployment phase	Fast, incremental development with a fast piloting phase and preferably developing in a real environment	Integration test is very important as that will uncover the larger problems Can be harder to solve problems in the implementation	Tries as early as possible to do integration test and work in a real environment
Internal sample		**I5**	**I6**	**I7**	**I8**
User centric focus		Even though it is technology driven it must consider the end user value which should be the focus, not only the business case.	No different from other services, needs to be close to customers and understand their need	Risk of being to technology focused, must get the customer needs to understand what AI to develop	

Figure 11: The final analysis template for the development aspects of AI services.

6. Analysis

The process framework is generated in this section by combining the challenges, development aspects and theories from both the literature review and empirical research.

The development aspects and challenges that were identified through the literature review and empirical findings will be addressed in a process framework. The framework draws from the presented service development processes and value theory. Thereby assembling an adjusted process framework for AI service development to assist in developing valuable and implementable AI based services. Figure 12 shows an overview of the process used to generate the AI service development process framework.

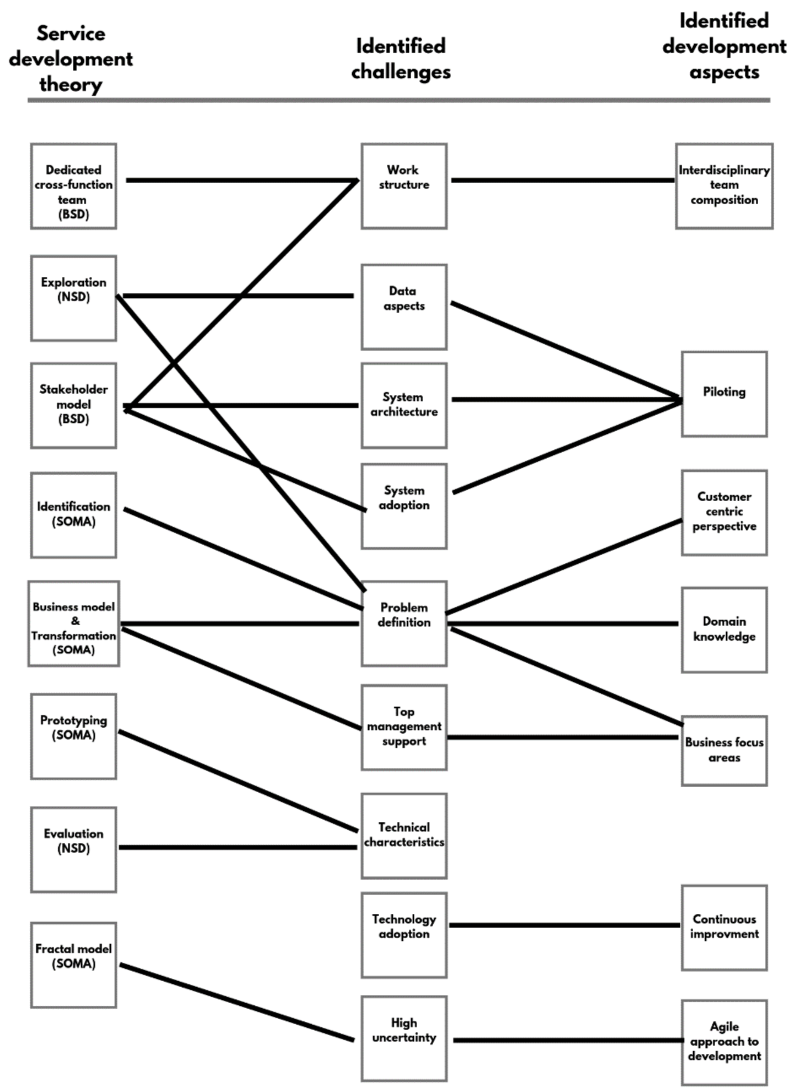

Figure 12: Overview of the process of combining the service development theory and empirical development aspects to the identified development challenges of AI services.

6.1. AI service development process framework

The proposed process framework is presented in Figure 13, derived from both the theoretical- and empirical findings. It consists of both development principles (left section), a process comprised of three fractured clusters of phases (central section) and a release train for implementation and maintenance (bottom section).

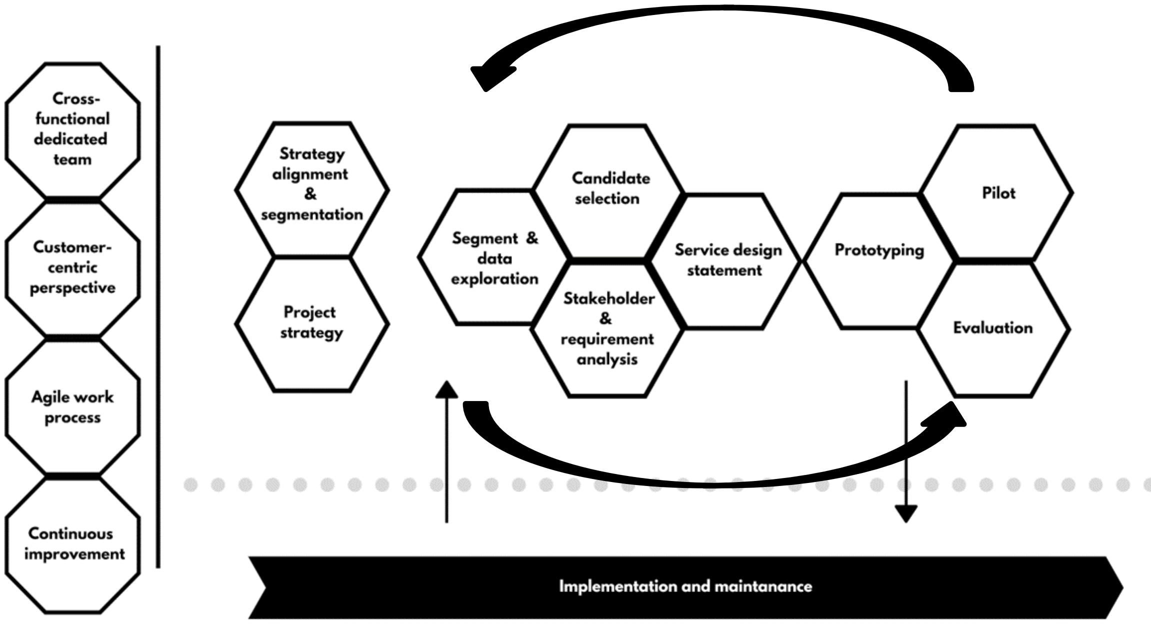

Figure 13: The proposed process framework for AI service development.

6.1.1. Development principles

As the model by Johnson & Paul de Rouw (2017), the process will start with development principles for working with AI service development. These are meant to frame and guide the development work.

Cross-functional dedicated teams

The development should use a dedicated cross-functional team with an assigned project leader for the development. This principal is promoted in the BSD process (Johnson & Paul de Rouw 2017) and aims to address the development challenge regarding team composition (García & Pinzón 2017; Ransbotham et al. 2017; Ross 2018). This was also one of the empirical development aspects to deal with the multidisciplinary challenges and enable collaboration between the technology and the market.

As implementation has been a recurring problem of AI services (Davenport & Ronaki 2018), the implementation factor needs to be considered early on in the development (Davenport & Bean 2018). Therefore, a broader perspective of requirements and constraints needs to be considered, not only the technical feasibility but business viability and user desirability.

Further incorporating domain knowledge in the team was deemed central to the AI service development for the interviewees and Ross (2018). Sporadic communication between actors was observed to prolong and complicate the work in the observed project. Therefore, assigning a dedicated team is necessary to enable steady progress.

Customer-centric perspective

The principle aims to incorporate value creation in the service development process. In the value theory for service development, the problem definition should be sprung from an identified customer need. This is especially important due to the need for a narrow problem definition for AI. It requires the development team to understand or collaborate with the customer sphere to provide a solution to the customer current and future needs (Grönroos 2011). The principle is also in line with the BDS process (Johnson & Paul de Rouw 2017) of a customer-formulated target and the user requirement.

Agile work process

An aspect that was sprung from the empirical findings was agile project management to handle the characteristics of AI development. Using sprints and fast iterations of the process framework should align with the explorative nature of AI development. With the data dependencies of AI on performance and the uncertain initial value and feasibility estimation, the project needs to have a fail fast mindset. Therefore, the process benefits of flexibility and a more trial and error approach more consistent with the agile approach. Also, both the NSD and SOMA featured a more iterative development.

Continuous improvement

The continuous improvement of the developed service is an important aspect both in the value perspective and regarding AI technology. Both in the development and deployment phase. Iteration between the development and testing was brought up frequently in the data collection, aligned with the agile process.

Then the iterations between the development and deployment for improvements were identified. The evaluation phase was added in the NSD process model to bridge the implementation and development. Thereby feedback the process and gain knowledge to improve the next version. This feedback also provides a potential for data acquisition through the deployed service as pointed out by Gao et al. (2018).

6.1.2. Development process

The process is inspired by the fractal design of the SOMA process to enable flexibility and iteration. It covers the phases of the development, highlighting the key considerations to manage the different identified challenges. Thereby opening for individual organisational processes and methods to be utilised.

The process is adjusted for an agile work process and designed to be iterated over between the design and testing clusters. Therefore, the process does not follow a sequential process but instead employs the relevant phases for the project.

Strategy alignment and segmentation

The purpose of the phase is to align and relate the AI development project to the overall business strategy, mission and vision of the company. The alignment need was identified in order to fit the AI project into the business strategy (Leuterbach & Bonime-Blanc 2016; Ransbotham et al. 2017). It further builds upon the business modelling & transformation phase in SOMA and will set the environment to work within (Arsanjani et al. 2008).

The segmentation part will aim to break down the business strategy a mapping it to a strategic segment that the company is pursuing. These are prioritised business areas that are identified and connected to the corporate goals and strategy. The strategic segments can, therefore, act to focus the effort in specific business areas, thus ensuring the project is aligned. It also limits the application area in order to manage the problem definition challenge by focusing the development. The segmentation was also argued by Davenport (2018) in his model on successful analytical programs, where it will help focus the initiatives in order not to get lost in the opportunities. Furthermore, the empirical findings argued for focus of the AI development. That the business development should lead, and the development should fit that direction.

The alignment can also assist with the sponsorship and resources commitment as the company is already investing in these segments. Top management support was identified as an essential aspect and challenge in the interview and the literature (García &Pinzón 2017; Plastino &Purdy 2018). Operating in a prioritized area may assist in this.

Project strategy

The next phase is the project strategy, where the frame of the development project is set. The project management was a key success factor in the research by García and Pinzón (2017). The phase aims to create a conjoint vision of the project with a clear link to business objectives (García & Pinzón 2017). It should consider the goals, project plan, roles, sponsors, way of work and importantly, an outcome definition. BSD focuses on the outcome definition in its second phase and SOMA uses the solution management phase to assist in project management and developing methods. The effort is to bridge the business and technical domains to understand the different perspectives and work in alliance as argued in BSD (Johnson & Paul de Rouw 2017). The project strategy was also emphasised in the internal interview to create a work structure enabling the development. The organisation structure may not be optimised for AI development and therefore, a key aspect is to enable the collaboration, find ways of work and connect the different capabilities.

Segment and data exploration

The segment and data exploration phase is a precursory step to a deeper dive into the identified strategic segments to create understanding in the selected area. The exploration was included in the extended NSD process by Yu and Sangiorgi (2018) to enable a user-centric perspective. It aims to facilitate the value creation by exploring the user domain to understand the different needs, problems, cost drivers or time-consuming processes but also how the user is working and how they determine value. Gaining and incorporating domain knowledge into the process is also essential for finding service candidates with business value (Ross 2018). This was also frequently pointed out in both the internal- and expert sample interviews.

In parallel to this, there should also be conducted an initial exploration of relevant, accessible data. As discussed, the data is a central part of the service and will greatly impact the technical feasibility of the project (Jenke 2018; Quan & Sandersson 2018).

Further, the access of the data was identified as a potential bottleneck and an organisational challenge to manage as most work cannot begin properly without it. Therefore, starting in an early stage to explore and work with the data is essential for most AI development. It was referred to as the "most important degree of liberty" in one of the interviews that need to be worked with.

The phase aims to gain better insights into both the business domain of interest and in the relevant connected data to better be able to judge service opportunities. A parallel domain- and data exploration allows for an iteration between the technical, domain and business side to identify potential service candidates.

Service candidate selection

The service candidate selection covers the generation and selection of potential services. It is an optional step unless a valuable candidate has already identified. It consists of three sub-phases; generation, screening and selection. These activities are featured in all three development processes but are foremost in the SOMA process. The customer-centric perspective is important part to ensure that candidates emanated from real customer needs. Three ways of generating candidates were put forward in the SOMA, the goal service modelling, domain decomposition and asset analysis (Arsanjani et al. 2008). As the application potential is extensive, there are numerous potential opportunities to identify.

However, the screening and selection process is more complicated as investment evaluation and technical feasibility for AI services are uncertain. The segment- and data exploration is designed to help mitigate this challenge and by operating in prioritised areas can assist with gaining support and funding. The screening can be done by a high-level value-feasibility ranking, benchmarking, light prototyping or direct monetary estimation but are highly dependent on knowledge and experience.

A central factor should be a clearly formulated customer value, identified in five of the interviews and was observed in multiple instances. The phase should result in a few selected defined service candidates.

Stakeholder analysis and requirement analysis

The stakeholder analysis and requirement specification phase are based on the BSD model (Johnson & Paul de Rouw 2017). The phase is critical to enable the implementation of the service as the purpose is to identify and gather all relevant requirements in an early phase. The stakeholder analysis is to identify all actors that will have a stake in the development and implementation of the candidate service. The identified challenges with AI services come from several different domains such as data managers, IT architects, data analysts, top & middle management and the domain-specific actors. These must be identified to be able to contribute to the requirement specification of the candidate service.

The requirement specification aims to early identify needs, challenges, risks, roles and components from the different stakeholders. It addresses the implementation challenge to ensure that the service is scalable after the proof of concept. It is aiming to manage the system adoption, technical characteristics and system architecture challenges that were identified. Especially the system adoption challenge identified in the empirical research to integrate and adjust the service to the greater system. In other words, to adhere to the constraints and requirements of the other parts can be mitigated by this phase.

Service design statement

The phase aims to summarise the intended service in a statement including the service offering, target customer, identified requirements and operations that need to be done to realise the service. The service design statement was used in the BSD process (Johnson & de Rouw 2017), and a similar approach was used in the specification phase of the SOMA process. It should reflect the entire lifecycle of the service, including delivery and maintenance. Further, the business model and data strategy should be detailed. The statement will be a way to communicate within the organisation and different actors to manage the technology adoption- and work structure challenges.

Prototyping

The prototyping phase is an important tool to manage both the value, feasibility challenges and the technology adoption factor. The unit test of a prototype firstly can validate the initial technical feasibility of the AI methods and the data used.

Then it can help to communicate the potential value to a less technical audience. Communication was emphasised in the interviews in order to get top management support and a prototype can be an effective tool in that effort. It can also be useful to assist in the technology adoption of an organisation that was a major factor from the internal interviews. Prototyping can, therefore, improve the internal communication of the capabilities and used to increase the knowledge level of the organisation.

Piloting

The need for an integration test was tightly connected to the system adoption challenge. The aspect was mainly empirically driven aspects based on the participant's own experiences. Doing the development in a real-world environment was frequently brought up across interviews as most major issues occur there. Therefore, the prototyping phase is not enough, and the piloting is included to test the service in a limited and controlled real-world environment before full implementation. Although the stakeholder and requirement analysis tries to identify the different existing constraints, it may be hard to foresee all. Failing to account for the system adoption factors may affect the scaling of the service and hinders implementation as for many projects. Modifying or solving these problems in the implementation phase is often more difficult than in a pilot phase.

Evaluation

The last phase to cover is the evaluation that was included in the NSD model used. Yu and Sangiorgi (2018) included the phase to ensure that the service delivers value based on how well it satisfies the identified need. As argued by Smith and Colgate (2007), the value is the difference between expected and perceived value of the customer. Therefore, the evaluation of the service should reflect a customer-based metric. Key-performance indicators was brough up in a interview as an important part in the evaluation to measure and ensure improvements from the former solution. It was also observed in a talk from a Spotify employee at the CHAIR event, where their success metric was adjusted for the user behaviour. The phase also includes a validation evaluation of the used AI method in order to reduce the risk of including bias and explainability factors.

Implementation and monitoring

The implementation and monitoring phase is separated from the other to adjust for the high uncertainty and agile work process. The separation enables fast iterations over the design and test phases in order to raise the technology readiness level (TRL) before implementation. It was also brought up in the interviews as adjustment and updates become harder to do when the service is in production. However, knowledge and feedback still need to flow into the development process as the actors within implementation and monitoring are a major stakeholder.

7. Discussion

This section will discuss the empirical findings focusing on the difference between the theoretical- and empirical development challenges, ethical and sustainability aspects of AI and the proposed process framework.

The master thesis sought to adjust the service development process to the technical and business-related challenges of AI technology. Therefore, development challenges were both gathered from theory and empirical research.

7.1. Theoretical and empirical challenges

Interestingly, the findings supported the observation that the research around AI has been primarily on the technical aspects (Russel et al. 2015). The main challenges that were identified through previous research were data, IT architecture and technical characteristics that are inherently technical.

The challenge of gaining top management support was also present in the literature and easily identified (Plastino & Purdy 2018; Troilio et al. 2017; Weill et al. 2019). These were then extended by initial empirical findings through the systematic combining process, which resulted in that further challenges could be found in the literature related to the business aspects. However, these aspects were not well researched within the AI field. Sources were scarce and some were transferred from the neighbouring field of BI where the aspect was more studied. Due to the similarities between the AI and BI field, these were used to support the empirical findings of this thesis.

Although the same technical challenges were present in the empirical findings, the findings were more focused on the challenges related to AI within the industrial context. How the technology would affect the business and organisational aspect was emphasised. For instance, the implementation of AI-based services has been, as mention in the introduction, a problem for a large part of the industrial application (Davenport & Ronanki 2018).

The system adoption challenge that emerged in the empirical findings has direct implications on the implementation as new constraints can occur, rendering the application not viable. Inferring from these findings, then the majority of knowledge of AI has been concentrated around the "technical departments" development aspects. However, little research has looked into the development aspects in regards to the other departments.

In the effort to industrialise the AI technology and develop AI based services, the contextual challenges must be understood and addressed. Consequently, this represents an understudied area of AI development and more research is needed to understand the business- and organisational integrating of the AI technology. Current research provides ample support of creating technically feasible proofs of concepts but does not lend to become business viable and user desirable services.

The cost calculation in Appendix II also illustrates the need for the three different aspects to work in unison. The cost function connects the feasibility through the accuracy of the technology to the economic viability in the form of cost savings. The calculation shows that relative low accuracies would have a positive effect due to the relative cost difference of planned and unplanned stop. However, the calculation is relatively simple, and several additional factors need to be considered before implementation. With too high false positive rate, the user could be forced to visit the service centre more frequently and in some cases, unnecessarily. Consequently, the service centre would have an increased volume of customers and the administration for the system would be larger. Furthermore, offering the uptime service contract but still suffer road breakdowns could have an even larger negative customer experience as uptime was guaranteed. Therefore, even if the cost savings could be achieved at a low level of accuracy, both the user and intended service system could require higher levels. It is aligned with the need for fitting the AI service to the larger system discussed in the interviews.

An important note is, however, that some of the identified challenges are temporal as they are consequences of the current position of the technology. The knowledge level will increase as the technology matures and more organisations adopt it, reducing the challenges of top management, technology adoption and work structure. Thus, the effect of each challenge is dependent on the current position of the organisation in digitalisation, data analytics and service development. They are therefore case-specific and needs to be adjusted for each new case.

7.2. Ethical and sustainable aspect of AI development

The focus of this thesis is the implementation and adoption of AI, but another important consideration is the effect it will have. There is a high interest in the technology and the value it provides, but it has also generated debate about the sustainability aspects of the technology.

These aspects were addressed in one of the interviews as the participant also actively worked with some of these questions. Consideration of the ethical and sustainable consequences of a higher implementation rate of AI services needs to be done.

In regards to the sustainable development goals of the Agenda 2030, Vinuesa et al. (2019) find that AI is a key enabler but can also potentially inhibit some targets. The technology can be used as a powerful tool for social welfare, increasing the productivity rate by optimising and automating time-consuming tasks. Thus, increasing the global welfare and the GDP. It can further assist in the welfare, where more personalised healthcare and education services that have been discussed as applications.

However, there are also instances of adverse effects on sustainability. Automation has been feared as a major job displacer, increasing the segregation of classes and countries (OECD 2017). Different cases have been argued of what the effect will be. One effect could be that the major displacement will be middle-income work as it can automate routine tasks within an office environment (Makridakis 2017). Others argue that the change will have the most effect on low skilled labour bearing the brunt of automation as the labour market reskills to complement the AI competences, increasing the inequality (OECD 2017).

From an ethical perspective, two major considerations of AI have been presented as challenges. Bias has already caused controversy of including non-ethical features in decision making recruitment and parole decisions (Larsson et al. 2019). Further implications were brought up by Larsson et al. (2019) where the monitoring, pattern recognition and recommendation application that could personalise your experience also could be used to reinforce social bias and prejudices. For instance, OpenAI, a non-profit company researching AI, declined to publish their research of its text generator. The reason was for fear of potential misuse the technology as fake content or fake news generator (Hern 2019). Liability became a discussed issue in a fatal accident of an autonomous car that occurred during a test drive (Delsh 2018).As the technical adoption becomes more mainstream and more AI services are implemented, these effects will become increasingly essential. As with any new technology, a perversion of it is an ever-present risk. It represents a broader challenge with AI as it has a "dual use" nature (Brundage et al. 2018), where a text generator can be used to write thrilling manuscripts also can be used to distribute fake news to affect public opinions.

Autonomous delivery drones to optimise last mile deliveries could also be used as weapons if armed it an explosive payload (Brundage et al. 2018).

Therefore, considerations in not only how to use the technology but also in what to use it for is an important complement to the development process. In addition to the implementable, valuable factors then sustainable or ethical should be included in the AI services development. These factors could help the AI service developer to consider the implication and better take responsibility for the result. Preparation and guidelines for the use must be done in parallel to the implementation efforts and sustainability is an important aspect of AI development.

7.3. AI and service development theory

To manage the identified challenges, this thesis used service development- and value theory to generate the proposed development framework. Both theories were found to benefit the process and provide capabilities to manage the challenges. The framework aimed to promote valuable and implementable AI services. Therefore, the focus of the framework is upon organisational integration. As one participant referred to the fact that the AI component is often only a small part of the service, and the major consideration is how it fits into the overall system.

That refocuses the perspective of fitting the organisation to AI development to rather fitting the AI development to the organisation and its business. Viewing from this perspective, then the implementation issues can be seen caused by isolating the technical development. The presented framework aims to handle this by introducing the principle of cross-functional teams as well as the stakeholder & requirement analysis and piloting phase. Each represented and supported by the selected service development processes. The process focuses on gathering the different aspects of implementation and testing those before going through with a full implementation with the delivery department. The strategy alignment & segmentation and project strategy further aim to ensure the integration to both the business and organisation.

The segment & data exploration phase is a key phase for AI development as it complements the data-driven way of work. Data is the central foundation for many AI system (Quan & Sandersson 2018) and therefore, must be explored in parallel to the domain exploration.

Another key element is the principle of an agile work process to handle the uncertainty of the development that was featured in several of the interviews. These two phases are more specific to AI development. The value theory was also found beneficial to AI development as it provided a needed focus for the technology. The customer-centric perspective promotes value creation in the development but for AI, it also provides guidance in order to specify narrow problem definitions. This view focuses the process on the problem rather than on the technology, which was a common mistake brought up in the interviews.

This master thesis focused on the adoption aspect due to the low successful implementation rate for the wider population of companies (Bughin et al. 2017). The presented process framework adopts a focused approach, successively narrowing down the business into problem definitions. This approach was selected in order to coordinate the AI development within a single setting and thereby to enable tighter collaboration, support and better control. However, this may also limit the AI contributions to existing business areas, focusing on operation rather than disruption or innovation. It might be at odds with the disruptive promise of AI and the potential of new business models for the company. Again, the current position of the organisation´s AI adoption needs to be considered. This case study was done in relation to the transportation industry, which is a non-digital native as well as traditionally product-centric. Therefore, the integration of AI technology would create several major process changes for the case organisation. The use of service development represents a transformation to a more service-centric perspective and its way of work. As observed by Edvardsson et al. (2013), there is still a high failure rate of new service development, as high as 43% in their findings.

Furthermore, AI development is a data dependent and analytical driven process, which also represents a new way of work for most non-digital native organisations. These two aspects, combined with working with a new technology to move into a new business model will incur a high risk to the development project in this case. Therefore, the thesis focuses on the adoption of the technology in existing business areas. However, these aspects may also point towards why digital native companies like Google, Amazon and Baidu have greater success with the technology (Agrawal et al. 2017). Their processes for digital and web-based services may be closer to AI development, reducing the change necessary to develop AI based services.

8. Conclusion

The section outlines the main findings, managerial implications, limitations and suggestions for future research.

The research of this thesis highlights a currently understudied research area within the field of AI. Regarding the business and organisational challenges associated with industrialised AI development. The empirical findings of this thesis identified the technical challenges frequently found in the literature but also several business and organisational related challenges. These challenges were less prominent in the existing literature. The identified challenges could affect the implementation of developed services and therefore, should be studied further.

Ethical and sustainable aspects of AI was only approached in one of the eight interviews but are frequently found in literature within AI. In literature, it has been seen to have an important part in the development with several examples of ethical and sustainable implications for AI development. The focus of this work, however, was on the implementation and value aspects of AI development. It is left to future research of finding ways to incorporating those aspects into the framework.

Lastly, to contribute to the identified research gap, the thesis generated a process framework for AI service development. The framework combined the field of AI with service development- and value theory to manage the identified challenges. Both theories were believed to provide benefit to AI development and promote implementation and value creation. The result must, however, be tested and validated in future research as it was not in the scope of this thesis.

8.1. Managerial implications

The thesis has practical implication for managers that wants to develop AI based services. The design process framework can act as a guide in order to identify and understand common challenges as well as how to avoid them. It further emphasises the wider scope of such a development and the need to engage larger parts of the organisation, not only the technology department. Managers would need to consider and plan for the technical, business and organisational aspects in order to effectively utilise the technology. The proposed process framework promotes adoption before disruption and therefore, could be more suited for organisations with a low technology readiness level in regards to AI. The current position of the organisation in regards to AI needs to be considered to the process framework.

8.2. Limitations and recommendation for future research

The thesis work was constrained to 20 weeks with limited resources and had to be reflected in the scope of the research. The work was also conducted by a single researcher, further limiting the available work hours. However, as the research targeted an understudied research area with little previous research combining service theory and AI, a more explorative and holistic approach was adopted to provide a base for future research. The use of both an expert- and an internal sample aimed to capture multiple perspectives. However, the width comes at the expense of depth and only four actors of each sample were managed within the timeframe. The population of the respondent was, therefore, highly limited. Further, the study also used a single case approach, which is why the findings should be considered tentative. The empirical findings gained some support by the systematic combining approach where a theoretical connection could be found. Case-specific considerations should be made if the presented findings should be transferred to another case and new challenges could emerge.

Further research can build upon this work and make deep dives into the identified areas. The implications of the identified business-related challenges on the implementation of AI services would need further studying. Also, ethical and sustainability aspects can further be studied in order to be incorporated into the process framework to ensure human-centred AI services. Then the proposed process framework would need to be tested in order to validate the potential benefit to AI development.

Two additional future research opportunities were discovered during the work concerning AI service development. A better understanding of AI development could be gained by researching the differences between digital- and non-digital natives companies. This research could lend insights into the success factors of some companies and beneficial organisational aspect for AI development. Secondly, research of a technical and organisation strategy of AI adoption in legacy organisational structures could further benefit the AI technology. The thesis identified the importance of fitting AI to the current organisation. The integration represents a change-management and strategic journey for the company and further studying could aid in the organisational adoption of AI.

9. References

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Appendix I – In-depth overview of AI

Another step in clarifying AI is to specify its terminology. Chiefly the difference between AI methods, AI application, AI agent, and an AI service, where all could and are being referred to only as AI, often without specifying what it consists of. This unclarity makes it more abstract because it can refer to several things and be used in various situations. Therefore, it may clarify to explore the parts that are used to build AI systems.

Figure 14 shows an overview of the terminology of AI that will be used in this thesis. An important note is that the boundaries of the model are not definite, and some overlap exists.

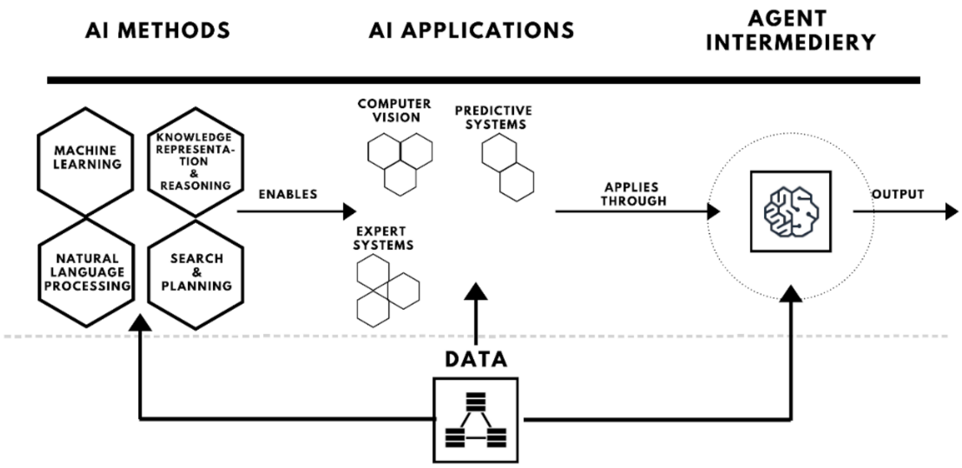

Figure 14: an overview model of the proposed AI terminology.

In this report, the AI methods refer to the underlying techniques or "blocks" that the AI applications are built upon. There is a body of different methods, each containing several sub-methods and algorithms. These can be used interchangeably depending on what the problem is. Essentially, the AI methods can be thought of a large toolbox with a wide variety of tools to assemble an application. Within this toolbox, there is machine learning, search- and planning algorithms, knowledge representation and reasoning, natural language processing, among others.

The AI applications refer to assembled solutions that perform specific tasks to enable the desired solution. The applications would then be, continuing with assembly analogy, the purchased preassembled components like an engine or transmission of a car. An engine has the specific task of propelling the car forward by extracting energy from some fuel.

For AI, computer vision is an excellent example of a developed application where different AI methods are applied to extract information from visual mediums. The application could be used to provide perceptual input for the AI system (Hofmann et al. 2017) and is one of the core applications used to create autonomous transportation services. Other AI applications are facial recognition, speech recognition, expert systems, recommendation systems etc. By using the methods in different ways, numerous different applications can be developed. These can either be the foundation of a service or be combined into a more sophisticated AI system, like autonomous transportation solutions.

The methods and applications then need to be executed, coordinated and the results need to be handled to solve a problem. That is in this perspective done through a software agent. That can interact with its environment by taking in perceptions and converting them into actions (Russel & Norvig 2010). The software agent concept is abstract as it can be considered as several different things, but its function is that it acts as an intermediate entity. The intermediary is formed to feed the methods & applications with the data and perform an action based on the result. In the analogy, the agent can be seen as the assembly line that uses the different parts to assemble the car to be used by the customer. This action is performed on some hardware that can be a computer, cloud server or embedded device, that in this terminology is called the hardware agent. The hardware agent would then be the factory that houses the assembly line. The combination of software- and hardware agents will be referred to as the agent. Russel and Norvig (2010) use the example of an automatic vacuum cleaner as an agent where it implements the onboard software to perceive if its current position is dirty and act to clean it up.

Lastly, the AI based service is considered to be the entire process of providing a service to the user where the output of the AI system is combined with the support functions and packaged into a complete solution. As with the car analogy, the car is only one part that is offered to the customer and is combined with several different surrounding services. The same is with the output of the methods, applications and agent that are only one part that makes up the AI based service.

As can be seen in figure 14, the data is a core part that fuels the entire AI system and used in all three parts. Modern AI technology is a highly data-driven process (Stone et al. 2016) and is an integral part of the AI systems performance (Quan & Sandersson 2018).

The method and application can both be trained or programmed to handle the data beforehand. Then they are fed data by the agent to create the desired output.

Another critical term that needs to be defined is "narrow AI" which refers to that it only achieves artificial intelligence within a narrow, specific problem area (Honavar 2016). For instance, the chess playing AI Deepblue that won against the world champion Garry Kasparov only works in chess. It would fail at any other game, which makes it a narrow AI. All currently existing AI is narrow and requires a limited specified domain to produce satisfying results (Honavar 2016).

Overview of the AI methods

The presented approach separates the AI methods from the applications. Following that logic, the application consists of combining the different methods in different ways to solve a specific problem. That also highlights the benefit to understand the underlying methods that enable the AI services and will, therefore, be covered in this section.

Machine learning

Machine learning (ML) is a central part of the AI field and has been fuelling most of the recent developments (Agrawal et al. 2017). It is also an integral part of the learning feature of AI as it is based on a learning from examples approach (Osvaldo 2018). This approach is getting computers to act without being explicitly programmed and instead learn from the provided data (Bakashi & Bakashi 2018). It is, therefore, useful to solve problems that have many observations and result recorded, but a formal model is hard to create (Angra & Ahuja 2017). The ML methods are using the training data to estimate a model over the properties found within the data, called features, with the use of statistical computing that finds correlations in large data sets (Jordan & Mitchell 2015). These correlations can be used to solve desired tasks or identify otherwise hidden relations, providing valuable insights (Angra & Ahuja 2017; Bakashi & Bakashi 2018). The field of machine learning can be further divided into two sub-groups, Supervised- and Unsupervised learning.

Supervised machine learning methods uses already assigned input/output data-pairs to train its model to predict the output on unseen input data (Bakashi & Bakashi 2018).

The supervised methods are then mapping how the input is related to the output from the labelled data set and forms the model to replicate that function (Jordan & Mitchell 2015). Louridas and Ebert used the metaphor where a supervisor hands a student a set of solved problems with the task of figuring out how to solve similar future tasks. The "student" is then evaluated in a test to see how well the student understanding is, as the estimated model is tested and validated. This process is how the methods can mimic behaviour from domain experts without been given any detailed instructions, just data (Bakashi & Bakashi 2018).

Unsupervised learning represents a collection of methods used to analyse unlabelled data where only the input is known, and it must find the solution on its own (Louridas & Ebert 2016).

The data-set consists of several different features or value dimensions that will be explored. The methods search for potential structured properties or "hidden patterns" within the data that can be used to extract knowledge from it (Jordan & Mitchell 2015). Following the student metaphor, this time, numerous of feature values are provided per data point. The mission is to find if any patterns that significantly separates and clusters the points (Louridas & Ebert 2016). Clustering algorithms are used to finds partitions in the data based on features. It groups together those data points with similar features and that can be used to predict or classify future data.

Both the learning are simplified, ways to map the A → B patterns in the data which can be used in many different applications (Ng 2016). It to be used to automate specific tasks that can benefit the work of data-intensive and time-consuming work tasks (Agrawal et al. 2017). For instance, consider warranty handling, where the human worker uses an experience-based framework to determine what action should be taken in each case. If those decisions are documented, it can function as a labelled data-set for a supervised model. This framework could then be reflected in the data as a pattern that an ML method could estimate and optimise the handling process by directing the manual work to prioritised cases (Ross 2018).

The prediction property of ML further has many applications and are used frequently in predicting outcomes based on a large amount of data. For instance, in predicting stock exchange (Shah 2007) or predicting failure by assessing the failure degradation of a component (Angra & Ahuja 2017). Other uses of the A→B model is monitoring as the prediction can also be used for detecting anomalies that defer from the expected behaviour.

For instance, Telia explored ML-based models to detect fraudulent behaviour in their media-on-demand system (Holst 2002). Recommendation systems are another common application of ML that matches users and products/services based on feature similarities between users. (Jannach et al. 2016). This application is utilised by both Spotify and Netflix in their streaming platform to provide the users with personalised suggestions.

Knowledge representation and reasoning

Despite the potential of machine learning to learn from data, there could still be a need for representing domain expert knowledge. Knowledge representation is a way to store the knowledge from a person to be used by the computer (Ren et al. 2010). That way, it is an alternative to the learning approach of machine learning and formats the knowledge base that the AI system can draw from to solve problems in a specific domain. It is based on the perspective on AI where domain knowledge is acquired and conceptualised as formal structures or "ontologies" to be used by the system. The ontologies explain the nature of the domain that the application will operate in by representing the concepts, objects and relations of that domain (Vassev & Hinchey 2018). The representation can be done through the use of different logic-based programming languages expressing the ontology through first-order logic. It is a way to represent the information through logical statements that combine objects, relations and functions (Vassev & Hinchey 2018).

The knowledge base enables problem-solving expert systems, inference and decision-making capabilities in an agent. Logic reasoning is possible through the logical chain of representations, called entailment (Russel & Stuart 2015). Essentially it is the process of drawing conclusions from what is known, using the ontology of the domain (Khayut et al. 2014). A simplified example of this could be "all humans become hungry after 5 hours; John has not eaten for 6 hours; John is a human; therefore, John must be hungry". The most common techniques are forward- or backward chaining that is dependent on whether the conclusion is known or not (Russel & Stuart 2015). By using these methods, knowledge-based systems or expert systems enables it to make intelligent decisions within the domain or provide decision support to users (Mohammed et al. 2019). It also becomes a way to utilise and manage knowledge for an organisation (Tan et al. 2016).

Search & Planning

One of the presented definition of AI included the property of acting with foresight in an environment. Therefore, the ability to plan is a part of an AI system making search- and planning methods relevant as a branch of automated planning (Baier 2011). They represent a way of finding a solution to a problem from the collection of all possible states. This is done by defining a goal state that would solve the problem and through different techniques finding that corresponding state. The difference between the two is the way that the state is represented (Russel & Stuart 2015) and can be illustrated with the travelling merchant problem. In where a merchant must visit each of a set of cities once and should use the optimal route.

A search method deals with atomic states (Russel & Stuart 2015), which means each state has one property such as city names, positions or word strings attached. In the travelling merchant, a search problem would only consider the distances to each city. The planning methods deal instead with factored states (Russel & Stuart 2015) that consist of multiple variables that describe the model for the states. It deals with constraints and multi-criteria optimisation when searching for a solution to the problem. That would be to include more parameters to the travelling merchant problem such as destination dependencies, traffic or time constraints. AI-driven search and planning can thus be used to solve complex combinatorial problems such as route planning, scheduling and logistic planning.

Natural language processing

Hirschberg and Manning (2015) define Natural language processing (NLP) as the methods that help a computer to learn, understand and produce human language content. The methods do no longer only consider words because of its apparent limitations but rather work with syntactic- and semantic analysis are deployed on a pre-processed text (Pons et al. 2016). The pre-process is mostly to "clean" up the text and to splitting up sentences and words for the analysis (Fahad & Yahya 2018). Then the syntactic analysis labels the different words whether if it is a noun, verb or adjective, their grammatical structure and dependency (Fahad & Yahya 2018). The semantic analysis links the different words to concepts such as names or meaning (Hirschberg & Manning 2015).

Enabling machines to understand human language has many uses as it allows for better communication between man and machines. Solutions such as smart agents as Siri, Alexa and so on are possible because of NLP methods. This represents an excellent potential for user engagement (Hirschberg & Manning 2015). Further, a great deal of information is stored in unstructured formats like text and audio that can be better accessed through the use of NLP (Chowdhury 2013). This, therefore, has significant implications on the field user interaction but also in translation, speak to write and as perception applications (Hofmann et al. 2017).

Although these four methods were presented separately, they are used overlapping and in different compositions. Machine learning is used heavily in natural language processing and in collaboration with knowledge representation to create hybrid statistical expert systems (Sahin et al. 2012).

Appendix II – Cost-saving calculation for the predictive maintenance case

The cost case builds on the move from the current preventive maintenance to predictive though an AI-powered service that predicts faults in a component, schedules a service appointment and orders the relevant spare part to the appointed slot. Thus reducing the maintenance time and reduce the road break-down cost.

The calculation builds on the equation proposed by Prytz et al. (2015) that uses two scenarios, where the prediction is correct and when it is not. These senarioes is represented by a true positive- and false positive factor of a percentage derived in the validation of the algorithm used.

The first scenario is when a real fault is correctly predicted and, therefore, the savings will be the difference between an unplanned and planned maintenance. Seen in equation 1.

$$(C_{unplanned} - C_{planned}) = C_{M\&R} * (t_{transport} + t_{diagnosis} + t_{wait} + t_{work}) + C_{part} - (C_{part} + C_{M\&R} * t_{work}) =$$

$$C_{M\&R} * (t_{transport} + t_{diagnosis} + t_{work}) \qquad (1)$$

The second scenario covers when the algorithm predicts a fault, but there is not a real fault. The cost will then be for the unnecessary planned maintenance work. Seen in equation 2.

$$C_{planned\ work} = C_{M\&R} * t_{work} \qquad (2)$$

A third scenario is added to this, covering the event of an unpredicted failure resulting in a road breakdown. The service contract for predictive maintenance moves towards selling uptime and that would lead to a cost for the service supplier to cover. Seen in equation 3.

$$C_{failure} = C_{penalty} * (t_{transport} + t_{diagnosis} + t_{wait} + t_{work}) \qquad (3)$$

Equation 4 represents the cost saving for predictive maintenance for the three scenarios.

$$Cs = Q(Tp * C_{M\&R} * (t_t + t_d + t_w) - Fp * C_{M\&R} * t_w - (1 - Tp) * C_p * (t_t + t_d + t_w)) \qquad (4)$$

Where:

Cs = cost saving [kr]

Q = quantity of vehicles [#]

Tp = True positive[%]

Fp = False positive [%]

$C_{M\&R}$= cost of maintenance and repair [kr/h]

t_t= time for transport to the serrvice centre [h]

t_d= Time for diagnosis [h]

t_w= Time for waiting before service can start [h]

C_p = cost penalty for uptime service to supply with new vehicle [kr/h]

This cost equation can be used to determine the required prediction rate of the algorithm in order to save cost. The accuracy is dependent both on the data set and algorithm used, which is why an estimation for the needed rate could help the business validity of the service.

The function 5 is therefore set up with two independent variables Tp, Fp and Cs as the dependent. The input data are collected from the case environment but must remain confidential. The cost case is based on a vehicle population of 20 000 with a set amount of vehicles with faults that would have resulted in an unplanned stop.

$$Cs = f(Tp, Fp) \tag{5}$$

The result is plotted in figure 15 as a plane in the 3-dimensional space with cost savings on the z-axis, Tp on the x-axis, Fp on the y-axis. The plane is tilted slightly due to the higher difference in cost between the planned and unplanned stop. The cost spans from a loss of 29.7 million to a saving of 17 millions sek.

Figure 16 uses a heatmap to project the result on a 2-dimensional space with the cost represented by the colour-scale, Tp on the x-axis and Fp on the y-axis. From the heatmap the corresponding Tp, Fp values for a specific cost saving can be read. A tilted line can be perceived that represents a zero-line. For instance, with an Fp rate of 20% would require a Tp of around 60% for a million in cost savings and closer to 80% for 10 million. These numbers could provide an initial guide of what accuracy the predictive model needs to results in an business viable service.

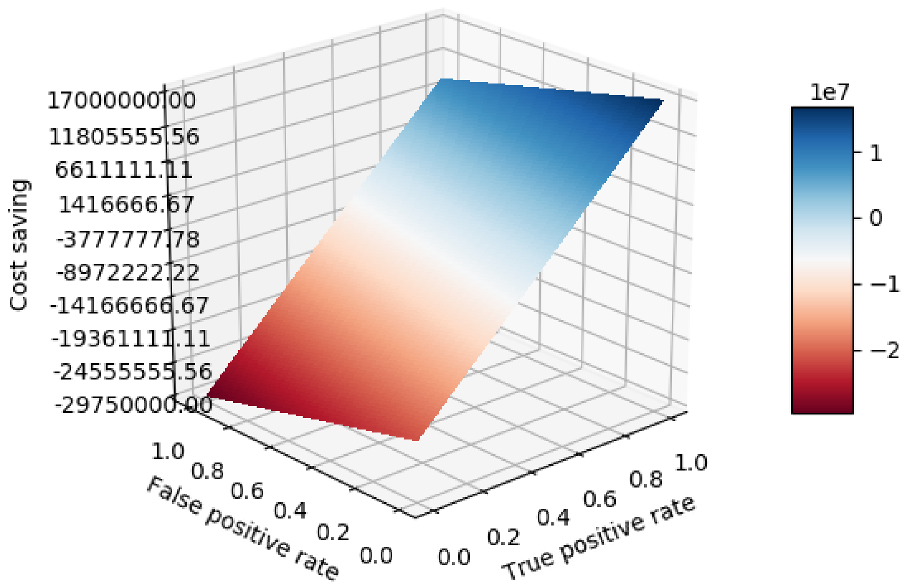

Figure 15: 3-D surface plot of function 5 with case data.

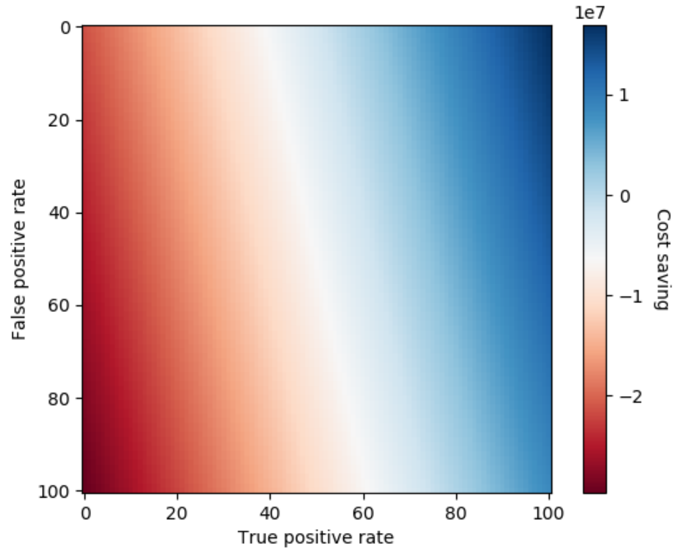

Figure 16: 2-D heat map plot of function 5 with case data.

Appendix III – The expert sample group interview guide

Bakgrund

1. Kan du beskriva företaget/organisation du arbetar för?
    - Vilka industrier är ni aktiva i?
    - Vad är din roll?
    - Hur arbetar ni med Artificiell Intelligens?
    - Vilka tjänster erbjuder ni inom området?
2. Kan du beskriva dina erfarenheter inom området artificiell intelligens?
    - Har du något exempel av projekt du arbetar med inom/berör AI området?

Teknologi

3. Vad innebär artificiell intelligens för dig?
    - Det finns många olika perspektiv på AI så därför tycker jag det är viktigt att utgå från vad AI är för dig?
    - Vad räknar du till artificiell intelligens?
    - Vad karakteriserar ett AI system för dig?
    - Finns det några egenskaper du skulle tillskriva AI?
4. När det kommer till att utveckla industriella AI tillämpningar, sätter tekniken några särskilda krav på arbetet?

- Finns det några egenskaper som måste tas hänsyn till vid tjänsteutvecklingen?
    - Vilka är det största generella riskerna med utveckling av AI baserade tjänster?
    - Relaterat till data hantering?
    - Relaterat till IT arkitektur?
    - Relaterat till affärs sidan

- Relaterat till kunskap?

5. Skapar tekniken några organisatoriska utmaningar i utvecklingsarbetet enligt dig?
   - Tror du det kan påverka samarbetet mellan de olika delarna inom en organisation?
   - Kan det ha påverkan på samarbetet mellan IT/tekniska- och affärs sidan?
   - Kan det ha påverkan managements roll?

6. Något som har uppmärksammats är att många AI utvecklingsprojekt stannar i Proof of concept fasen, varför tror du det blir så?
   - Finns det några svårigheter att skala upp och implementera AI tjänster tror du?
   - Hur ska det kunna undvikas tycker du?
   - Vilka frågor måste besvaras innan tjänsten är redo att utvecklas?

Tjänsteutveckling processen

7. Hur tycker du att arbetet i ett AI tjänsteutvecklingsprojekt ska vara organiserat?
   - Hur skulle samarbetet vara organiserat?
   - Vilka roller tycker du det behövs för att kunna erbjuda en AI baserad tjänst?
   - Hur ser ansvarsfördelningen ut mellan dessa roller?
   - Vart tycker du arbetet skulle vara placerats? (centralt eller decentraliserat?
8. Finns det några viktiga perspektiv/principer som projektgruppen ska följa för att främja arbetet?
   - Hur skulle du vilja att gruppen arbetade om du drev projektet?

- Hur kan processen skapa förutsättningar för att möta dem?

9. Om du skulle göra en utvecklingsprocess för AI tjänster, vilka delar skulle du säga vara viktigast i relation till AI teknikens egenskaper?

    - Vad skulle vara viktigaste i en initial fas, i en design fas och i en implementerings fas?
    - Hur ser processen från koncept till färdig idé ut?
    - Hur identifierar man värdefulla koncept?

10. Vad tycker du att man behöver tänka på i implementationen av AI baserad-tjänster?

- Hur ser processen ut från färdig ide till implementerad tjänst?

Värde

11. Hur ska projektgruppen se till att arbetet skapar värde för kunden?

- Hur ser processen till att projektet är kund fokuserat?
- Hur förs kundkunskap in i projektet?
- Vilka steg är extra viktiga för att skapa värde?

12. I mitt arbete så har relationen mellan teknik och organisation blivit intressant, hur ser du på påverkan av en komplex teknologi på det interna samarbetet mellan funktioner?

- Hur påverkar det samarbetet mellan affär, teknik och management?
- Hur kan processen skapa förutsättningar för att teknik och affären ska arbeta i allians?
- Hur säkras stöd från styrelsen i projekt där majoriteten har svårt att förstå tekniken?

13. Utifrån vår diskussion, vad tycker du om denna definierade utvecklingsprocess för AI tjänster?

    - Feedback på ett förslag på process utifrån ditt perspektiv
    - Finns det något som saknas?
    - Något som ska ändras?

Avslut: Är det något du känner att vi missade eller inte utvecklade tillräckligt?

Appendix IV – The internal sample group interview guide

Bakgrund

1. Kan du beskriva din nuvarande arbetsroll?
   - Vad ingår för arbetsuppgifter?
   - Vilka instanser arbetar ni närmast med?
   - Har ni tidigare arbetat med advanced analytics gruppen?

Teknologi

2. Vad är din uppfattning av artificiell intelligens?
   - I vilka samband har du kommit i kontakt med begreppet?
   - Hur mycket vet du om arbetet med AI inom företaget?
   - Skulle du kunna vara med och driva ett AI tjänsteutvecklings projekt?

Tjänsteutvecklings processen

3. Hur arbetar ni med tjänsteutveckling idag?
   - Följer ni någon särskild tjänsteutvecklings process?
   - Vad finns det för utmaningar i arbetet idag?

4. Utifrån din egen arbetsroll, finns det några viktiga aspekter att betänka i ett AI tjänsteutvecklings projekt?
   - Vad skulle du säga skulle vara de största utmaningarna?
   - Sätter er roll några speciella krav på projektet?
   - Finns det något som skulle kunna hindra att ett AI tjänsteutvecklings projekt?
   - Hur tycker du ett sådant arbetet ska vara organiserat?

5. Utifrån ditt perspektiv, vilka krav finns det för att kunna implementera och erbjuda en AI baserad tjänst i full skala?
   - Vilka är de största riskerna som kan hindra en upp skalning?
   - Hur ska ett projekt identifiera dessa?

6. Hur skulle du vilja arbeta i ett sådant projekt?
   - Vad skulle din roll vara i ett sådant projekt?
   - Vilka andra roller tycker du är viktiga för att erbjuda en AI baserad tjänst?
   - Vilka faser skulle ni vara aktiva i?
   - Vem tycker du ska vara drivande i ett sådant projekt?

Värde

7. Hur ska projektgruppen se till att arbetet skapar riktigt värde för kunden?
   - Vem ska göra den bedömningen tycker du?

Avslut: Är det något du känner att vi missade eller inte utvecklade tillräckligt?