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TAMPERE UNIVERSITY OF TECHNOLOGY

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VALUE CREATION AND IMPLEMENTATION OF ANALYTICS

Master of Science thesis

Examiner: Professor Nina Helander
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ABSTRACT

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Analytics can be approached from different perspectives. Usually analytics is seen as technological issue that includes data technologies, big data, computing algorithms and use of different software to compute data into different forms. Technical approach can be too complicated to most of people to understand even though analytics is seen nowadays more and more as an issue that concerns the whole organization and not only the technological people. This has evolved the need to bring analytics closer and more understandable to people that have not considered analytics as an important thing until now as analytics is beginning to have strategic significance in the business environment.

This study acknowledges the need to understand analytics from different perspective and tries to find answers how this transformation can begin in organizations and what it takes to be analytic driven organization. The aim of the study is thus to understand how value is created with analytics in organizations and how the processes should be changed to become analytic driven organization. To understand these issues this thesis has two parts that together provide insights for the aim of the study.

In the first part of the study a literature review is conducted to introduce relevant theories for the reader so that the matters that affect to the organization transformation regarding the topic can be understood as well as possible. The second part of the study is empirical study where series of semi-structured interviews were conducted for two different samples to gain more understanding of how the professionals of this topic see the approach and how different organizations perceive the change in their strategies and businesses.

The results of the study challenge the traditional ways of developing analytics in organizations by presenting value based approach and implementation of analytics. Instead of starting to develop data capabilities as a priority organizations should start by finding a business problem that can be solved with analytics. After identifying it, a roadmap for the value chain of analytics should be developed, where the changes to capabilities and working ways are agreed. Implementing analytics is then an agile process where the whole value chain of analytics is being iterated from actions to decision to insight to modeling and data in a way that not only new technology is being added but the whole process is changed accordingly to support analytics and decision making.

TIIVISTELMÄ

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Analytiikkaa on lähestytty aiemmin hyvin teknologialähtöisesti ja sen sisällön on ajateltu olevan erilaisia teknologioita kuten datan käsittelyä, big dataa, algoritmien tekemistä sekä erilaisten analytiikkatyökalujen käyttöä. Kun analytiikan merkitys liiketoiminnassa on kasvanut, työntekijöiden, joilla ei ole teknistä taustaa, voi olla vaikea ymmärtää analytiikan hyötyjä ja vaikutuksia organisaatiossa. Tämä kasvanut merkitys liiketoiminnassa on herättänyt tarpeen ymmärtää analytiikkaa laajemmin kuin pelkästään teknologisina ratkaisuina.

Organisaatioilla on tarve ymmärtää teknologisten ratkaisujen lisäksi sitä, kuinka analytiikka vaikuttaa koko organisaation strategiaan ja toimintoihin. Tämä tutkimus pyrkii vastaamaan tähän tarpeeseen. Tutkimuksen tarkoituksena on ymmärtää, kuinka koko analytiikan arvoketju muodostuu ja millä tavalla organisaation tulee muuttua, jotta he voivat muuttua yhä enemmän analytiikan avulla ohjautuviksi ja luoda arvoa analytiikan avulla. Vastauksena tähän tavoitteeseen tässä tutkimuksessa on kaksi osaa, jotka käsittelevät tutkimuksen kannalta olennaisimpia teemoja, jotta lukijalle syntyisi kattava ymmärrys siitä, mitä analytiikan arvonluonti vaatii organisaatiolta.

Tutkimuksen ensimmäisessä osassa tehdään kirjallisuuskatsaus aiheeseen liittyviin teemoihin. Tarkoituksena on antaa käsitys siitä, mitä asioita tieteessä on liitetty analytiikan arvon tuottamiseen. Toisessa osiossa käsitellään empiirinen tutkimus, jossa tehtiin useita teemahaastatteluja kahdelle eri kohderyhmälle. Toinen kohderyhmistä oli analytiikan asiantuntijoita tutkimuksen tilanneesta organisaatiosta, jotka olivat työskennelleet menestyneesti eri analytiikan projekteissa pitkään. Toinen kohderyhmistä koostui eri yritysten analytiikan henkilöstöstä, joilla oli käsitys oman organisaationsa analytiikan prosesseista.

Työn tuloksena on arvopohjaisen analytiikan lähestymistavan esittäminen analytiikan kehittämiseen ja implementointiin organisaatioissa. Arvopohjaisessa analytiikassa huomioidaan koko organisaatio ja siellä vaadittavat muutokset analytiikan ratkaisuja implementoidessa. Pelkän teknologian implementoimisen sijasta organisaatiolle rakennetaan oma muutoskartta, jossa huomioidaan prosessit ja ihmisten kyvykkyydet sekä niiden tulevaisuuden muutostarpeet, jotta koko organisaatio voi muuttua dataohjautuvaksi organisaatioksi ja tuottaa arvoa analytiikan avulla ketterästi ja näin saavuttaa liiketoimintaetua.

PREFACE

The start of this project and the whole process that mainly took place in the summer of 2017 has been one of most interesting time of my whole studying career. During the intensive 12 weeks that the main body of this research was written the whole process of generating the topic, conducting the interviews and writing the literature review was enjoyable. The idea and the subject of the thesis came from EY Finland and fitted perfectly for my interest as analytics was my mean target of interest during the major studies. I'm grateful for the time that the company invested in me to give me time to make this thesis and also for all the resources and knowledge that my colleagues and mentors helped me with.

Writing of this thesis within tight time frame has been possible with the help of my professor in Tampere University of Technology and my councilor in EY. Thus I want to thank Professor Nina Helander who was more than eager to help me with the thesis and gave valuable advices throughout the process. The other person that I want especially thank is my councilor Kim Hacklin who helped me with all the issues and made sure with his sparring that all things were considered in this thesis. I want also send my thanks and regards to Norway for the people that I interviewed who gave me more knowledge that I could have ever imagined and to all the people that I interviewed in Finland.

Finally there are two particular persons that I want to mention who motivated me to make this thesis and helped when there were problems. Thanks for my wife who gave me cheers whenever it was needed and especially thanks for my little daughter who when writing this thesis was still coming to an existence but gave me the necessary boost and motivation to complete this research.

Helsinki, 1.10.2017

Juho Poutamo

CONTENTS

LIST OF ABBREVIATIONS

BI	Business intelligence
VRIS	value, rarity, imitability and substitutability
IT	Information technology
MVP	Minimum viable product

1. INTRODUCTION

In this chapter, the motivation and research background is presented, where we introduce the context of the thesis and why this thesis is important. After that the research problem and the objectives of this thesis are presented, where we introduce the research question. After the research questions the scope of the work and research structure is introduced where we go through some limitations that affect this research and how the whole research was compiled.

1.1 Research background and motivation

The business environment for companies is constantly changing nowadays. At the same time technology is evolving faster and faster and new technology is enabling and disturbing markets. This has led to a situation where information technology (IT) is not a supporting factor anymore but an asset, As Aral & Weill (2007) point out that IT has enabled to become more efficient in their processes and performance. Analytics has been one way to gain competitive edge and improve performance within the last decade. Now the importance of it is increasing rapidly as it's been predicted that a zettabyte of data, that is the fuel for analytics, will be generated in the internet (Kiron & Shockley 2011).

The research field around analytics is constantly growing and publications have increased a lot within the last couple of years. For example online library ProQuest gives 916565 results for search term "analytics" within the whole history and 714190 results within years 2010-2017. The number of research papers about analytics have grown exponentially in this decade and more papers are being published all the time. This has led to the situation where the field of analytics is diverse and different terms are being used for different contexts and purposes. Terms like "big data analytics", "business analytics", "predictive analytics", "customer analytics" and "visual analytics" are being used in different papers just to name a few. On top of the different terms used there are also different approaches to analytics as Holsapple et al. (2014) show in their research. Technological approach seems to be more dominant approach, where analytics is defined through technical solutions. The less researched approach to analytics is the management and "soft" side of it that concentrates to analytics' strategic and organizational viewpoints. Because the company that the thesis is done for is much more focused on the strategic and management viewpoint of analytics this thesis focuses also on that side of analytics.

The value of analytics is also a big discussion in companies. Kiron & Shockley (2011) say that vast amounts of data will place new challenges for companies to utilize it and gain value from it. Morabito (2015) continues that valuable insight can be gained via analytics only if technological but also organizational resources support the value creation of analytics. When companies are investing money to analytics it becomes a relevant question to think how much value they are getting from analytics. When considering the value creation, it's not always about the technology and the best tools but also the organization behind the tools and working practices to utilize analytical capabilities as best as possible (Kiron & Shockley 2011). To achieve the competitive edge from analytics and use it in company's everyday decision making it should be part of the company's strategy and culture (Ransbotham et al. 2016). Having the tools and technical capabilities is a big acquisition for an organization but on top of that they should change the way they manage the company. Organizational change required can be big and long process to implement so the understanding of how this change should be done to maximize the value from analytics is critical. Throughout the whole business environment, business analytics have been identified as the next big innovation that gives value and competitive advantage to organizations but at the same time the value chain of the analytics has been left unexplained (Corte-Real et al. 2017).

As different sources have identified that the value creation view of analytics has not been studied as much as there would be a need of, it's more than clear that the subject needs more studying. The company that this thesis is made for also has an interest for this approach that makes the subject of this thesis even more relevant for the writer to conduct.

1.2 Research problem, research questions and objectives

The aim of this research is to look at the value creation of analytics and how to concretely implement the value to customers via projects. This is achieved by identifying the needs of the customers and benchmarking best practices from working analytics teams. In order to find answers to the objective a research question to answer is stated.

The primary research question for the study is:

- How is the value of analytic solutions created and implemented?

To answer the research question subjects possibly relating to it must be considered. Analytics and value are the main themes in this research so to get answer to the research question those themes must be studied. At first we must understand how value in analytics context is considered in literature and how the implementation process of analytics is considered in the literature? Before we can address the value creation in analytics we must also define analytics to gain understanding of what factors are included in it.

- How is analytics defined and perceived?
- How is value in analytics created?
- What is analytics implementation process?
- How value can be implemented in analytics process?

All the research questions are being answered in some level in the literature review section but also in the empirical section in the interviews to gain more insight to the questions and how they are related to the main research question. In the empirical part the holes that the literature review couldn't answer are being studied and in the conclusion part the main research question is answered.

1.3 Research limitations and scope

The scope of this thesis is defined largely by the organization this thesis is made for. The organization is a very large management consulting company that is present in almost every country. This thesis is not meant to provide insight globally for analytics value but only for the Finnish markets. Because the case company is heavily specialized on management consulting and not to technical solutions this thesis excludes the technical side of analytics and focuses on the management and business side of the analytics value creation process. In this thesis analytics is also distinguished from the business intelligence (BI) literature so the concepts like data warehousing and other BI-related topics are not being handled. From the implementation point of view a scope is set only to agile methods as the nature of analytics is highly agile. Even though there might be different implementation methods in the analytics literature they are not being reviewed in this thesis.

Since part of the interviews are conducted in the Norway office of the company, the results and insights gained from there must be thoroughly reviewed how they apply in Finnish markets due the fact that Norwegian business environment might vary from it. Since the customer interviews conducted in Finland are mostly the case company's customers and do not represent any particular field of business, the business environment must be taken into consideration when generalizing the answers. Other limitation that affected especially the amount of customer interviews was time frame in which this research was conducted. Summer time, holidays and tight 12 week schedule made the acquiring of customer interviews hard why there were only three interviews conducted. The amount of interviews was still considered eligible as the main emphasis was in internal interviews. Also the people interviewed in the companies have different backgrounds and positions so their vision about analytics in their company might vary. This must be taken to consideration when making conclusion about the interviews. The companies are also in different positions in their analytics maturity so the answers from the companies might vary quite drastically from each other as their analytics maturity level is not assessed in this study.

1.4 Research structure

This thesis includes a literature review and an empirical research. It is done abductively in a way that the theoretical background is established first to gain insight about the research domain. Then, the empirical research is conducted based on the findings and insights gained from literature review. Analysis is made from the empirical research where the literature review and empirical research results are combined to conclude the findings of this research. This research follows figure 1 which is presented below.

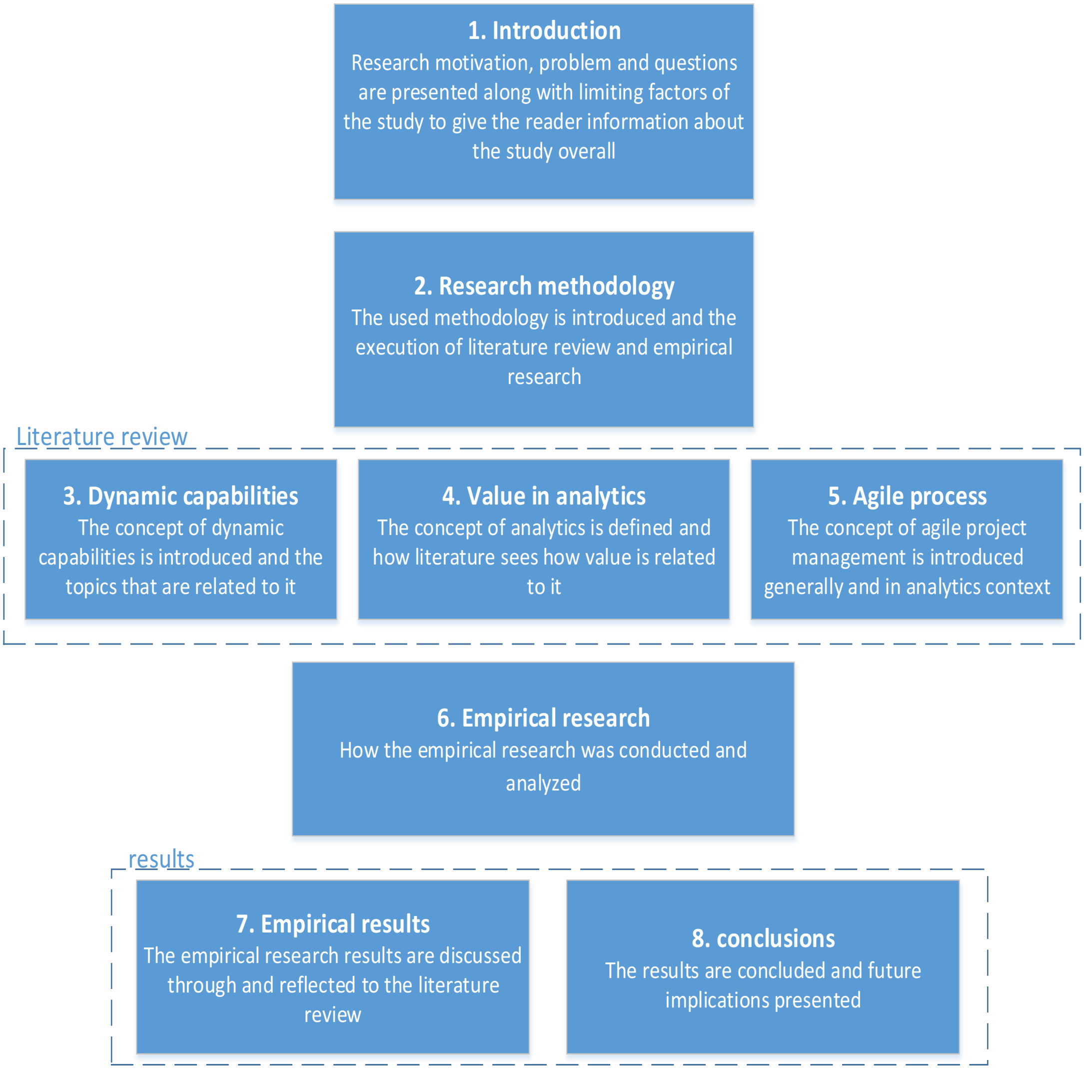

Figure 1: The structure of the thesis

The introduction part of the research gives the reader an overall view of the research motivations and research questions that guide the research. The scope of the research is also explained to give an understanding of what factors and theories affect the end result. The second chapter of the research handles the methodology used in this research. Data gathering methods and empirical research theory related to this thesis are introduced to give information about what methods were used and what was taken into account during the research.

Third, fourth and fifth chapters were dedicated to the literature review of this thesis where related theories were introduced and discussed. Topics handle dynamic capabilities literature, analytics and the value of analytics literature that are closely related to each other when approaching analytics from the value and strategic perspective. Before introducing dynamic capabilities a concept of resource based view of organization is presented to give the reader background information about where dynamic capabilities have evolved. Then dynamic capabilities are defined and topics related to it are introduced so that the concept of dynamic capabilities could be understood thoroughly. In chapter four the concept of analytics is defined and after that the value perspective of it is concluded from different viewpoints. On top of these theories agile processes literature that handles mostly project management perspective is presented to give insight of how analytics should be implemented in organizations.

The sixth chapter presents how the empirical study was conducted. Both interviews and how they were conducted are explained so that a complete picture of what kind of professionals were interviewed. Then the analysis methods for the interview results are introduced and explained to give and idea of how the researcher come to the conclusions. In the seventh and eighth chapter the final results are discussed and concluded. In the discussion part, the empirical material is reflected on the literature review and deductive conclusions are made and argued based on the research material. Finally the research is evaluated and future implications are presented to give an understanding of how this study could be continued.

2. RESEARCH METHODOLOGY

In this chapter the used methodologies of this research are introduced. This section is meant to give an idea of the philosophical approach and methods used in this study. After introducing the methodology, the data gathering methods and empirical research are introduced. This section gives the reader a description of how the literature review was conducted and the materials picked for the research but also how the empirical research and interviews were conducted and what has to be taken into consideration in them. Lastly the analysis methods of this thesis are displayed to give the reader an understanding of how the results were derived from the material.

2.1 Methodology

When conducting a research the researcher must consider how to conduct the research and how it is scientifically well formed. One approach to conducting a research is the research onion that Saunders et al. (2009) introduce. The idea is that the researcher peels the research onion's layers when the researcher is designing the research project. In figure 2 the research onion is depicted. It consists of six different layers that represent different scientific issues that have to be considered when conducting a research. According to Saunders et al. (2009) the researcher must consider different scientific philosophies and the way to approach the research first. Then different research strategies can be chosen along with scientific choices, time horizon and techniques used in the research.

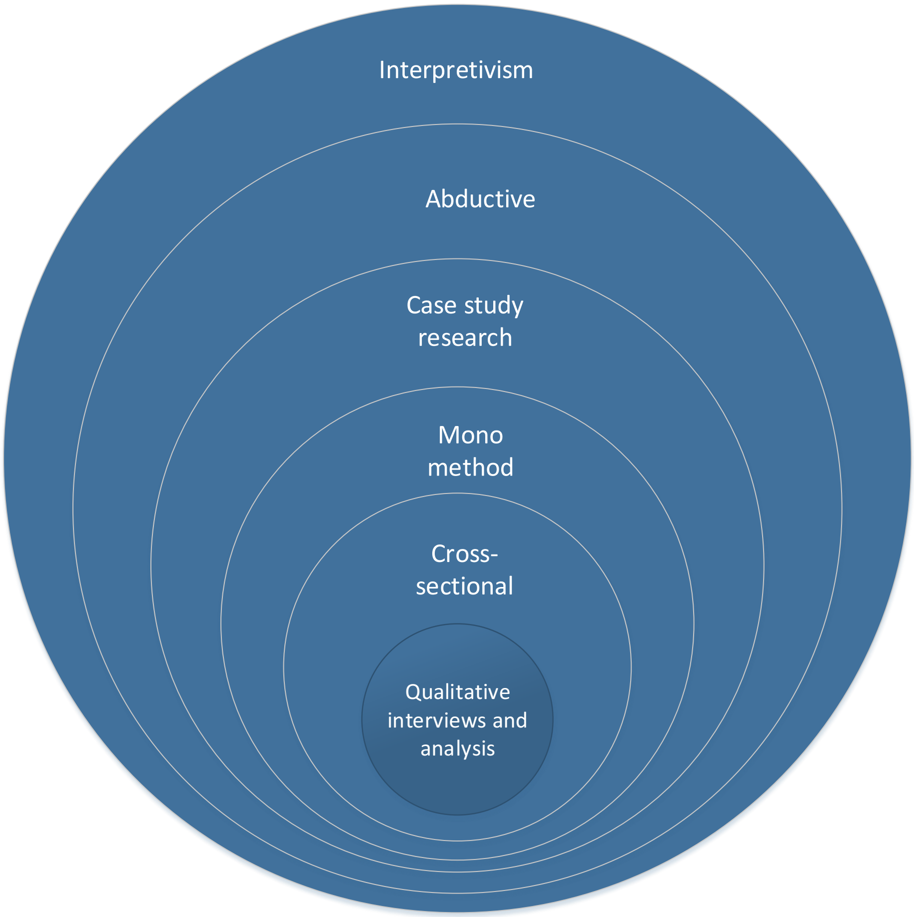

Figure 2: Chosen research approach based on Saunders et al.'s (2009) research onion.

When conducting a research the way one is approaching the field and the knowledge related to the field is important. A chosen research philosophy tells the reader how the researcher approaches knowledge in the research and how he or she views the world. Research philosophy also affects the strategy and methods the researcher chooses to use in the research and thus affects to the outcome of the research. There are four known research philosophies to be recognized: positivism, realism, interpretivism and pragmatism. (Saunders et al. 2009). This research is conducted with interpretivism philosophy because the issue studied relates closely to people and organization. Even though analytics has a technical side, which is very important, but when considering the value of it we must take actors like people into account because they define the value. Also when delivering value and implementing analytics, this study handles challenges related to people and organizations more than the technological challenges.

The scientific approach to conduct a research can be done in two ways or the combination of them. The other way is called deductive and the other is called inductive. Deductive approach relates much more to positivism and the idea behind it is to use theory and test it with different hypothesis (Saunders et al. 2009). The other approach is inductive approach to research which is the opposite of deductive approach. In inductive approach, the researcher collects data and based on the data new theories can be build (Saunders et al. 2009). This research has features from both approaches thus making it abductive approach to the subject. The theory part represents deductive part of the study and the empirical part of the study represents more inductive part of the study as the analysis methods are not derived from any previous studies from the field.

After the research philosophy and approach are decided, the research purpose and strategy can be chosen. The purpose of this study is exploratory. Exploratory researches are according to Robson (2002, p. 59), researches that try to seek new insights and see things in a new light. Saunders et al. (2009, p. 140) continue that usual methods used in exploratory research are searching the literature and interviewing experts in the subject. Both methods are used in this research hence the objective of this study is to gain new insight about analytics for the purpose of the study is exploratory.

The research strategy chosen for the research is a case study strategy. According to Robson (2002) case studies are conducted whenever a researcher wants to understand contemporary phenomenon and to understand it use multiple sources to study but which is also context related. Saunders et al. (2009) point out that the strategy answers well to questions like “why” or “how” and data gathering methods that can be used in a case study are usually interviews or observation. In this thesis main question was “how?”, so case study research strategy fits well in this frame and theme interviews suit to the exploratory nature of this research. Theme interviews provide better information qualitatively to the research and supports the objective of the research, which is in understanding how value is seen in analytics field and how it can be created so the material required is highly qualitative to understand the research question fully.

The data collection methods used in this research were literature review and theme interview. Since there are two different data gathering methods used in this study, which both are for gathering qualitative data, this study is according to Saunders et al. (2009, p. 152) a multi-method research. A multi-method research is a research where multiple data gathering methods are utilized but they are all either qualitative or quantitative. Since all the used methods are qualitative in this research they can be analyzed with the same qualitative methods and same principles about reliability and validity have to be met. This study is also a cross-sectional study in time horizon, since the interviews conducted and materials used are collected considering the present time (Saunders et al. 2009).

2.2 Literature review

A literature review was conducted in this thesis in order to gain better insight from the research field. Saunders et al. (2009, s. 58-59) emphasize that a literature review has two reasons why it is conducted. The first is that a literature review helps a researcher to generate better research ideas and questions about the topic. The second reason why literature review is made in a research according to Saunders et al. (2009) is that the literature review gives the researcher detailed knowledge about the subject but also an idea about the big picture around the topic. This is also the reason why the literature review was conducted in this thesis. Kitchenham & Charters (2007) continue that literature review is also done to identify any gaps in the research field and to position own research to the field correctly. In this thesis literature review steered the course of the study along the research and helped to understand different aspects of the analytics field and especially how value in analytics was studied in literature. With literature review a gap in the research field regarding to the agile implementation of value in analytics was also identified and added to this research as one main theme.

The literature review was conducted following Saunders et al. (2009) steps to write a critical literature review. First, after the research questions and objectives were set, key words were generated to steer the search of articles. When proper articles were found, they were obtained and evaluated based on the parameters shown later on in this chapter. After evaluation, the writing of the review started based on the materials. Simultaneously new search words were generated based on the new ideas that came up when reading the literature. Then more searches were conducted based on the new words and same procedure took place again. This way new materials were searched during the whole time of writing the literature review and more insight was gained. At the same time scoping of the study was done continuously to prevent the thesis from including too many aspects of the research field and that the material answered to research questions. Exclusion criteria were set to keep the material relevant throughout the research (see Kitchenham & Charter 2007). Articles that dealt with business intelligence instead of analytics and technological articles were excluded completely.

The first key words that were generated when searching articles started were “analytics” and “value”. Search words used during the whole research are listed below but the initial information search was conducted with these words in order to gain insight what kind of publications are made about analytics in general. Used sources in the search were different databases and a service that Tampere University of Technology provides its students called Andor. Andor is a search engine that searches different databases like ProQuest. On top of using Andor for searching articles a few other databases and search engines were used and other method that was used was to utilize the reference lists of the articles. After the first round of searching materials new field related to the value of analytics was identified: dynamic capabilities. Also after conducting the interviews a need for introducing agile methods rose and agile project management related literature was searched. To gain understanding from all of the three different fields of science the search terms had to be combined. Search terms related to the research were:

- “Analytics” AND “Value”
- “Dynamic capabilities” AND “Analytics”
- “Agile” AND “Analytics”
- “Agile project management”
- “Resource based view” AND “Dynamic capabilities”.

When searching with different search words some filters were applied. The first filter was set based on the year of release. Analytics-related articles were searched between years of 2007-2017. This timeframe was chosen because the amount of articles was very low before the year 2007 since the research field is new. Other filter set for the search was a requirement for full text about the article. Articles with only abstracts or part of them available were disqualified. This decision was made because the researcher wanted to have a complete understanding from the articles used in this thesis. Third filter considered about the language of the article. Only articles that were written in English were qualified for the research. Fourth filter was the literature type of the article. Peer reviewed journals and conference papers were the main types of materials used in this research. This way the scientific quality of the materials were high and the results from the materials could be considered relevant for the research field. Same filter were applied agile methods and dynamic capabilities searches except the year filter.

The decision about what articles were to be included in this literature review was made based on parameters chosen above and based on the researcher's evaluation. Picking was made firstly by reading the headline of the article. If the headline was relevant to the literature review then abstract of the article was read and evaluated. The decision was made based on the abstract if the article was relevant and the article was stored. During the writing process, articles were read thorough and used if the content was suitable. The suitability of the articles were assessed if the content somehow answered to the research questions of the thesis.

2.3 Empirical research

The research methods chosen for the study were chosen based on the possibilities and the nature of this thesis. Because this thesis is exploratory in its nature, as it combines relatively new theories that are not thoroughly researched yet, a semi-structured theme interview was selected as a research method in order to gain deeper insight of the matter studied. Same research method is used to interview the case company's customers in Finland since the goal from those interviews is to gain insight about analytics processes and according to King (2004) semi-structured interviews are good way to understand issues like organizational culture and processes. The reason why semi-structured interview was selected was that according to Saunders et al. (2009) it fits well with exploratory study and with non-formal interview; the researcher can ask for more specific answers on certain themes within the interview. Semi-structured interview also provides a possibility to focus on certain theme depending on the conversation flow. King (2004) emphasizes that in semi-structured interviews the questions should not be followed strictly but the questions should be seen as interview guide where you put interesting topics from which you want answers. Since the interviewees were professionals in the analytics field, the questions that are presented in appendix A worked more as an interview guideline and were not followed strictly to gain better insight from the interviewees.

There are some issues to consider regarding to the execution of the empirical research as it is done conducting interviews. Things to be considered are according to Saunders et al. (2009) the reliability of the data, the form of bias that the researcher might have and also the validity and generalization of the data that is acquired from the interviews. Reliability, which is related to how applicable the answers are, can be concerned together with bias of the interviewee and interviewer. The interviewer bias according to Saunders et al. (2009) can be anything from different tones of voices to non-verbal behavior that tries to affect to the course of the interview and the interviewee. Interviewee bias on the other hand is beliefs and perceptions that the interviewee has that affect the answers. It can be for example that the interviewee doesn't feel comfortable about some topics and is giving false answers for the topic. Both forms of biases and how they were dealt are discussed more thoroughly in chapter 6.

Generalizability and validity in the study can be considered as a level of access to the knowledge of the interviewees and interpreting the answers that the interviewees have given in a way that they were meant to (Saunders et al. 2009). If there are biases in the interviews then also the validity of the interviews can be questioned, especially if the interviewer interprets the answers incorrectly. Also when dealing with qualitative studies and low samples one cannot make generalizations from the answers as they represent only opinions of few. Still considering the exploratory nature of the study the generalization and validation of the study is not a significant issue as the study is about finding something new. On the other hand King (2004) states that there is a chance of getting data overload from the answers as there is a huge amount of data to be interpreted.

After the interviewees are done the answers have to be analyzed. The method used to analyze interview results is chosen to summarizing. In summarizing method the interviews are summarized and key points are extracted to understand the main themes and topics of the interview (Saunders et al. 2009). Understanding the main themes helps to comprehend the topics and as the research is exploratory the main themes include the most interesting ideas.

3. RESOURCE-BASED VIEW AND DYNAMIC CAPABILITIES

This chapter explains different terms related to resource-based view of the organization but also dynamic capabilities. At first, we define resource-based view and then derive the definition of dynamic capabilities from it. Then we discuss different aspects of dynamic capabilities and how they affect the business and learning of the organization.

3.1 Resource based view of organization

One of the ways management has been approaching the field of competitive advantage and improving organization comes from strategic literature and considers organization through their resources. This field of study is called resource based view of organizations. Barney (1991) defines organization’s resources as all things that organization owns which enable it to improve its efficiency and effectiveness. He lists aspects like knowledge, information, assets and processes as resources of the organization. Barney (1991) makes a categorization of the resources in three different categories that are usually shown in the literature: Human capital resources, physical capital resources and organizational capital resources. Human capital resources and organizational capital are everything that employees possess like the knowledge and processes mentioned before. Physical capital on the other hand is the technology and tools that organization possess. Barney (1991) stresses the fact that not all the resources in those categories are necessarily relevant for strategic point of view of the organization. When developing the competitive advantage from the resource point of view it is critical to assess different resources that organization has and think how crucial they are in competitive advantage perspective and how organization can improve or acquire more of them.

Understanding what resources are valuable and critical for strategy might be hard to identify for organization. Four attributes are identified that can be used to evaluate the effectiveness of the resource: value, rarity, imitability and substitutability (VRIS) (Barney 1991). What these attributes mean is that the resource must have some sort of value in them and they must be resources that other companies don’t have in vast scales. Imitability is a continuation of rarity since even if competitors don’t have the rare resource now, they might be able to acquire it, which means that the resources should not be easily acquirable in order to be relevant for strategic point of view. Substitutability of the resources means that there cannot be equal resources available to be able to imitate strategically important resources. Figure 3 depicts how from organization’s resources only meaningful resources are funneled and have significance for organization’s strategy.

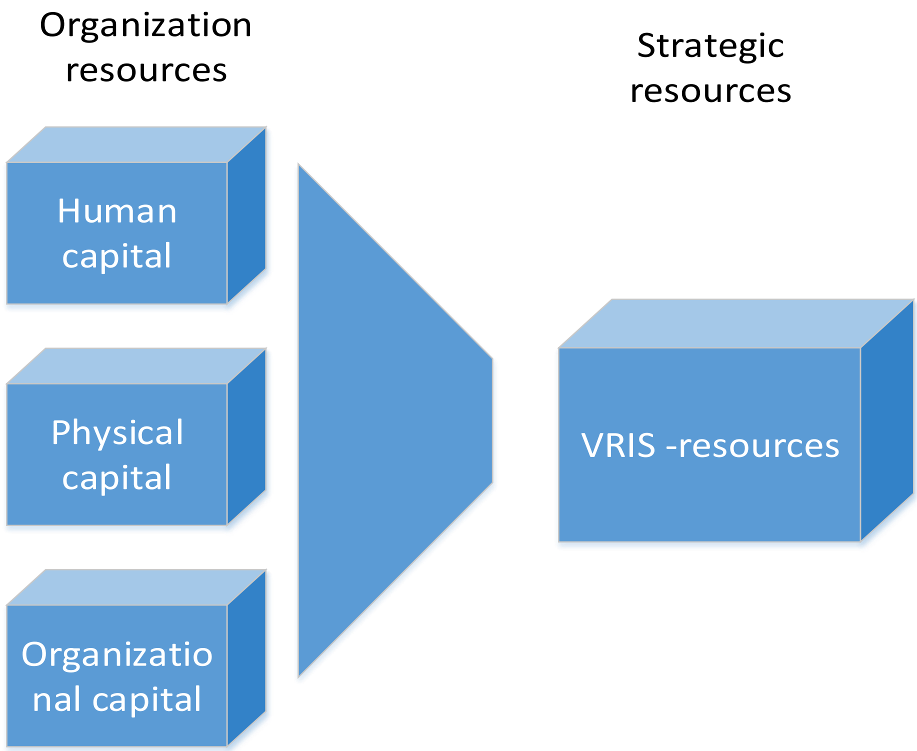

Figure 3: Basic view of organization's resources and how they are funneled to VRIS-resources.

Just by possessing resources that have the attributes mentioned above does not necessarily mean that a company can succeed in their competitive environment. Organizations must also actively manage the resources in order to keep them up and exploit them the best way possible (Barney & Wright 1998). In order to develop the resource based view theory, Teece et al. (1997) developed the concept and theory of dynamic capabilities which is built on resource based view but on top of resources takes all the actions into account also. We discuss about dynamic capabilities in the next section since the theory is a major contributor to the value creation theory of analytics and information systems that are handled in this thesis.

3.2 Dynamic capabilities

The concept of dynamic capabilities evolved from the resource based view of organizations that presented them as bundles of resources which enable long term competitive advantage. The leading thought of dynamic capabilities is the same as it is in resource based view theory but dynamic capabilities focuses more on the active managing of the resources instead of individual resources (Teece et al. 1997). It also answers to the deficiency that resource based view has - considering changing business environment. The concept of dynamic capabilities started to emerge in 1990s from the resource based view because of these deficiencies as many researchers started study them (Ambrosini & Bowman 2009). Because of rather short scientific history dynamic capabilities have been defined and approached from couple of different ways. Teece et al. (1997) define dynamic capabilities as organization's ability to renew own competences but also to adapt and integrate organizational skills, resources and competencies according to the changing environment. They stress that these actors must also be non-replicable and non-imitable (VRIS) by competitors so that the dynamic capabilities possessed are unique and thus provide competitive advantage.

Eisenhardt & Martin (2000) continue to define their view of dynamic capabilities as processes that integrate, reconfigure, and gain and release resources to create change in the organization and thus can be seen as the strategic routines that organizations use to adapt to markets. As Teece et al. (1997) already had proposed, Eisenhardt & Martin (2000) also say that processes are in the center of the dynamic capabilities concept and include same kinds of activities inside the process term that Teece et al. (1997) did like management processes and reconfiguration of resources. How Eisenhardt & Martin (2000) extend the concept of processes is that they introduce the importance of knowledge creation and external alliances which have significant role to develop and manage dynamic capabilities. They also have a different opinion to Teece et al.'s (1997) about the resources that dynamic capabilities are based on.

Eisenhardt & Martin (2000) challenge the view that Teece et al. (1997) and Barney (1991) presented in their publications where the concepts of resource based view and dynamic capabilities was based on the VRIS-aspects of resources. Eisenhardt & Martin say that dynamic capabilities are not merely unique for all the organization but there can be best practices that can be applied for all organizations. This means that the resources and processes are not necessarily rare or non-imitable. Eisenhardt & Martin (2000) yet correct their statement that even though there are best practices it does not mean that the dynamic capabilities are same in different organizations. Since according to Eisenhardt & Martin (2000) dynamic capabilities can be imitable in some extent, they say that dynamic capabilities can be a source of competitive edge but not a sustained source of competitive advantage like was previously stated (Teece et al. 1997, Barney 1991). Taking into account the constantly changing environment the statement makes a point, since having something sustainable in constant change can be hard. This is of course business field dependent since some business areas develop much faster than others. This implies that dynamic capabilities itself might not be the one and only theory to follow in business but rather a mix of resource based view and dynamic capabilities along with other strategic theories to develop own strategy.

Wang & Ahmed (2007) say that dynamic capabilities encase organization's wisdom from previous work done, different routines that organization has, knowledge that organization has, core competencies and different capabilities like core or architectural capabilities that organization has. They define dynamic capabilities as organizations behavioral orientation to constantly reconstruct the core capabilities and reconfigure resources and other capabilities to maintain competitive advantage over competitors. Wang & Ahmed (2007) also make a clear distinction between processes and dynamic capabilities which according to them are embedded in processes but are not only different processes. Wang & Ahmed (2007) define processes as explicit and codifiable combination of resources and capabilities as capacity to deploy different resources and combinations of them in a way that it also involves tacit aspects of the resources and processes. This makes capabilities firm-specific since tacit aspects are different in every organization. Their approach is similar to what Teece et al. (1997) have presented about the definition. On the other hand Wang & Ahmed (2007) approach to dynamic capability framework differs from Teece et al.'s (1997).

Pavlou & El Sawy (2011) bring the concept of operational capabilities alongside to dynamic capabilities as they propose that dynamic capabilities are the capabilities that enable changes to operational capabilities that can be defined as the everyday processes that make the organizations run (Winter 2003). The problem that Pavlou & El Sawy (2011) identify is that dynamic capabilities are hard to measure and thus makes them hard to manage and develop. Reflecting this claim to previous studies where dynamic capabilities are defined and explained (Teece et al. 1997, Teece 2007, Eisenhardt & Martin 2000, Wang & Ahmed 2007) there is a problem that organizations might not have the capability to understand and identify their capabilities even though different sources have explained them. The problem is that dynamic capabilities are usually tacit, which makes them hard to see and measure. When something can't be measured it can be hard to explain the importance of it to use resources for identifying and developing dynamic capabilities. As discussed earlier, developing dynamic capabilities is not the core business of the company but rather takes time of from the money making actions so if someone can't prove the value of them before something radical happens in the market, organizations might lose their competitive advantage.

As there are quite a few different definitions for dynamic capabilities it may be hard to concise the definitions in one entity. Ambrosini & Bowman (2009) say that it might be easier to understand them if things that are not considered as dynamic capabilities are defined. Winter (2003) remind that dynamic capabilities are not ad hoc problem solving but the management of dynamic capabilities must be structured. Helfat et al. (2007) say that luck has no part in dynamic capabilities but rather the change on the right direction must be intentional. Ambrosini & Bowman (2009) also remind that dynamic capabilities and organization change do not always give competitive edge but can fail also.

As there are many definitions to dynamic capabilities there are also different frameworks or approaches of how dynamic capabilities can be understood. Teece et al. (1997) consisted the first framework and after that different researchers have presented their view of the contents of dynamic capabilities. Teece et al. (1997) establish a framework to understand dynamic capabilities more deeply and how they need to be managed to gain competitive advantage. They approach dynamic capabilities presenting them under three different terms: processes, positions and paths. the terms are considered broadly as ways the organizations do things (processes), different assets and relations that organization has (positions) and different alternatives that the organization has available based on their situation and previous choices (paths) (Teece et al. 1997). Later Teece develop his model further and saw them as actions of sensing or shaping opportunities, seizing opportunities and managing threats or reconfiguration. The model continues highlighting that dynamic capabilities are different processes and actions which are related to organization's actions like decision making, governance and knowledge management.

Continuing the work of Teece et al. (1997) and Teece (2007) a new model that enables the measurement of dynamic capabilities proposes that dynamic capabilities consists of four different capabilities that are sensing, learning, integrating and coordinating capabilities (Pavlou & El Sawy 2011). Basically the model has just combined different categories from Teece et al. (1997) and Teece (2007) frameworks but the novelty value that Pavlou & El Sawy (2011) model brings to the field is that dynamic capabilities bring value by alternating operational capabilities. This claim means that the measuring organizations operational capabilities and their changes we can see the effects that dynamic capabilities cause to organizations. Pavlou & El Sawy (2011) also stress the importance of acknowledging that dynamic capabilities and their implications affect to all levels of the organization which means that management has to communicate the importance of them to employees.

Differing from Teece (2007) and Pavlou & El Sawy (2011) approach to dynamic capabilities is Wang & Ahmed's (2007) approach where they present them as adaptive capabilities, absorptive capabilities and innovative capabilities. Even though the terms used are different, the contents of that Wang & Ahmed include in their definitions are similar to how other researchers see dynamic capabilities. Newest model of dynamic capabilities was composed by Eriksson (2014) where she divides dynamic capabilities into generic learning processes or specific internal processes in organizations. Her emphasis is on knowledge and experience accumulation which are part of the learning processes that comprise according to her the dynamic capabilities. The knowledge point of view is something that the other researchers do not stress that much but since work is transforming to more and more into knowledge work it is understandable that the role of it is included in dynamic capabilities as well. Table 1 compares different frameworks of how dynamic capabilities and the contents of them are seen.

Table 1: Different approaches to dynamic capabilities

Study	Dynamic capability approach
Teece et al. 1997	Processes, positions, paths
Teece 2007	sensing, seizing, managing
Pavlou & El Sawy 2011	Sensing, learning, integrating, coordinating
Wang & Ahmed 2007	Adaptive, absorptive, innovative
Eriksson 2014	Knowledge accumulation & Absorption, Knowledge integration, knowledge utilization, knowledge transformation

Integrating all the approaches together is done by comparing the contents of different terms. Based on that it can be said that Teece (2007), Pavlou & El Sawy (2011) and Eriksson's (2014) approaches focus on processes and Wang & Ahmed's (2007) approach even though presented with different terms is content wise similar to other models. Teece et al. (1997) idea of processes, positions and paths is higher level approach to subject but including positions and paths on top of the processes gives deeper consensus of the subject and thus is used to understand dynamic capabilities as whole in this thesis. Figure 4 depicts dynamic capabilities as a whole.

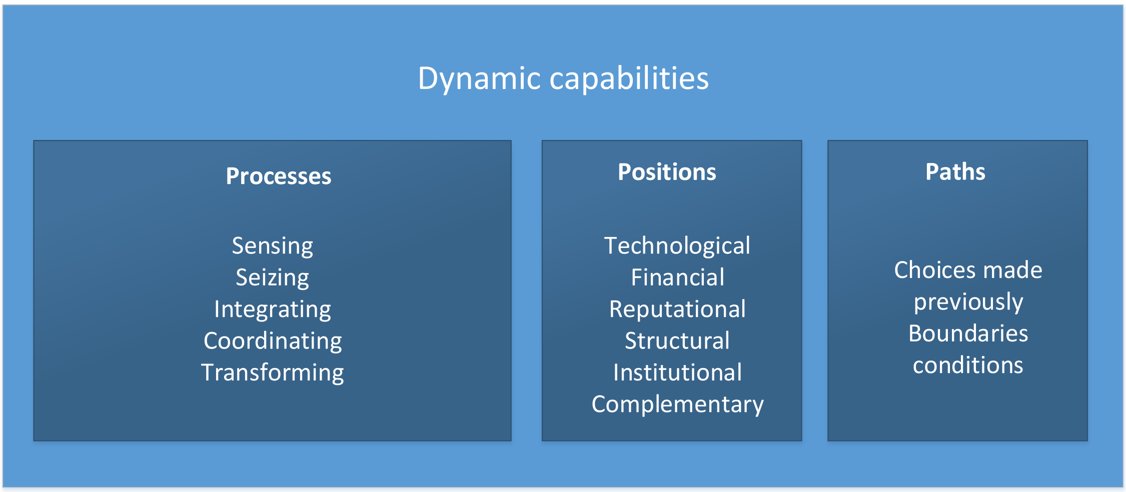

Figure 4: Summary about all the aspects that form dynamic capabilities

The whole entity of organization's resources and capabilities is depicted by Wang & Ahmed (2007) who present organization's resources and capabilities in hierarchical way where resources are the basis of the capabilities and referred as the zero-order of the hierarchy. This is because all the capabilities are based on and constructed from resources that organization has. On top of this baseline, Wang & Ahmed construct three different hierarchical capabilities that represent different aspects of dynamic capabilities. The first layer on top of resources are normal capabilities that according to Wang & Ahmed (2007) demonstrate the ability to deploy resources and achieve set goals. The second layer of the hierarchy are core capabilities which are defined as capabilities and resources that have significant strategic importance for organization and its competitive advantage. The third and the highest level of the hierarchical capability model is dynamic capabilities which Wang & Ahmed (2007) said to be actions to constantly pursuit of renewal and reconfiguration of lower levels of hierarchical model. Figure 5 in the summary chapter depicts whole entity of organization's resources and capabilities.

3.2.1 Processes

Processes are the most common way to understand dynamic capabilities as different approaches to them are presented in studies. As depicted previously, processes can be categorized in different categories based on what kind of actions they include. Categories are presented in this chapter to understand the whole entity that comprises dynamic capabilities and what organizations should take into account when trying to develop dynamic capabilities.

Coordination processes are related to management and thus have significant effect on what the company does and how well it does it. Teece et al. (1997) emphasize the importance of not only internal processes but also external processes like collaboration and sourcing that must be taken into account when talking about dynamic capabilities. Pavlou & El Sawy (2011) define coordination processes as ability to orchestrate and deploy tasks which in organization means assigning people and resources to right tasks and synchronizing the tasks to be efficient. Different processes should be put into smaller pieces so that the real reasons that effect to the processes can be found. For example product development itself is not a dynamic capability itself but the actions related to it might be, like knowledge flows from customer to development. Teece et al. (1997) continue that in addition to recognizing the important parts of the processes from the managerial perspective it is also crucial to understand the complementarities among and between different processes.

Learning can be seen as one important process in dynamic capabilities. It is even more important part of processes than coordination, since it helps to make things faster but also to identify new ways of doing and new opportunities to be exploited (Teece et al. 1997). As discussed earlier, the concept of dynamic capabilities tries to answer to the changing business environment that organizations face and learning is a big part of keeping up to the development. New technology for example usually requires new skills from the employees to learn new machines and ways to do things. Pavlou & El Sawy (2011) see learning capability as an ability to improve already available capabilities like in the example improved capabilities would be learning new information system. Zahra & George (2002) see learning as absorptive capability of organization. They define absorptive capability as construct of four different actors: exploitation, assimilation, transformation and acquisition of knowledge. Zahra & George (2002) say that for example the acquisition capability means the ability to identify and acquire information and knowledge and assimilation is defined as routines and processes that the company uses to interpret outside knowledge from the operational environment. Same theme continues with the transformation and exploitation where using knowledge and cultivating it is key to learning. Todorova & Durisin (2007) stress the importance of feedback loops when developing absorptive capabilities since with them the real outcomes of the development can be seen and thus new development objects can be identified. Wang & Ahmed (2007) also claim that organizations that have high absorptive capability have tendency to able to learn more effectively from business partners and utilize the partnership to embed knowledge to own organization.

The skill to understand how e.g. new technology could be used more effectively is closely related to the third concept that Teece et al. (1997) present as a part of processes in their dynamic capabilities framework. Reconfiguration and transformation processes are processes that are part of dynamic capability concept. In changing markets organization must keep an eye on the markets all the time and sense weak signals and coming changes that affect the operations of the organization. Teece et al. (1997) stress the fact that change comes always with the cost for companies which means that in the state of constant change organizations must find ways to adjust but with reasonable costs. Transformation processes includes actions like learning, governance and adoption that are required to make the lasting changes in the organization (Teece 2007). Transforming the organization needs innovation and Wang & Ahmed (2007) raise innovation capability as one important part of dynamic capabilities. Innovative capability can be seen as a capability to develop new services and products or developing new processes, methods and organizational forms (Schumpeter 1934). Annique Un & Montoro-Sanchez (2010) suggest that knowledge sharing, communicating and cooperating are key principles of innovative capability that can occur in either teams or in the organizational level of the organization. Pavlou & El Sawy (2011) include integration as part of the reconfiguring and transforming organization and its capabilities.

Sensing is about listening the markets and gathering information from different sources to gain better understanding of the on-going changes and, for example customer preferences (Teece 2007). Sensing and the concept of adaptive capabilities (see Wang & Ahmed 2007) are related to each other. Adaptive capabilities are defined as an ability to identify different opportunities arising from business environment but also an ability to capitalize them (Chakravarthy 1982). Sensing environment means according to Pavlou & El Sawy (2011) that business units should gather information about the needs in the markets but also about competitors and emerging trends in technology for example. Routines related to sensing capabilities are generating and disseminating market intelligence but also responding to it (Teece 2007). Teece et al. (1997) state that organizations that have high levels of adaptive capabilities also have great deal of dynamic capabilities. This is understandable if organization can utilize the knowledge and information that they gather and not just possess it. Utilizing the knowledge requires courage to try something new and capabilities to execute the ideas which are basically other sets of dynamic capabilities which are called seizing capabilities.

Seizing is the next step from sensing the markets where organization must be able to act based on the information and insight it has gained from the markets and seize the opportunities that it sees. This involves according to Teece (2007) not only investing on new ideas but also configuring business models and decision making processes to better fit to the new business opportunities. In literature adaptive capabilities (see Wang & Ahmed 2007) can be linked to seizing. In practice adaptive capabilities are abilities to experiment, manage and mobilize the resources of organization according to Oliver (2016). Adaptive capability is related to absorptive capability since it requires scanning of operational environment but adaptive capabilities include the implementation methods and capabilities that organization possess when they are changing something. Oliver (2016) mentioned experimenting and developing low-cost ideas, which is a quick way to test new ideas, learn from them and see the changes and results they make to organization, is a good example of methods that organization could utilize to keep up with the market changes.

3.2.2 Positions

Positions are seen as part of the dynamic capabilities concept that Teece et al. (1997) presented. Although the word itself is not particularly self-explanatory basically positions include the assets and competencies that the organizations holds already. Teece et al. (1997) list technological, complementary, financial, reputational, structural, and institutional and market assets as different categories of positions. Positions could be related to the core capabilities that Wang & Ahmed (2007) presented. Most of the assets listed above explain themselves and what is involved under the term but for example complementary assets can be defined as for example support units for the core business units and technical resources can be seen as part of the technical assets that companies have. In the case of market assets for example the correlation between organization’s resources is not that clear. Market assets are related to the market position of the organization but also to the whole market that they are competing (Teece et al. 1997), which cannot be seen as a resource in organization but rather as prevailing condition.

Ambrosini & Bowman (2009) explain positions as twofold issue that includes the internal assets but also the external issues like the domain market that the organization operates in. Internal factor that is mentioned by Ambrosini & Bowman (2009) is also the managers in organization whose role on dynamic capabilities is huge as the responsibility to develop dynamic capabilities is managers' job. Positions as existing assets can be considered to be important to acknowledge as they have clear impact on dynamic capabilities. Before developing dynamic capabilities positions in external environment but internally should be identified along with paths that the organization have taken and should take.

3.2.3 Paths

The third part of the Teece et al. (1997) framework is paths, which take the history of the organization into account. The governing thought of the path concept according to Teece et al. (1997) is that an organization can make the choices of where it is going but the past decisions, technological acquirements and prevailing conditions affect the choice. They continue that for example learning process that we discussed before has an impact to the paths that companies take, but also how companies adapt to the chosen path and vice versa. Teece et al. (1997) say that if too many parameters are changed by choosing a certain direction, organization might not be able to adapt to it very quickly but also if organization makes a choice based on learning too rapidly, the chosen path might not work as well as hoped.

Path dependency can be constricting factor that organizations have to deal with as in the past they couldn't see in the future and think the requirements of the future. Prevailing consensus is that creation of dynamic capabilities and the usage of them transforming strategically important resources is path dependent (Ambrosini & Bowman 2009). Since organizations can't really affect their current situation based on their past, the path dependency of dynamic capabilities should at least be acknowledge so that the some future directions can remain open as long as possible.

3.3 Capability development

Dynamic capabilities developed from the resource based view as it couldn't respond to the changing markets and thus the concept of market dynamism is central factor when discussing dynamic capabilities and their development (Eisenhardt & Martin 2000). According to Wang & Ahmed (2007) dynamic markets can be whatever markets where technology, regulation or economical change like new business models might occur and disrupt the normal state of the markets. Wang & Ahmed continue that the more dynamic markets are the faster the organization must build their core capabilities and dynamic capabilities to correspond the market needs and thus market dynamism is one of key drivers of developing dynamic capabilities. To contrast this statement to the present time and to organizations operating especially in industries where the rate of change has been moderate that Eisenhardt & Martin (2000) describe as moderately changing, rising digitalization might change even the moderately dynamic markets in a way that changes cannot be predicted.

The nature of dynamic capabilities might vary but as discussed, there are best practices that can be followed in all organizations. Eisenhardt & Martin (2000) make a distinction between high velocity markets and normal markets based on their research about the best practices in dynamic capabilities. They found that in normal markets where the market is somewhat predictable or at least is not changing too fast, dynamic capabilities like decision making processes are usually linear and have very precise routines and steps in their processes. In high velocity markets the best practices are the opposite. Since the market is not predictable and changes happen rapidly the markets do not rely that much on old knowledge but rather the ability to create new fast. This makes dynamic capabilities simple so that they more as guiding factors rather than boundaries so that organization can develop and learn rapidly to adjust market changes. Eisenhardt & Martin (2000) emphasize that when creating knowledge in changing markets experimentation and rapid testing are crucial to learn and get immediate feedback but at the same time keep the costs low. When talking about rapid development and experimenting we must also remember the paths and how they effect to the decisions of the company (see Teece et al. 1997). Choices made previously and the culture of the company might not be accustomed to the new working methods even though market changes are rapid. So whenever we are dealing with dynamic capabilities we must remember the past of the company but also the culture and people which are the key components of change and dynamic capabilities.

Wang & Ahmed (2007) present the correlation between organization's strategy and the development of its capabilities also a big part of the concept of dynamic capabilities and as the outcome of dynamic capabilities. As we discussed previously, to develop something we must be able to measure it and compare it to past. Pavlou & El Sawy (2011) stated that measuring and developing dynamic capabilities was highly related to the operational capabilities but also to other organizational capabilities like project, product development and service capability (see. Clark & Fujimoto 1991, Brady & Davies 2004, Athreye 2005). Still the development of dynamic capabilities is highly effected by the strategy that the organization follows since it dictates what capabilities are developed and where the organization wants to be compared to its competitors. This means that if the organization wants to focus on being more innovative than its competitors, they tend to develop capabilities that makes them more innovative but if organization's strategy is to cut costs they develop their capabilities to that direction. (Wang & Ahmed, 2007). Since there are as many strategies as there are organizations there isn't the right way to develop capabilities but it's critical to know where the organization is going and what capabilities would support that direction.

Helfat & Peteraf (2015) express the importance of management and managerial capabilities as a part of developing dynamic capabilities in organization. As we have discussed before, dynamic capabilities consists of multiple different aspects but they almost all are related to every level of organization from the management to the employees. Even though development of dynamic capabilities is a matter of whole organization, management plays still crucial part in it since they have the power to manage the resources and approve changes that are made. Helfat & Peteraf (2015) showed that individual skills of a person in management position can have effect on the development of the dynamic capabilities as well as the path (see Teece et al. 1997) that the person has went through in his or her career. The main finding is that manager can have significant effect on the activities of dynamic capabilities (sensing, seizing and reconfiguring) by encouraging co-operation and lowering the resistance to change (Helfat & Peteraf 2015).

Dynamic capabilities and their occurrence is dependent on the market that the organization is in but also the resources that it possesses and the paths it has taken in the past. Still these capabilities can be developed and built like previously Eisenhardt & Martin (2000) stated. Building dynamic capabilities is highly related to learning, codification of existing knowledge, making mistakes, pacing the experiences and combining previous experience (Eisenhardt & Martin 2000). Basically the people and the culture should be loose enough to give time for everybody to develop themselves and thus the processes but at the same time avoid wrong decisions and making futile costs. This can be hard since developing and learning takes time off from the core business activities that brings revenue for organizations. Balancing the available time and resources to develop dynamic capabilities can be hard because of this if the company does not see the need for it. In less dynamic markets this can be much more common since the changes don’t happen fast. On the other hand businesses cannot acquire ground breaking competitive advantage for themselves if they do not allocate resources to develop the capabilities and implement the capabilities to whole organization.

3.4 Summary

Dynamic capabilities as an entity are quite vague as they are different in each organization and thus can be hard to identify or even understand. Teece et al. (1997) emphasize the fact that because dynamic capabilities are usually tacit and tend to be for example organization culture related, the capabilities cannot be really acquired but rather must be built in time. Building them like have been discussed is path and position related as choices made in history and assets owned now effect on building dynamic capabilities. Still as Teece et al. (1997) and Eisenhardt & Martin (2000) stress that building them and succeeding in that can provide big competitive advantages over competitors as organization can adapt to changes in the operational environment.

Creating Dynamic capabilities requires still resources that can be scarce in organizations. Winter (2003) reminds that maintaining dynamic capabilities can be expensive as they require long-term commitment and the development takes resources away from the core business. Problem is to find the balance of giving resources for the development. Examples of companies not being able to change their ways of working and business are multiple. For example Teece et al. (1997) mention companies like IBM that have failed to maintain their position in the markets because they haven't been able to respond to the ever-changing market needs with their processes and capabilities.

Understanding that developing dynamic capabilities and building them are a continuous process that enables companies to change and adapt to markets is the key to understand the contents of them. Ambrosini & Bowman (2009) concise the concept of dynamic capabilities to process of creating value where internal and external factors play a role and which affect the resource base of organization with dynamic capabilities. Affecting the resource base provides outcomes that are identified as sustained competitive edge which separates the company from its competitors.

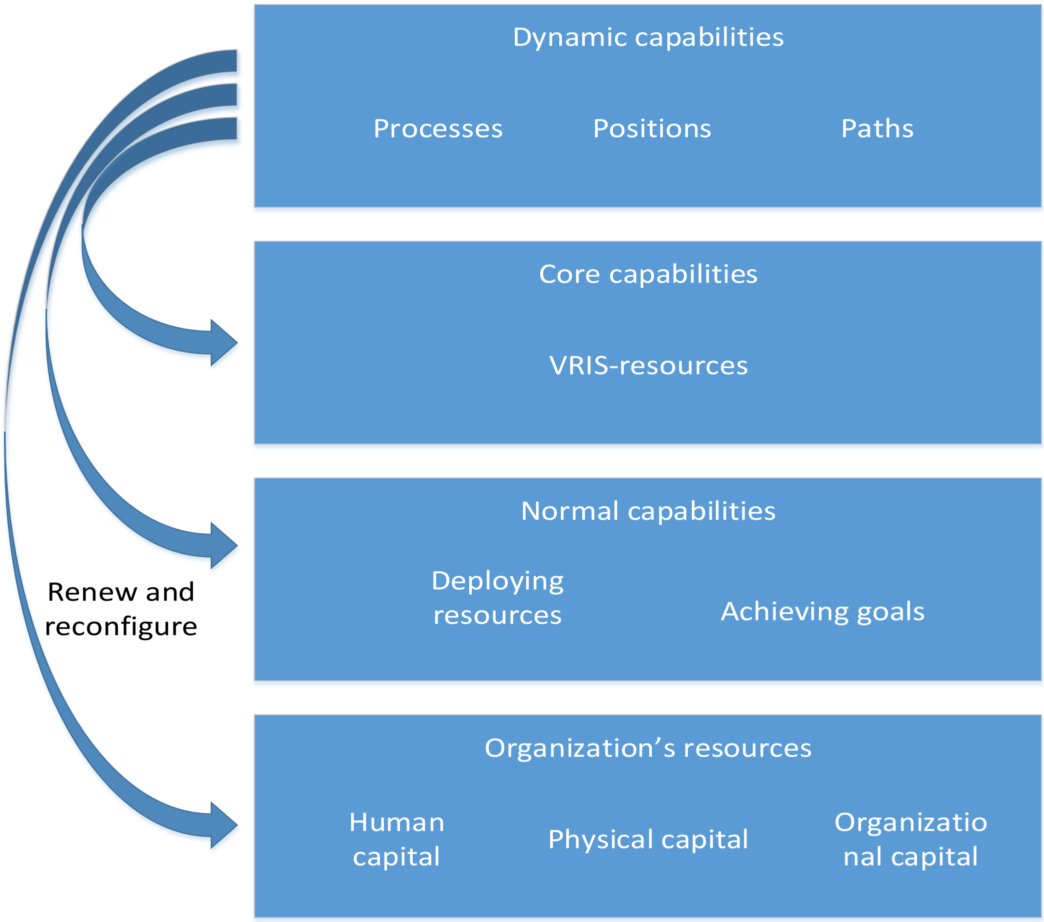

Figure 5: Concept of dynamic capabilities and resources (adapted from Wang & Ahmed 2007)

Dynamic capabilities can be considered as the highest level of capabilities that organizations have that require all the other capabilities in order to be present. The way that dynamic capabilities can be seen is that they themselves do not necessarily provide value since they are effecting to lower level capabilities that are providing the value and competitive edge but dynamic capabilities provide the constant ability to adapt and change the lower level capabilities so that organizations can maintain their competitive edges.

4. ANALYTICS AND VALUE CREATION

This chapter discusses analytics and how the value creation in analytics is perceived in literature. At first we define analytics as a whole so that we may understand what things are considered under the term analytics and what aren't. After defining analytics, we move to define the value chain of analytics where the different stages of creating value with analytics are explained. In the last section, we examine through literature, how dynamic capabilities are related to the value creation of analytics.

4.1 Defining analytics

Different kinds of analytics have been made for a long time in different domains with different methods and technologies. Analytics has its roots in the 1960s, when the first decision support systems evolved, even though only recently analytics is seen as an important competitive advantage (Watson 2011). The term analytics is a very broad term and holds different topics under itself for different people. Some approach analytics from the technologic perspective, some from business perspective. The broadest definition of analytics that is broadly agreed is that it's about creating knowledge and insight to help decision makers to improve performance (Holsapple et al. 2014, Elgendy & Elragal 2014, Lavalle et al. 2011, Watson 2011).

Watson (2011) expresses that analytics today is seen as an umbrella term like business intelligence for example. He also presents the idea that many people see analytics as part of the business intelligence term that is seen as a larger entity including technological context like databases within the term. Still according to Sheikh (2013) analytics must not be confused with business intelligence but it is rather something that you can build on top of business intelligence solutions. Sheikh continues that with analytics you can answer to questions of what should be done and what can happen whereas BI answers more history related questions such as "how did we do?". Nevertheless, how people see analytics as being part of business intelligence or not, it's only relevant to understand what kind of actions the term itself holds.

Holsapple et al. (2014) have studied business analytics field to determine a definition for analytics. They say that on the academic context analytics is usually seen as a mathematical and a statistical way. Yet they recognize the different approaches to analytics such as business analytics, where the definition is not so technologically oriented. Holsapple et al. (2014) continues to define business analytics and proposes a division of three dimensions that analytics can be divided and studied: domain, orientation and technique (Table 2). By domain Holsapple et al. (2014) mean different analytics fields like financial, risk, process or web analytics. Chen et al. (2012) also study analytics from this approach as all of these have their own distinct operations and research fields but they fall under the same category of analytics.

Table 2: Analytics different dimensions (adapted from Holsapple et al. 2014)

Domain	Orientation	Technique
Subject fields that analytics can be applied to: web, software, marketing, customer, finance, risk, supply chain.	**What kind of analytics is made (present, future):** Descriptive, predictive, prescriptive	**Tools that are used to perform analytics:** Technology tools, Techniques

By orientation Holsapple et al. (2014) mean how analytics can be approached inside the company. They mention three distinct categories of orientation which are defined as descriptive analytics, predictive analytics and prescriptive analytics. This approach is also supported by other researchers (see for example Watson 2011) and usually used to define different kinds of analytics. The Third dimension of analytics is technique which means the way analytics is performed in company. This dimension is vast and contains multiple different approaches. According to Holsapple et al. (2014) different perspectives from different sources can address the technique dimension from qualitative and quantitative point of view, structured and unstructured point of view or even from different mechanisms like data mining, data warehousing or visual mining point of view. The three different dimensions represent the landscape of analytics and give understanding how it can be studied.

On top of the three different dimensions Holsapple et al. (2014) present six different definitions that different sources has defined business analytics. The definitions tell how companies can see business analytics in their own company. The definitions see business analytics as movement, a collection of technologies and practices, a transformation process, capability set, specific activities or decisional paradigm. What is common for all of these perspectives is that the search and use of facts in decision making in some way (Holsapple et al. 2014).

Some researchers define business analytics as a culture, philosophy or movement where decision-making and gaining insight should be encouraged and strived (Larsson & Lundgren 2009, Ramamurthy et al. 2008). Even though business analytics is considered as something intangible in these definitions they still acknowledge the importance of data gathering and refining data, which are more technical activities related to analytics. Defining business analytics as a culture or philosophy means that it can has a much bigger effect on organizations than just technical. When talking about organization culture or philosophy it means that it considers all the employees in multiple levels to understand and utilize the possibilities of analytics.

Some researchers see analytics mainly as technological practices done in organizations. For example, Bose (2009) defines analytics as a set of tools that are used to make operations to gain and analyze information but also predict outcomes of problems. Different tools can be, for example, analytic software like visualization or machine learning software. Bose's (2009) approach is very similar to what Holsapple et al. (2014) presented about technical dimension of analytics that can be for example text – or audio mining. Holsapple et al. (2014) continues, that technological approach to analytics usually also includes techniques that are not so related to technological tools. They mention that as much as 80% of the data in companies is still in qualitative form which needs also non-technological techniques to be processed. Still this definition and approach varies from the culture or philosophical definition since analytics is only seen as tools and not as a mindset or something that is constantly on the background of companies like culture is.

To improve the definition of analytics being just tools and techniques researchers have also defined it being a process of transformation and change. Business analytics can be seen as a process of transformation where data is processed into actions making analysis from the data and thus gaining insight from it (Liberatore & Luo 2010). In this definition decision making and problem solving become more evident objectives. The whole process according to Liberatore & Luo (2010) is made in order to make impact on decision making and performance management in organizations to gain competitive advantage. They also mention that the process can help organizations to address problems or even help to learn and explore. The process that Liberatore & Luo (2010) address concludes from four steps that include steps considering data, making the analysis, gaining insight from the analysis and lastly taking action based on the knowledge gained. Holsapple et al. (2014) point out that in transformational process view of analytics the issue is usually how to make the process as good as possible and how to measure it so that it can be improved.

Taking the definition of business analytics even further than the process point of view, some researchers have presented analytics as a set of capabilities. This definition includes the process point of view but also the practices and technologies that analytics includes. For example, Kiron et al. (2012) define analytics as the use of knowledge and insights which are gained from different models such ass predictive or quantitative and used to make fact-based decisions, management and learning. In other definition analytics is seen as discipline of applying different analytical methods to make decision making better (O'Dwyer & Renner 2011). Holsapple et al. (2014) continue that in capabilities point of view analytics is considered as different competencies that organizations holds. Competencies can be anything from tools to people and their knowledge that they use to solve problems and use technologies. They stress that having good capabilities in technologies and techniques might not be enough because organizations need capabilities to manage and coordinate analytic capabilities to improve innovation or design new processes. This definition is the closest definition of analytics when talking about value and managing of analytics since it takes in to account peoples' capabilities and abilities to use analytics.

Cosic et al. (2015) develop the idea of analytics being a set of capabilities and combine analytics with resource based views and dynamic capabilities of companies. This view has a history in the relationship between information systems and companies value creation (Saraf et al. 2007) but since business analytics is also partly information systems it is relevant to extend the resource based view from information systems to business analytics (Cosic et al. 2015). Extending the work of Holsapple et al. (2014) who said that capabilities are technological but also people related, Cosic et al. (2015) distinguish also governance and culture as capabilities. These four capabilities are categorized as capability areas that include the real capabilities that are technology, people, culture or governance related. These four factors comprise the whole capability of business analytics in companies and provide the value from it.

On top of the four different definitions of analytics, Holsapple et al. (2014) had also identified some definitions that conclude analytics as being specific activities. Specific activities are considered to be more activities of aggregating and analyzing data (Tyagi 2003). The actions that are mentioned in this definition are very much the same that they are in previous definitions. Yet in this approach Tyagi (2003) concludes the rationale of using analytics from the implementation of new ideas and innovations point of view. Comparing this view to the usual rationale of analytics which is improving decision making, the activities viewpoint sees analytics much more as a possibility to innovate and create new ideas rather than just gaining better knowledge for decisions.

From all the different definitions Holsapple et al. (2014) concluded that there are a few major reasons why organizations acquire analytics and how analytics might improve them:

- Achieving competitive advantage
- Supporting organizations strategy
- Improving organization performance
- Improving decision making and decision making process
- Knowledge production
- Creating value from data.

To achieve mentioned goals Holsapple et al. (2014) developed a framework (figure 6) that represents all the factors of different business analytics sectors and includes necessary organizational factors in order to succeed in analytics. They say that analytics should be based on a movement or culture in the company. This way it becomes part of the company's everyday decision making and strategy and enables problem solving and recognition throughout the company. On top of the culture a set of capabilities must be developed. Capabilities should be as defined above when we discussed about the capability definition of analytics. It means that companies should have right tools, processes and people to manage their analytics. On top of capabilities company should have decision making processes and related activities to conduct decisions that gain benefits mentioned earlier. The framework is good way to understand the whole entity of analytics in organizations. Different parts of the framework include multiple entities and one can approach them from different perspectives as we have discussed in this chapter. A conclusion that can be made based on these sources is that analytics is mainly a process in organizations that includes different tools and processes but also people and enables competitive advantage from uniting these different factors together.

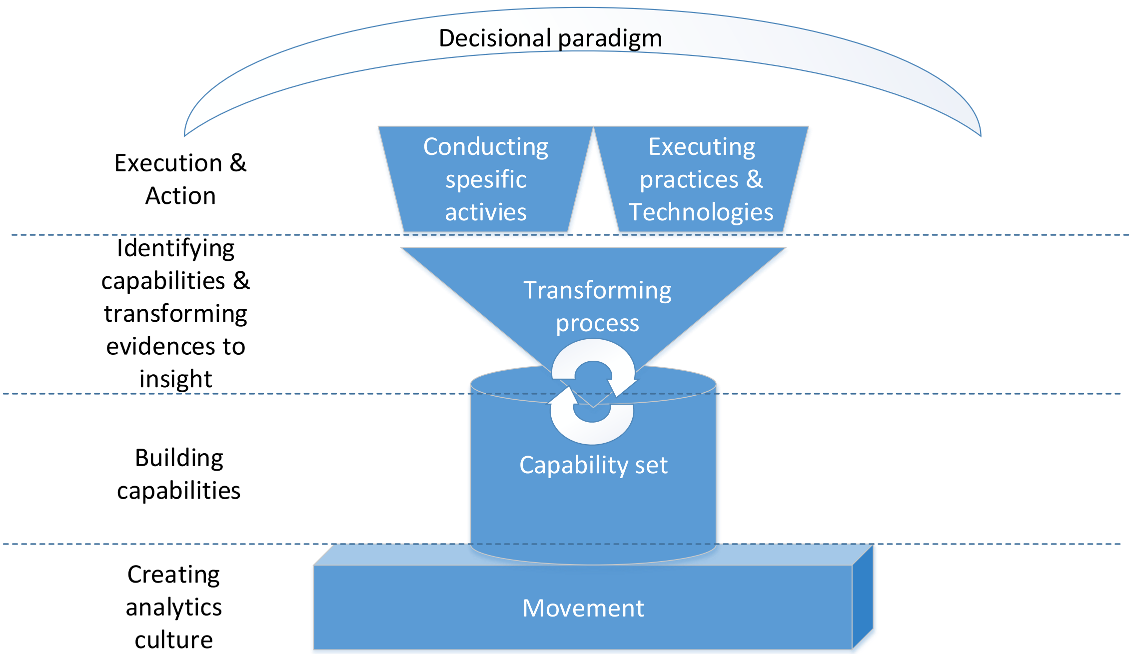

Figure 6: Business analytics entity (Holsapple et al. 2014)

The whole scope of analytics is vast and contains different dimensions and definitions that are used in different studies. The framework that is proposed by Holsapple et al. (2014) gives an idea what factors can be taken into account when talking about analytics even though it is presented in very high level. Each part of the framework could be studied itself but for this study this framework presents the crucial parts of analytics in organizations since this study tries to understand the analytics as a whole and not parts of it like technologies involved or processes needed. Therefore, in this study, analytics is defined according to the framework as a field that tries to improve organizations decision making and thus give competitive edge.

4.2 Value chain of analytics

The use of business analytics in companies has increased tremendously in last decade and the challenge now is to understand how to create business value from it. Even though the value of analytics is becoming increasingly more important question for organizations and researchers (Gillon et al. 2012) only in recent years have companies started to address the problem thoroughly. To become data- and information driven organization, organizations need to a clear strategy to become one, they need the right people to make the cultural change required to become data-driven but also consider the ethics of data use when they are using data. Becoming data-driven organization is not only a technological change but also strategic change where new strategy has to be aligned to between analytics and business. This transformation needs new capabilities from the organization. Employees, for example, must be able to identify problems or issues or even innovate new ways to use analytics in their work to achieve maximum value from it. (Vidgen et al. 2017).

Different researchers are rationalizing the use of analytics by explaining that it helps businesses to better understand their markets and gain leverage from the data (Chen et al. 2012) or using analytics in decision making makes companies to perform double the rate of normal companies (LaValle et al. 2011). Still Sharma et al. (2014) argue, that even though many researchers say that business analytics creates value to organizations, it is not self-evident. They explain that because analytics is closely related to decision making and resource allocation processes, those need to be understood more properly in order to understand how value is gained from analytics. Comparing Sharma et al. (2014) proposition to the whole picture of analytics (see Holsapple et al. 2014) it's relevant to say that the value does not only come from implementing analytics models but taking the whole analytics framework into account and changing to support organization needs.

Since so many different factors in organizations affect to value creation in analytics, different organizational fields and their relationship to analytics must be explored. That is why Sharma et al. (2014) suggest, that strategic, behavioral and organizational issues are important when discussing about value of analytics and the change required in these factors on top of decision making and resource allocation changes. Previously the research about the value of analytics has been related to data and analytic tools that support decision making but including the factors suggested above the decision-making process of analytics might have much larger impact (Sharma & Shanks 2011). The other point that Sharma et al. (2014) stress on their work is that the idea that when acquiring information system capabilities in organizations, a common understanding has been that the organization does not have to change around them since the tools are powerful enough to create value on their own. This idea is challenged in the case of analytics because of the changed required in important processes like decision making and resource allocation.

To understand better how the organizational factors related to analytics can affect the value creation of analytics we need to look at the whole value chain of analytics. There are multiple propositions on what steps the value chain includes and what each steps contains. Common steps are insight creating step from the data, decision making step based on the insight that is gathered and the action step to gain the value from the decisions (Sharma et al. 2014, Seddon et al. 2017). The value chain of analytics is depicted in figure 7.

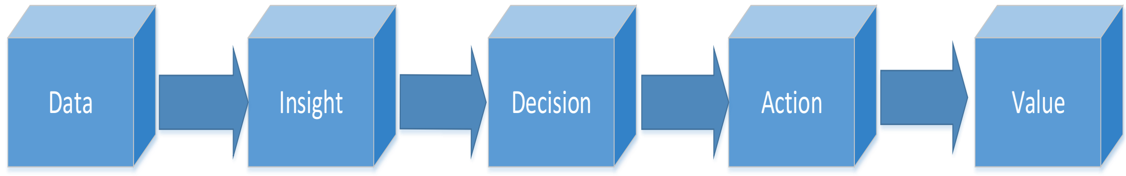

Figure 7: The value chain of analytics (Adapted from Sharma et al. 2014, Seddon et al. 2017).

The value chain in figure 7 is simplified version but it includes all the important parts of it. What needs to be taken into account also from the picture are the arrows that represent actions that are made to get to the next phase. Next we go through the value chain and the actions in it to gain understanding of how value creation happens with analytics.

4.2.1 Data to insight process

In the first section of the analytic process, data is converted to insights for the decision makers. This section of the process involves technology the most since in this section different kind of data from different sources is being processes with different data analytic technologies (Sharma et al. 2010). Davenport et al. (2010) remind that without data there really can't be analytics either. Regarding to data there are 7 things that organizations must consider and actively develop: structure, uniqueness, integration, quality, access, privacy and governance (Davenport et al. 2010). What Davenport et al. are saying is that organization's data and processes related to it must be in good condition to so that the data can be used to gain value. Although Döppner et al. (2015) emphasize that it is not relevant to understand all the data sources but only the most promising so that insights and ideas can be generated from them.

Sharma et al. (2014) emphasize that even though analytical tools are sophisticated, they don't produce insights on their own. Insights according to Sharma et al. (2014) arise from the active process of communication between the people who are doing the analysis and the people who are using the analyzes. Communication between two sides enables knowledge transfer from both sides to the other which helps analysts understand what business people need but also business people can gain important insight from analysts when they are communicating. This whole process is called insight generation process where different people owing different capabilities are discussing with each other to understand each other and to create new insight (Sharma et al. 2014).

Usually companies are composed from different teams that operate in business units. Sharma et al. (2014) point out that team composition and structure of organization affect the insight gaining process because if team members do not communicate to other teams or to each other, the insight gaining process is constrained by the people. It is also the people's know-how in teams that matter on top of the communication methods and principles that teams use. If team members know only one way of doing things and don't search new knowledge, team constrains itself even more and they generate insight even less. Also, things like leadership and management affect to gaining insight. Teams are usually run by their leaders so the leaders might also be a bottleneck for knowledge transition process and communication process between different teams and analysts.

To overcome issues related to process of gaining insight from the data some researchers have suggested different solutions. For example Lycett et al. (2013) approach the issue with "datafication" process where the data is dematerialized, liquefied and recombined. Other approach to deal with the issues is presented by Davenport et al. (2010) where they suggest that establishing own unit for data analysis would solve issues like competency problems. Own unit could possess more skills to analyze data but as we discussed earlier, problems with communication can occur if teams do not understand the importance of communicating. In some studies it has been shown that establishing own unit for analytics the insight generation process is not as good as it would be without own analysis unit (Shanks & Sharma 2011). Own units can make silos inside of companies when communication and knowledge sharing process is not as effective as they could be.

4.2.2 Insight to decision process

After gaining insights from different data sources, the insights should be utilized to make decisions. According to Sharma et al. (2014) the value gained from the process can only be achieved if meaningful decision are made based on them. They stress that one issue between the insights and decision making is to see, if really the insight is the factor that correlates to decision making and how the insight is related to the decision making action.

To understand decision making there needs to be understanding of how it works. Simon (1947) described decision making as a three step process of intelligence, design and choice. In the process the intelligence that the decision maker already has and the intelligence that can be gathered are used to design different possible options. From these options the final decision is chosen to be executed. The issue that Sharma et al. (2014) pointed is relevant for many reasons. Firstly it is not unheard of that the insight generating process produces multiple different insights that might even be controversial to each other or point out two different positive possibilities. It's in these situations where the role of decision maker or makers is important and the knowledge and experience that they have from different factors regarding the decisions like business domain. Sharma et al. (2014) address the issue by reminding that decision must not be made based entirely on insights but rather use them as part of the process with other information gained elsewhere.

Kowalczyk & Buxmann (2015) remind that the decision making process contains pitfalls that can be easily be fallen into if analytical people and decision makers do not collaborate openly. The decision making processes in organizations are generally non-routine and non-formalized (Eisenhardt & Zbaracki 1992), which generates challenges to the use of analytics in decision making situations. Viaene & Van den Bunder (2011) see the possibility that if analytics is too much emphasized in decision making and the decision maker does not have significant analytics know-how, decision can be hard to make based on the knowledge as it is hard to assess the quality of it. Bonaccio & Dalal (2006) continue the subject by pointing out that the situation might lead to the information asymmetry where decision maker does not rely on the information and neglects the insights gained. Then the decision is more made from the basis of personal experience which always poses risk to do wrong decisions.

To answer these challenges Kowalczyk & Buxmann (2015) found different tactics to overcome the challenges. To answer the challenge of domain and method knowledge gap between the decision maker and the analytic people they propose a solution where analytical people specialize in certain domains to understand the decision makers there. The other problem is related to the analytics methods and data used. Different methods must be tried constantly and data changes all the time so insights for decision might change also rapidly. Tactic to overcome the challenge is to make processes transparent in both ways and standardize processes as much as possible. Other challenges that are related to the decision making process are the scope of the problem and the complexity of analytics used. Collaborative communicating between the creators of analytics and the users of analytics is needed to for example identify and model different aspects of the decision and how relevant they are.

Taking all the affecting issues in to account, it can be said that the decision making part of the analytics value chain has significant role for the end result. No matter how good quality analytics can be provided for the decision makers, there are still so many other factors affecting to the decision making. Like Kowalczyk & Buxmann (2015) said that close collaboration and educating the decision makers about analytics possibilities and methods is a way to improve decision making process and produce quality decisions.

4.2.3 Decision to action and value process

Even though the analytics processes in organization are well formed and organization can acquire insights and even make decisions out of the data, it does not mean that value is automatically generated. Sharma et al. (2014) discuss that well performed insight gaining leads to high quality decisions. What happens after the decision making does not necessarily mean value increasing actions. They say that making high quality decisions does not mean only that the decision is able to achieve its objectives but also how well it is accepted by different parties and sides in organization. Acceptance is the major problem that analytics might not solve since usually the ones who are implementing the decisions are not the ones who are involved in the insight gaining or decision making process (Sharma et al. 2014). This issue can be related to previously discussed issue that whenever organizations are implementing analytics solutions they trust that the tools themselves create enough value and the organization around them doesn't need to change to complement decision making and resource allocation processes.

Successful implementation of decisions can, in the end, produce meaningful value for the whole organizations if the challenges can be answered and the value chain of analytics works. Sharma et al. (2010) have studied different cases where significant value have been achieved through analytics in organizations. For example one case organization improved their performance by managing to identify trends. Other improved by speeding their process and optimizing their pricing. Third organization managed to design more effective marketing campaigns based on their customer data. These are just examples of what has been managed to do with analytics when right decision has been made and the execution of the decision has gone right. For example making marketing campaign based on analytics does not rely on the data that has been analyzed but the people who interpreted the data and managed to use it to make right decisions and create something valuable out of it. Value-category contained three identified items that were identified in companies: improving decision making, measuring customer value impact and establishing a business case.

4.3 Analytics value creation capabilities

The value chain of analytics is simple way to understand what steps are usually needed in analytics process to improve performance. Still the chain does not acknowledge the whole entity of analytics like Holsapple et al. (2014) depicted it in their work. Their model proposes that the analytics process should stand on capability set which is steered by the analytics culture of the organization. To understand the analytics value creation fully the whole entity should be addressed where the value chain process is just a part of it.

Studies about the value in analytics stress usually few factors which are organization's culture and capability related. Seddon et al. (2017) whose model depicts the value chain of analytics but also takes the element of different capabilities into account. Figure 8 shows how Seddon et al. (2017) include analytical capabilities but also organizational capabilities to analytics value chain. Similar models to Seddon et al.'s (2017) are Shanks et al.'s (2010) and Shanks & Sharma (2011) frameworks that extend the value chain model further to account different capabilities but also strategy to value creation of analytics. Analytical capabilities, the people who are doing the analytics and using analytical tools, are understandable concept and can be thought as for example centralized analytics team in organization that produces analytics. Organizational capabilities are seen by Seddon et al. (2017) as much larger entity that holds for example people, processes and technology and they refer to the resource based view of organization (Barney 1991) but also to the dynamic capabilities (Teece et al. 1997). Value creation of analytics and dynamic capabilities that have been discussed already in this thesis, come together in order to understand value creation entity and requirements needed to do create continuous value.

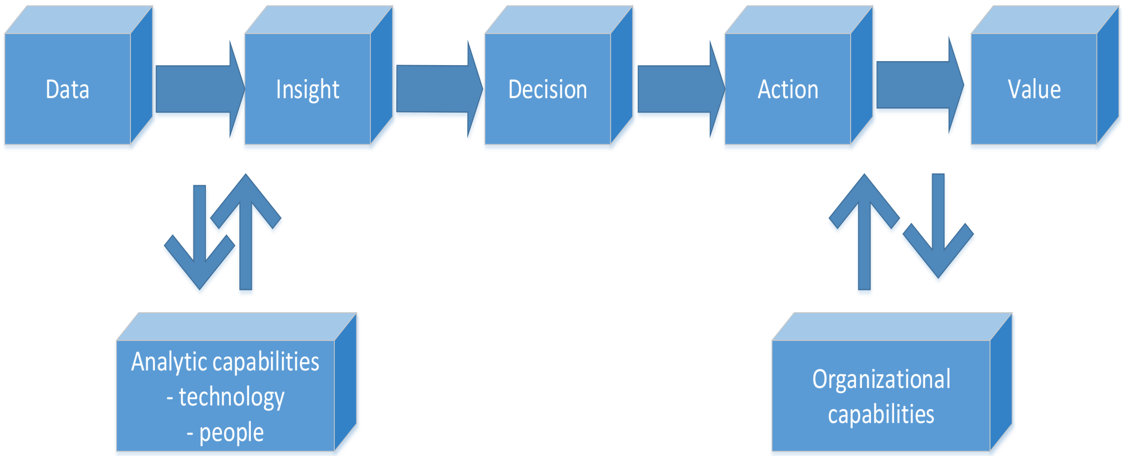

Figure 8: analytics value creation (Adapted from Seddon et al., 2017, Shanks et al., 2010, Sharma & Shanks, 2011).

What Seddon et al. (2017) model brings more to the theory is not just the use of capabilities but also the development of them as an outcome of analytics process. For example the use of analytical capabilities does not only produce insight but develops the capabilities itself and educates people. In the case of organizational capabilities the outcome value that the analytics process produces can also be in a form of developed capabilities and not just profit. This outcome is aligned with the dynamic capability theory and gaining competitive edge that Teece (2009) have studied. By learning or developing capabilities that other organizations don't have one can gain competitive edge in the future (Teece 2009).

Sharma et al. (2010) gave insights about what kind of value can be produced with analytics like creating new marketing campaigns. Seddon et al. (2017) presented that the outcomes can also be development of different capabilities. They divide the organization's value benefits into short-term and long-term benefits that analytics process can bring to the company. Short-term changes happen according to Seddon et al. (2017) through different projects that organization internally does where tools, data and people are involved. On top of the data and analytical capabilities that are developed in short-term there are also the change in the whole organization that slowly and incrementally changes towards becoming successful analytic organization. That also involves change in management.

Long-term changes are according to Seddon et al. (2017) related to analytic leadership, enterprise analytics orientation, innovation and decision making. Davenport et al. (2010) opens the meaning of long-term changes as for example analytics leadership means how well people in the organization take analytics as part of their projects. Enterprise orientation is according to them about how well the whole organization uses analytics. Innovation on the other hand is already not so related straight to the analytics value process but rather how well people identify new opportunities to use analytics. Decision making like

Sharma et al. (2014) already explained is a combination of multiple things where analytics is only one part of the whole process. Seddon et al. (2017) propose that the long-term and the short-term benefits together are basis of the value creation in analytics.

Similar thoughts about the issues that effect on the value creation process have been studied quite broadly by different researchers. They all approach the factors from slightly different perspectives that are shown in table 3, but all have based their research on the same theories of resource based view of organization and dynamic capabilities.

Table 3: Different capabilities affecting to value creation of analytics

Researches	**Organization's capabilities, which are related to the value creation of analytics**
Vidgen et al. (2017)	People, Technology, Organization, Process, Data
Wamba et al. (2017)	Infrastructure, Management, Expertise, Process
Corte-Real et al. (2017)	Knowledge, Agility, Process
Cosic et al. (2015)	Governance, Culture, People, Technology
Popovic et al. (2016)	Data, People, Strategy, Management, Engagement
Sharma et al. (2010)	Users (people), Process, Entrepreneurial actions, Agility
Kiron et al. (2014)	Culture, Innovation, Management, Strategy, People
McAfee and Brynjolfsson (2012)	Management, Culture, Leadership, Technology, Decision making
Davenport et al. (2010)	Data, Orientation, Leadership, Targets, Analysis

All the categories identified are relevant to the analytics and could be studied separately. In this research four main categories that cover basically all the organization's main capabilities affecting to analytics value creation have been chosen. The categories are based on Cosic et al. (2015) study where governance, culture, people and technological capabilities have significant impact on the value creation of analytics. Categories are viewed more deeply to understand better the whole entity of value creation.

4.3.1 Governance

Governance itself is a broad term that describes how organization manages its processes and people. Cosic et al. (2015) include for example decision rights, strategic alignment, dynamic business analytics capabilities and change management under the term which all are quite large entities in organization. Strategic alignment, which can be hard as strategic work is conducted by the boards of the organizations where there aren't necessarily people who understand analytics enough, is still seen according to Vidgen et al. (2017) as one of the most important matters. Strategy should include clear definitions on how value should be created from data and analytics and what kind of value it is (Vidgen et al. 2017). Shanks & Sharma (2011) conclude also that strategy impacts analytics value creation actions but can be achieved via different strategies that rely either on high or low standardization of processes and high and low degrees of integration in processes. Kiron et al. (2014) on the other hand propose that analytics insights should guide strategy and not the other way around like Vidgen et al. (2017) propose. Either way studies show that if analytics are part of the strategy or even guide it organizations are mostly more efficient than companies that haven't embed analytics in their strategy (Kiron et al. 2014).

Dynamic capabilities like have been discussed are basically capabilities to enable and adapt to change. Dynamic business analytics capabilities are part of the dynamic capability entity that Cosic et al. (2015) have included to governance capabilities. Shanks & Sharma (2010) consider dynamic business analytics capabilities as all the specific capabilities that use data to develop, resource and implement value actions. Their broad definition emphasizes "search and select" and "asset orchestration" routines where the first basically is related to identifying need for using analytics and selecting involving creating actions and resource allocation. Asset orchestration according to Teece (2009) is capability to combine and align resources.

Decision making in organizations and especially in analytics decision making there are multiple factors to be taken into account. Decision making process like have been discussed previously in this thesis involves decision makers and analytics people together collaborating. On organizational level decision making can be supported by putting information and the rights to make decisions in the same place and encourage cross-functional cooperation (McAfee & Brynjolfsson 2012). Basically organization might have to re-organize their decision making responsibilities to become less rigid and bureaucratic decision makers and giving power to not only managers but to people who have the ability and capability to use data.

Change management can be the hardest part to govern and carry out. Kiron et al.'s (2014) study tells that companies, using analytics and being in the front row of it, have had to change their way of doing business as a result of implementing analytics. This means new products and services that are data or analytics based or have been derived from the data. Change management is basically a larger entity even though it's been put under governing category. Change that analytics might trigger in organizations or in organization units might happen in multiple fronts. Not only new services and products can be developed which bring for example new information to selling to people but in analytics context and dynamic capabilities context there are mentions about changing processes, people, technology which all are big entities that require a lot from the employees to adapt. Ways to answer to the change are discussed further in this thesis to find ways to ease the transformation phase.

4.3.2 Culture

Organization culture and its transformation to become more supportive to analytics is one theme that have been studied a lot and has emphasis whenever researchers are talking about value creation of analytics. Holsapple et al. (2014) identified it already as a basis of analytics that the processes are built on. Culture capabilities according to Cosic et al. (2015) include evidence based management, embeddedness, executive leadership and communication. All of which are again broad terms and big entities to manage and quite intangible topics which can be hard to see concretely.

Embeddedness as itself is not necessarily any capability but rather a degree for communication, support and evidence based management that how well organization performs in them. Evidence based management on is a good example of how well organization culture has embedded analytics in their organization. Evidence based management basically depicts how much analytics is used in managing projects (Davenport et al. 2010). That of course is related to the decision making process that have been discussed previously but from there we can argue that decision makers and their knowhow is crucial part of the management entity and how they respond to the analytics they are given.

Leadership support in organization is an issue that is mentioned on many occasions when there is a change in context. Kiron et al. (2014) describe executive leadership as a pressure to employees to combine expertise between analytics and business to become more data-driven organization. Other implication of support is according to them analytics investments that they allocate money to like training or technologies. McAfee & Brynjolfsson (2012) stress the vision or human insight that guides the culture. Executive leadership and support like change management is much about giving opportunities with new investments or encouraging people to create something and at the same time supporting them to take actions and decision based on the insight.

Communication which holds specific role and meaning to everything that is related to analytics should also become part of the analytics culture. Analytics requires people with different backgrounds and skills to collaborate and communicate (Holsapple et al., 2014). Strategic changes and supportive actions from executive level need communication to all levels of organization so that the employees understand what is required from them in analytics context. At the same time communication from employees to managers and executives is equally important as new ideas and innovations that could be supported with analytics can rise from employees' minds.

4.3.3 People

People as a business analytics capability according to Cosic et al. (2015) are employees who use business analytics as a part of their job. Like in other capability areas that we have discussed the people theme includes skills and knowledge that different employees hold like technology, business, management or entrepreneurial skills (Cosic et al. 2015). People have a role on other capability areas as well since culture and governance are basically developed by the people based on their knowledge. On the other hand people possess a big challenge for organization as there are as many ways to do something as there is people which means that some for example adapt to change better or some have a creative mind that can innovate better than others. That's why people are the most important part of the analytics entity as they create the culture and processes that guide analytics value creation in organizations.

Analytically skilled people are usually put in organization's analytics team which is responsible for delivering analytics for different business units. Vidgen et al. (2017) emphasize that analytics people should be people who have strong IT and statistical skills but at the same time also business understanding and even innovativeness to be able to come up with unique solutions for different business problems. McAfee & Brynjolfsson (2012) mention same requirements and remind that these kind of people are very hard to find.

Analytics as have been discussed is not only the analytics team's actions in organization but other people too who can use analytics in their work. Sharma et al. (2010) remind that analytics consumer are business people who use it to improve for example marketing or sales actions. Business user's should have also an idea of what analytics can enable for their operations and communicate new ideas for the analytics team and so that they could rely on the results that analytics can provide for them (see chapter 4.2.2). Innovation and entrepreneurship that was also seen as important part of people's capabilities apply to business people also as they are the ones who understand their business can identify new opportunities rather than the analytics team which doesn't necessarily have required domain knowledge to do it.

4.3.4 Technology

Even though the thesis is much about the people, governance and culture which can all be thought as soft or intangible regarding to analytics the technology is still required. Cosic et al. (2015) include it in their business analytics framework as one capability area and it's supported by Davenport et al. (2010), Vidgen et al. (2017), Popovic et al. (2016)

and McAfee & Brynjolfsson (2012). Capabilities can be roughly divided into data management, system integration, reporting technology and discovery technology (Cosic et al. 2017). Here is where business intelligence and analytics overlap quite easily and can in many occasions considered the same thing.

In Chapter 4.2.1 data requirements and topics were discussed and Davenport et al.'s (2010) list issues that have to be taken care of was introduced. Getting the data ready and making it high quality and usable is one part of the technological process. After preparing the data there are still the actual modeling and analytics to be done. Coding is required when manipulating the data (SQL) but also when modeling the data with for example R-language (Vidgen et al. 2017). New technological requirements can be a challenge for organizations to master as there might not be competencies in organization that can handle new technologies (McAfee & Brynjolfsson 2012). On the other hand technology might just be the thing that is being developed. Even though the maturity wouldn't be high yet, most companies, since they have identified that analytics might provide future competitive edge, have started to develop data capabilities and actually it's the other capability areas that are not developing as fast.

4.4 Summary

Approaching and defining analytics is not unambiguous as there are different approaches from technological to business approach and different dimensions that the field can be studied and viewed. There are multiple analytics terms that are used like big data analytics or business analytics and different researchers include different entities under the terms. Analytics in this chapter is seen as separate entity from business intelligence that holds factors like decision making, culture and insight generation that Holsapple et al. (2014) have identified.

The value aspect of analytics is also quite unambiguous as there are concepts that contemplate analytics through value chain and actions or through organizations resources and dynamic capabilities. Both approaches, the value chain and capabilities point of view, are presented in the chapter to create a whole picture of issues that affect to the value creation of analytics. The insights that this chapter provides are used to mirror the results from empirical study to understand more deeply how value creation in analytics works and what it needs from organization.

The relation between dynamic capabilities and analytics value creation comes from the information system literature that is extended to analytics. Aral & Weill (2007) explain that the benefits from information systems comes from combining the information system resources to organizational and human capabilities. Human resources and especially managers and their actions according to Helfat et al. (2007) is in critical role to gain value from business analytics. The value chain of analytics was mapped in chapter four and Holsapple et al.'s (2014) framework for analytics gives insight about the organizational and human resources involved in analytics. As it was stated in the value chain that analytics is not only data and analytical modeling but also about using knowledge to derive insight, decision making based on the knowledge and thinking about the concrete actions that in the end create the value, the role of dynamic capabilities to make these steps efficiently is critical. Analytics bring change to the processes and takes people even from their comfort zone if the data shows that the ways that they have been working are not the best ways. This means change which always has resistance which makes dynamic capabilities even more relevant in analytics context.

5. AGILE PROCESSES

Agile Project management is not a new thing since the subject has been around for at least from 2001 when agile manifesto was introduced. Even though it was originally developed for software industry, even more studies have been made where agile project management has been studied in other industries as well (see Conforto et al. 2014). To understand better what is agile in project management and what it means in the context of analytics, the definition and the meaning of agile is first introduced in this chapter and then agile principles are discussed in project management and analytics context. This is done to help understand the results of this thesis when the implementation of analytics is handled in this thesis.

5.1 Definition of agile

The need for agile project management has risen from the failure rates of conventional projects since the changing environments has posed new demands and challenges to projects (Serrador & Pinto 2015). Fernandez & Fernandez (2008) continue that as the projects have become more complex customers have more difficulties to say their needs from the projects but at the same time they expect more from the delivery. As conventional project management techniques were not flexible enough to rapid changes and new requirements, new light weight techniques had to be invented when agile methods began to emerge. Dybå & Dingsoyr (2008) compress the main idea of agile methods that the initial planning part which is heavy on waterfall projects is lightened so that the planning at first does not take as much time but planning happens throughout the whole project. Serrador & Pinto (2015) continue that on top of sifting the planning agile methods also emphasize continuous design, flexible scope, embracing customer interaction and modifying the project team. Iterative nature is also big part of the agile project management as the projects are meant to run in iterations and not in a straight line.

Serrador & Pinto (2015) argue also that conventional project techniques can have multiple different downside outcomes in dynamic environments. They mention excessive work and customer dissatisfaction as examples of unpleasant outcomes that conventional projects might have as changes in the environment happen. Collyer et al. (2010) states that conventional techniques have difficulties whenever goals, materials, resources or relationships with other projects change. Of course it has to be kept in mind that changes in markets or in technologies do not usually happen overnight so the outcomes that were mentioned are not always the case. Rather the contents of the project and the timeframe it is done have effect on the positive or negative outcomes. Massive projects have multiple factors that have to be taken into account and they usually take a long time which means that it is more probable that something goes wrong because not all things can be planned.

Especially in these cases agile project techniques give more possibilities to adapt and learn within the project and adjust the outcome to more favorable. Serrador & Pinto (2015) emphasize the context of the project also as they remind having a balance between agile and traditional methods depending on factors like the size and requirements of the projects.

Conforto et al. (2014) define agile project management as an approach that has different principles which are included to the approach to achieve simplicity, flexibility and iterative processes to perform better in cost, time and quality. On top of the performance goals Conforto et al. (2014) also mention higher innovation, less management included in the project and higher value to customer. The different principles that were mentioned are discussed further in this chapter but as Serrador & Pinto (2015) discussed the principles are related to iterations and sifting the planning throughout the process. The definition overall is not unambiguous as Dybå & Dingsoyr (2008) speak about the field of agile development which means that there are multiple techniques and not the one and only right way of doing things. Even though there are multiple definitions in the field of agile project management they still all follow at some extent the principles and practices that were developed in the agile manifesto. Dybå & Dingsoyr (2008) have depicted the main differences between traditional project management and agile methods that are shown in table 4.

Table 4: Differencies in agile and normal project management (adapted from Dybå & Dingsoyr (2008).

	Traditional project management	**Agile management**
Fundamental assumption	Built systems are specifiable, predictable and planned thoroughly.	Built in small teams using continuous improvement and testing based on feedback.
Management style	Command and control	Leadership and collaboration
Knowledge management	Explicit	Tacit
Communication	Formal	Informal
Development model	Lifecycle	Iterative

Organizational structure	Mechanic	Organic
Quality control	Heavy planning and testing	continuous control and design

Fernandez & Fernandez (2008) explain the concept of agilism through different project strategies. They distinguish traditional project strategies as liner or incremental whereas agile project strategies are distinguished as iterative, adaptive and extreme strategies. Linear and incremental strategies rely on clear goals and definitions with set resources. The processes themselves do not have feedback loops and do respond well to changes in the process. Fernandez & Fernandez (2008) stress that the traditional project strategies work well within certain conditions but agile project strategies answer to the problems that traditional strategies have. In iterative and adaptive strategies partial solutions are delivered to customer and then feedback is collected. Adaptive strategy varies from the iterative strategy in a way that the design of the project can be changed whereas in iterative only the end product is changed. Challenges in these strategies are to involve customer in these strategies and communicate the end result as it is not always clear. Especially in extreme strategy where not only the solution is iterated but also the possible goals. (Fernandez & Fernandez, 2008). The strategies give some understanding on how agile projects vary from each other and from the conventional projects. Considering the agile project strategies and conventional projects to the analytics context some deductions can be made. Analytics in organizations start usually by identifying the targets where analytics are to be used. This means that the customer doesn't necessarily know what they really need if they don't have the knowledge to understand analytics in the first place or they can't recognize the problems that the analytics could provide answer to. As discussed previously agile strategies in these cases are more suitable because with customer involvement the project can develop the needs of the customer. This is related to the other thing that speaks for agile implementation in analytic context. The users of the analytics are not usually the ones who are creating the models and the analytics so in that sense customer involvement in analytics projects is even more important.

5.2 Agile principles and practices

The agile manifesto dictates:

Individuals and interactions over processes and tools

The first principle of agile manifesto is quite vague at first glance. Juricek (2014) explains that the meaning of the principle is about self-organization and motivation that project members should be active members in the project and influence the team positively. Conforto et al. (2014) studied practices that set agile approach apart from the conventional approaches to projects and identified that in agile projects the communication tools and processes are simple to emphasize the interactions and figures and prototypes should be used to communicate the project. Other agile related practice was the use of self-guided teams where individuals and teams decide their own tasks and at the same time monitor themselves on how they are progressing (Conforto et al. 2014). This way the teams are more involved to the project and its outcome and thus it motivates them to perform. In the analytics context Larson & Chang (2016) emphasize that as analytics environment is becoming faster and faster more important is the first steps of analytics process that are discovering the data and creating insight from it. Creating insight especially is closely related to individuals and interactions as different knowledge is required to create meaningful insights. For example the analytics team needs someone who knows the domain where analytics is being implemented but also knowledge about different factors to create good analytics. The teams usually don't have all the knowledge available in their own team so they must interact with different stakeholders to produce meaningful analytics.

Working software over comprehensive documentation

Even though the second principle of the agile manifesto might not be implemented as such to all projects and especially to those that do not include any software at all, there are some practices that can be applied to different projects in some extent. Serrador & Pinto (2015) state that the lesser documentation helps facilitate flexibility and responsiveness in projects and focuses the team to develop concrete results rather than long documents about the project. Like Conforto et al. (2014) expressed in their study that documentation in agile projects should include much more visual tools like pictures and sticky notes so that the descriptions would be simple but understandable to different parties. Visualization in documentation is emphasized also in analytics as it increases the usability of the documentation much more than precise describing in text and it visual documentation is also produced much more rapidly than normal documentation (Larson & Chang, 2016). Keeping in mind that the dynamic nature of analytics context making comprehensive documents might be too time consuming as they do not add value that much compared to the analytical solutions and are outdated quite quickly.

Customer collaboration over contract negotiation

Customer involvement and collaboration in agile projects is one of the main issues that benefit the project as their opinion is heard through the whole project and thus achieving a solution that pleases the customer is easier. The involvement should be continuous if possible and feedback should be the main thing where customer opinion is taken into account (Serrador & Pinto, 2015). Juricek (2014) reminds that customer involvement is not always possible depending on the end-user of the project but at least a representative of the customer group should be involved. Considering the customer involvement issue to the discussion that we had earlier about how organization units might not have time to participate in projects as the projects are not the source of income and thus are not seen as important it might be hard to have comprehensive end-user opinion on the project. One way to address this probable issue is to show the value through iterations to the end-user group so that they understand how it helps them. Building a working minimum viable product (MVP) at first can be a good way to show the value and sell the idea to customer but also to involve them before starting the big project. On top of the customer there are usually other stakeholders in projects that should be also involved in the in the projects and listen their ideas and inputs. Juricek (2014) emphasizes the role of face to face conversion when different stakeholders are being involved in the project since usually they come from the different context (e.g. business context in IT-project) so mutual understanding from the project much be achieved. In analytics Juricek's (2014) claim about face to face conversations is supported by Larson & Chang (2016) as they state that different stakeholders like data scientists and analytics end-users must work together to facilitate discovery from the data. They also mention the validation of analytical models as important part of the process that requires collaboration between the users and the scientists.

Responding to change over following a plan.

Dynamic environments and changes happened in the project environment usually affect to the requirements of the project. Juricek (2014) points out that even though requirements change the timeframe and the budget usually stays the same which makes the project implementation challenging. Juricek (2014) proposes that workshops where common understanding about the prioritization and requirements are decided are key to respond to the changes in a way that budget and time frame won't have to be changed. Incremental implementation is also one way to overcome changes since if change happens the project team can react to that in the next iteration (Conforto et al. 2014). The benefits of iteration do not only include reacting quickly but also help to deliver smaller parts of the projects already when the whole entity is still being delivered. Smaller parts of the projects makes also the overall monitoring of the project easier as one can see what things are concretely ready compared to normal project where one sees only what milestones have been achieved. Change in the analytics point of view is inherent as the data that is being used constantly changes and might be unstructured or undefined (Larson & Chang, 2016). Different analytical models although can be used for different data but on top of just the changes in the data there are other factors that we have discussed which can trigger change. For example change in competitive environment might mean that different models are needed to respond to it even though the data would be relatively unchanged.

5.3 Agile analytics

The development of agile methods in software business has started to effect also on the analytic methods of organizations. Analytics are closely related to software in some areas as different computing tools are used to deploy analytics but analytics cannot be directly compared to software development since they have different processes and workflows.

What makes agile a good fit with analytics is the dynamic nature of analytics (Larson & Chang 2016). Analytics in its nature is quite much about trial and error as in analytics you are usually playing with different models and probabilities since there is no straight correct answer necessarily available in the start of the project. This makes analytics quite dynamic environment where the end user might not know what they want and of course agile approach as we have discussed is fit approach in these kind of environments. Figure 9 depicts the implementation process of analytics.

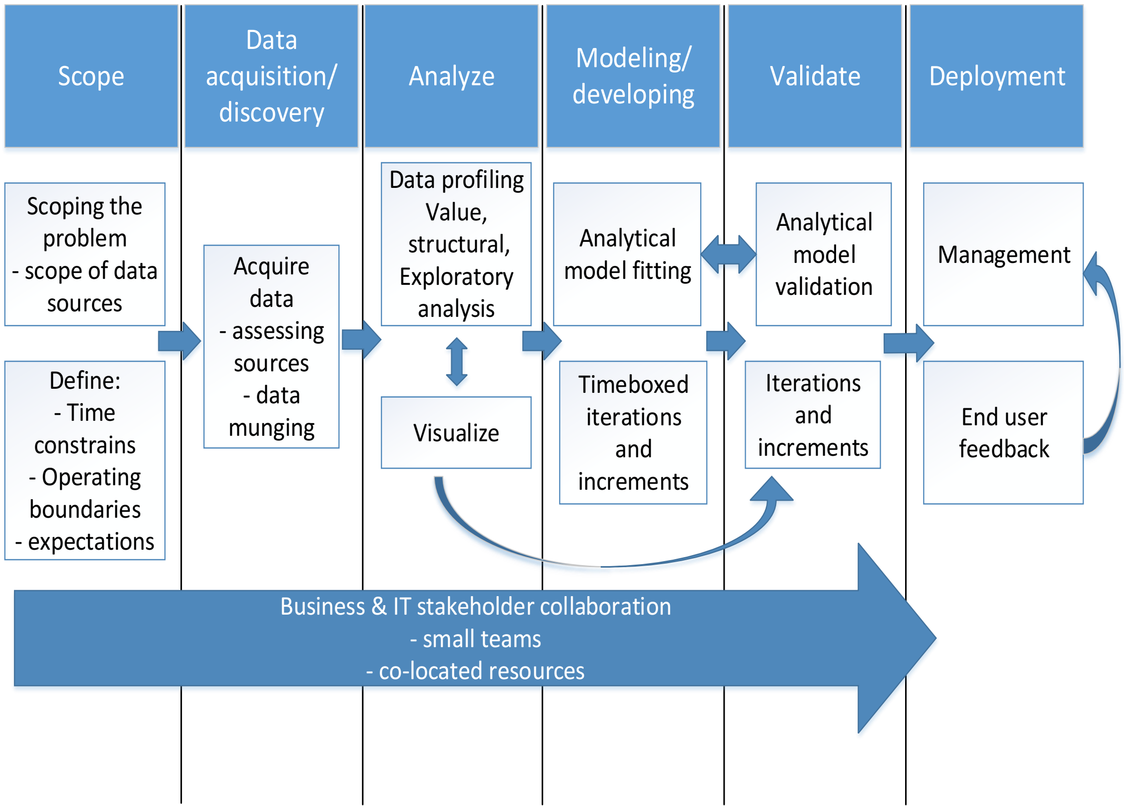

Figure 9: Agile delivery of analytics (From Larson & Chang 2016)

Larson & Chang (2016) depict their lifecycle of analytics that shows how different analytics should be implemented on organizations while obeying agile principles. According to them the lifecycle starts from scoping the problem statement and data sources that are used to solve the problem. Next step is data discovery and then follows analyzing the data which is then put in to analytical models. After producing the model the results are validated and finally deployed for use. Different iterations and feedback loops exist along the process to gain insight for the end product. Due to the nature of analytics the whole lifecycle is very fluid so that resources can be allocated especially to scope the right problem to solve (Larson & Chang 2016). This framework for lifecycle of analytics can be used as good reference to get an idea of how the technical implementation of analytics would follow agile principles and how analytics teams should develop analytics in their organizations. On the long run different factors have to be also considered like dynamic capabilities when developing the analytics but those are discussed further in this study.

5.4 Summary

Agile approach to project management and especially analytics can be an answer to many problems that organizations face in present time as changes happen constantly in the business environment and technological development is faster than ever. The benefits of agile methods have been studied within software development for a long time but now the change is also happening in project management and different technology fields. Serrador & Pinto (2015) study outside the software context found that agile and iterative approach in projects really rose the success rate of different projects in every category measured. The project efficiency rose but at the same time with agile methods the stakeholder satisfaction increased. What was even more interesting in Serrador & Pinto's (2015) study was that the project complexity or the experience of the project team did not have impact on the success rate of the projects. This is finding is significant, although has to be interpreted with healthy common sense as projects differ hugely in their size and industry and some require experienced people to pull them through. This result still has valuable insights to be considered as it is a result from over 1000 projects. Complexity usually means that there is more variables to be taken care of in the project and team experience on the other hand means that the team acknowledges those variables and knows how to handle them. In agile methods communication, stakeholder involvement and responding to change are factors that are exploited and those might the answers to the result that Serrador & Pinto (2015) presented. On top of the mentioned results Juricek (2014) concludes that that agile approach is about solutions that work through management strategy context that supports the goals of the company by bringing transparency and simplicity to the projects.

Like the implementation of agile methods to project management the implementation of them to analytics is still quite new to science. Some models and studies (See Larson & Chang 2016) have been made but mostly the models still consider only business intelligence and not entirely about analytics. Still, like Larson & Chang (2016) described that the nature of analytics is very much agile where there is constant change in resources or requirements that have to be dealt with meaning that communication and know-how for the teams must be constantly up to date and ready to learn. These requirements relate to the dynamic capabilities which we discussed earlier as they are the capabilities that enable the organization to act when change occurs.

Agile methods have been studied with analytics like Larson & Chang's study shows but agile methods and dynamic capabilities theories haven't been studied together. Touch points between the two theories can be hard to find as agile methods are usually related to projects and short iterations whereas dynamic capabilities depict assets of an organization and how organizations can become better against their competitors in the long term. Some points which are similar between the two theories are at least the objectives of the theories. Dynamic capabilities are defined as assets to gain long term competitive advantage (Teece et al. 1997) and agile methods' objectives are to have better results from project work (Serrador & Pinto 2015). So both are developed to improve performance. Other similarity is changing environment that triggered the development. Teece et al. (1997) developed the concept of dynamic capabilities as resource based view of the companies didn't answer to changes in dynamic environments and agile methods were developed as the environment changes affect changes in the projects too (Fernandez & Fernandez 2008). Both theories have dependencies regarding to the end result. In dynamic capabilities learning was one of the capabilities that are included in dynamic capabilities. Learning is a capability that allows organizations adapt to changes. In agile literature, learning is part of the process and iterations that are done in projects. So even though dynamic capabilities and agile methods aren't studied together, they have much similarities and both are part of the value creation chain in analytics.

6. EMPIRICAL RESEARCH

This chapter describes how the interviews were conducted. The execution of them is explained and the qualitative analysis methods that were used to analyze the results are introduced. Before presenting the execution, the interviewees are introduced shortly to give information about their position and background in their respective companies.

6.1 Interviewees

As this thesis is made for a consultant company whose employee the researcher currently is, two sets of interviews were conducted for two different sample groups. Other group was consultant company's employees in Norway who had been working in analytics projects and have long experience about analytics in this thesis' context of management and business. Norwegian employees were interviewed to gain insight of how they have been doing analytics solutions for their customers and what kind of things has to be taken into account when implementing analytics to different companies. The selection of the persons to be interviewed was made with an assistance of the first interviewee who recommended all the other interviewees. The main condition was that the persons had to have experience working with analytics and have good impression about how analytics is developed.

The other sample was the consultant company's customer companies whose representatives were people who are working with analytics in their companies. They were chosen based on their willingness to participate to the study so different people with different backgrounds and positions were chosen. The reason why they were interviewed was to gain insight about the analytics maturity and prevailing models of using and developing analytics in companies so that the data from the consultant company's Norway office could be reflected upon the data from the customer companies. The interviewees and the information about their companies and positions is shown in table 5.

Table 5: Interviewees

Code	Position in the company	Company's field
I1	Senior manager - Consumer products & Retail analytics	Consultancy company
I2	Manager – data analytics	Consultancy company
I3	Executive director – financial sector analytics	Consultancy company
I4	Partner – financial sector analytics	Consultancy company
I5	Senior Manager – financial sector analytics	Consultancy company
I6	Senior manager – data analytics/IT advisor	Consultancy company
Customer companies representatives		
C1	CIO	Manufacturing and retail
C2	Manager	Retail
C3	Manager	Finance

6.2 Interview execution

The execution of the interviews were done in semi-structured interviews so that themes related to the topic could be discussed deeply during the interview and new insights can be generated. Semi-structured interview allowed to deviate from the question list to discuss about matters that rose during the conversation that were considered valuable. One example of this was the topic of agile methods that rose from one interview and was then added to the question lists so that it would be covered in all interviews.

The study included two sets of questions that were asked from the interviewees. The other set for the consultant company's employees and the other for the company's customers.

The question lists are presented in Appendix A. Both questions lists were developed considering the research questions and thinking what kind of information is wanted from them to answer to the main research problem. There was no framework or readymade question list available as the research field is quite new so the questions were developed based on the research questions and iterated after first interviews.

Interviews within the company were done mainly in the Norway office of the company and in the customer premises regarding the customer interviews. Couple of interviews were held via Skype because of scheduling issues. Interviews were recorded so that they could be analyzed afterwards and the discussion would flow without interference. Interviews lasted usually around 40 minutes and all the questions and themes were discussed during this time.

Interviews that were conducted in Finland were customer interviews that were done in customer premises. At first the interviewees were asked about their position in the organization and relationship with analytics. After that the questions were asked from the question list to cover different areas of from the organization’s analytics. Like the other interviews these were also conducted semi-structurally so if something interesting was risen from the discussion the issue was discussed more deeply.

6.3 Interview analysis

Interviews were analyzed thoroughly by using qualitative analysis methods. Methods that were used were summarizing and categorizing the data. With the summarization the main point were extracted from the data and categorization helped to understand the main themes of the data and the issues related to them. Summarization also helped to understand larger entities and how different interviewees saw same things differently. It helped to generalize different quotes under same categories, which were developed after summarization to deepen the analysis.

Saunders et al. (2009 p. 492) propose, the step before categorizing the data is to develop different categories meaningful for the research. The grouping categories developed for this research were derived from the main themes that were present in the interviews as there was no theory background to use as grouping categories. Analytics played the most important part in the categorization but related themes like agile methods and dynamic capabilities categories were made to understand the whole entity between the three themes. The categories and the analyzing process is described in figure 9. After developing the categories they were analyzed and the main findings were extracted from the categories.

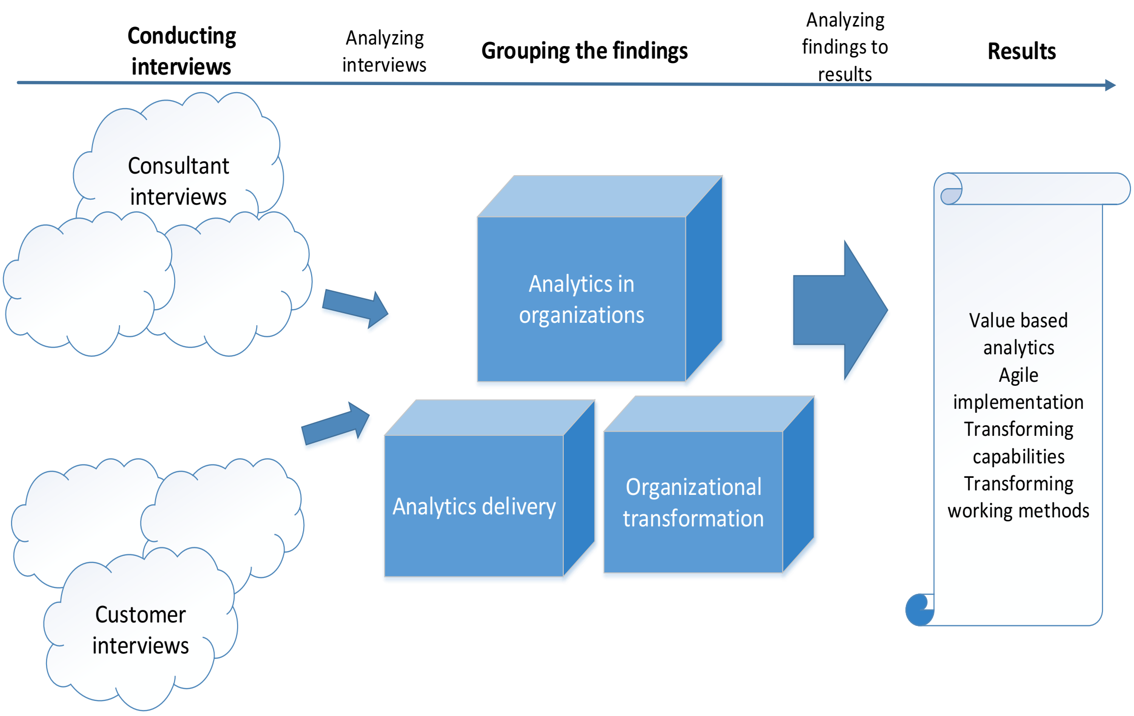

Figure 10: The steps of conducting analyses from intervies showing the main groupings that were derived from the interviews and the main results that were deriverd from the groups

Like figure 9 depicts, the results from the interviews were analyzed by listening the recordings of the interviews. After that grouping was done solely on the themes that were derived from the literature and from the interviews by the researcher. After grouping the results were derived from them by connecting quotes to certain perspectives and issues. Not all the quotes were used and included in the study but the most relevant ones to show the point that the were relevant for this study. When writing down the results they were more deeply analyzed by the researcher by writing bodytext betweem quotes and derive the meaning from the quotes in them. This way the quotes were put in to a context in this study.

7. EMPIRICAL RESULTS

In this chapter the results from the interviews are discussed via the main points and groups that were developed in the analysis phase. This chapter gives more insight to all the research questions that were already handled in the literature review to understand how analytics is perceived not only in the academic world but also in the real world organizations.

7.1 Analytics in organizations

In this chapter we discussing about the present state of analytics in couple of organizations that were interviewed for this thesis. We compare the thoughts of their representatives to consultant company's experts' thoughts about the subjects that rose from the interviews.

Present solutions

Analytics in organizations can be approached from different perspectives and as there is no right way to do it, many organizations are in different phases developing their analytics capabilities. There are as many definitions as there are different people as we can see from the different approaches that the respondents said when asked about defining analytics. Also different aspects of the data field are included in different answers as some see analytics larger term that holds terms like business intelligence and master data management within and some approach it more from the decision support side.

C2: *"Analytics in our company the way I see it using different data sources to help the decision making of our company."*

C1: *"The way I see analytics is that there are two kinds of analytics. The other is about history and reporting where you are trying to analyze historical actions and understand why they occur and what happened. The other analytics is more future oriented where the analytics tries to predict something that is going to happen."*

I2: *"Analytics is umbrella term: under are master data management, BI, information management."*

I5:*"Whatever you call an analytics, it is a part of the toolkit to cause a change so it's never a goal in itself and it's never a tool in itself because if you want to enable change you need to know what you want and not just the buzzword. But in analytics there needs to be some sort of analysis and not just looking at the data."*

However analytics is defined or described in organizations the solutions that organizations have implemented vary as much. In some organizations the maturity level is still quite low in analytics point of view as the solutions that the organizations have done are mostly more BI related. Data and the importance of it have been recognized in all organizations by 2017 but the solutions are in this sample relying on large data warehouses and mostly BI-tools and visualization tools. As it can been seen from the interview answers from different companies it shows that there is no lack of technologies and tools that the data is handled.

C2: *"At the moment the basis of our analytics is one enterprise data warehouse that holds some amount of data. Then we have different data warehouses that are related to our ERP-systems for business lines. On top them we have couple of smaller SQL-databases and we are moving towards cloud based solutions. In the reporting side we have different reporting tools like Cognos and on the analytics we are using for example Qlik sense for data visualization and data discovery. We also have our own centralized digital unit in our organization, which produces deliverables from these systems to be used so overall our capabilities for analytics are quite good."*

C1: *"During my time we have built common data warehouse for the company that I think represents the right solution for our company. With the data warehouse we've been able to start measuring operations and beginning to lead with data so that the decision could be based on knowledge. So our analytics road is just beginning."*

C3: "In our organization analytics is usually seen as data storage and reporting but I see that it is much more."

The answers support the observation that analytics is perceived still heavily via technological solutions. The common approach is to build data warehouses where all the enterprise data can be stored to be utilized at some point of time with different tools. The tools on the other hand are not the solution for developing analytical capabilities. Respondents in the interviews when asked about their maturity and how they are now utilizing their data said that the deliverables that they are producing are mostly descriptive analytics like dashboards and visualizations.

C2: *"Our analytics maturity still is mainly in descriptive analytics as we produce mostly dashboard deliverables for different units so the predictive analytics should be developed further."*

C1: *"We've done reporting and history analytics for a long time but we see even more potential in the predictive analytics but the challenges in that are related to combining business and analytics."*

C3:*"In our business unit the maturity of analytics is zero as there is no really advanced analytics. In our organization it differs from business unit to business unit but overall I'd say that it is still very much reporting."*

The implications that can be made from this are that more developed analytics such as predictive analytic models are not yet broadly utilized in these companies. This means that there is still quite a bit of value that can be derived straight from the data as the value now comes mostly from the visualization and not from the sophisticated analytical models. The answers from the companies are mostly supported by the experts interviewed in this study. From their experience the maturity levels of analytics are usually quite low and analytics is perceived too technologically in a way that the business side has not been taken into account.

I2: *"A lot of the clients are low maturity so their analytics is quite low level analytics"*

I1: "*Customers might say that we do analytics, we do churn modeling, but that is not analytics. For example, a Churn model is just a model but it is much more important to understand how the business works and how does for example customer service work and how you talk to your customers."*

Comparing the answers from the customer company representatives to the consultant company's experts the biggest gap is how analytics is perceived as an entity and how it should work in a company. The experts see analytics as an enablement to change organization's processes and people to become more data driven at least in some areas of business. They include not just the technological issues to analytics but emphasize the business's importance to guide analytics. The representatives from different companies were working with analytics in their respective companies and personally shared many of the ideas that the consultant company's experts presented but on the organizational level their companies were not committed to analytics in the extent that the experts were talking.

Use of analytics

Even though organizations seem to have a lot of different tools for analytics and people who are creating reports for example, it's also important to know who is using the analytics that is being created in companies, how people are using it and for what they are using it. Data and analytics are used to support decision making as the literature and the respondents said so we must look at the decision making processes and people who are making the decisions based on data to find answer to these questions.

C1: *"For now we have analytics tools mostly for our controllers, for example, in the finance department and we also have data cube for business and sales directors so that they can plan and scenario their work."*

C2: *"We produce mostly dashboard deliverables for different business units. Our organization support analytics with different ways. First of all we got very good tools to do analytics. Secondly, our organization has invested in our analytics team so we got capabilities and assets there. Problem is that in business units they feel that they don't have* *time to do for example KPI specification since that time is away from their core business. So to deliver the message that analytics can help business units is a challenge."*

The use of analytics happens on the director level where in many companies the decisions are made. Considering the structures of organizations, usually the leaders are the ones making big decisions but also responsible for the consequences of them. When relying on small amount people who are using the analytics support in their decision making there is a risk that the operational level insight of problems don't achieve decision making level. This might lead to a situation when it's hard to produce analytics to possibly solve the problem. The other aspect is of course time and the amount of communication that happens between the decision maker and the operational level. For example if analytics provides valuable insight that the decision maker can use, the decision and the implications of it must be implemented through operational level. If communication does not work there might be an issue where operational level is not doing as the insight is telling.

As discussed in the literature review that analytics should become also part of the organization culture in order to provide value as efficiently as possible. Using analytics only in the director level is a good start but there is a room for improvement where analytics could become more significant part of the organization and the deliverables could be used in multiple levels. One of the interviewees said that they do not use analytics in their everyday life but sees possibilities in it. It's more a matter of managing the change on all levels of the organization.

C1:*"We don't use analytics everyday but for example there are big possibilities in supply chain management where I see it could be done."*

C1:*"The domain that the analytics could be used in our case is quite vast as there different producing facilities that are an environment on their own where analytics could be used but then there is also the consumer factors where data can be gathered and analyzed so there are quite different domains of use inside our company."*

C3: *"When adapting to organizational change I think people divide into two categories where the other half doesn't really care about the change and just do as they have always done but then there are other people who realize the value and are ready to change. One effecting factor is of course the management support that affects to this change."*

The respondents saw different possibilities where analytics could be used in their organizations but like the second quote proves, within one company there can be multiple domains that all are significantly different from each other and have their own domain related needs and issues. This of course, on the other hand, opens possibilities to utilize analytics differently in different domains like the use of predictive maintenance in production facilities and environments or the use of customer pricing models in the consumer environment. These different domains and situations inside one company pose different challenges that cannot be solved with one analytics solution or a process that can be implemented in all environments. One of the experts of analytics said that the analytics is all about working agile and fast but doing that in some environments can be hard and like discussed before. Developing something that is not necessarily closely related to the core operations the development work can be seen rather a waste of time than something positive.

I3: *"The essence of analytics process is to stretch ourselves to work agile and in fast iterations."*

The significance of analytics and data is acknowledged like we have seen from the answers. We have talked about the change that analytics is enabling in organizations that it becomes part of the culture and everyday life little by little. When asked if the organizations had data or analytics strategy the answers were mostly aligned together. On a strategic level data is considered still quite minimally and on a broad level.

C1: *"Regarding our strategy there are mentions about data use in our enterprise architecture so in that way we see the relevance of data significant and in the future when we are renewing our IT strategy I think we are going to include data and analytics more but we don't have so clear data strategy but rather than vision of what we are trying to achieve."*

C2: *"We don't have analytics strategy at least organization wise."*

C3*:"We don't have analytics strategy but there are money allocated to it so it is seen strategically important matter."*

Considering the answers that were quoted above to the consultant company's experts experiences, they said that the maturity levels are quite low in many organizations and it is understandable that on a strategic level there are no clear goals regarding to analytics. It might be on the other hand one way to improve communication about analytics and thus raising the awareness of the possibilities that analytics can prove. Like one of the interviewees said that analytics shouldn't be taught just to do analytics but the awareness should be raised so that the benefits of it can be understood.

I5: *"I think that more awareness of the potential benefits of analytics are and what you can use it for is often beneficial to organization but it's important not to cross the line of training people into analytics just because it's a buzzword. It needs to be for something."*

Problems

The problems that different organizations have regarding to analytics are usually capability related in this interview sample. Some of the problems were stated:

C1*: "One of our biggest problems has been seeing the big picture of analytics and where it can be used and what's the "steak" in that. Also the largest challenge for us is the lack of processes around analytics as we lack common way of thinking about analytics as processes are considered different from different people. That's why it's hard to harmonize the ways of working and thus data is in bad condition."*

C2: *"As data ownership is one big problem the time allocated to it in organization pose huge challenge as we do investments on the tools but we should find more employees' time to realize value from those tools. We spent quite much resources to the technological investments but we should have time to realize the investments also."*

C3:*"Problem is that banking holds challenges like legacy systems which makes handling the data hard and the speed of development is very low as systems are big and rigid."*

C3*:"One of the biggest challenge in analytics is actually using the information from to it to do decisions."*

The number of problems that is identified with the broadness of them tells how large entity the whole analytics field is in organizations and how hard it can be implement and especially make the changes on an individual and organizational level. Seeing the big picture of analytics on its own is a huge issue that has no right way to dealing with. We have discussed already about the domains that the analytics relate to in organizations, the people that are using and producing the analytics and the processes that analytics is changing that all are part of the big picture. Since there is no right way of solving the problems a good starting point is to acknowledge them and gradually make actions to solve them.

I5: *"So many companies have gone to a point where they are actually just sorting data and building data warehousing structures and have completely forgotten why they are building them. They have more or less ignored the fact that this is supposed to be used for something by someone. Organization might spent a lot of time and effort to develop their analytical capabilities, which can be good thing, but without knowing what they actually want to do with the capabilities which then causes that making mistakes is easier".*

The issue where organization is just building data and analytics solutions without clear goal can also lead to a situation where it can be hard to know what to develop and how much. One principle of developing something is that one must be able to measure it. The common answer from the sample was that organizations do not have measures to see the effects of data and analytics efforts even though they see it significant and invest in it.

C1: *"Right now there are no measures that can measure the implications and benefits of our analytics overall. We do have measures in different projects where we can measure in some extent the effects of analytics in that domain".*

C3:*”We don’t have measures to see the benefits from the reports that we produce as our job is to show how the benefits from the changes are realized. In project we do have measures to see for example how marketing results are improved.”*

C2: *“We can’t measure the whole data and analytics investment values but of course projects have their own measures.”*

I6: *“If one is not able to define what and how you measure the success of analytics you’re not doing the right thing. The reason why companies have problems with analytics is that they are building data structures and not solving business problems.”*

The other problem that was also raised from different answers was the data quality, which was seen important matter to develop but also a pain point for many organizations due to multiple sources and forms of data. There was a significant difference between the organizations representatives that were interviewed and the consultant company’s experts that were interviewed. Although the quality of the data is not diminished by the experts, it’s not seen as important factor in analytics.

C1: *“Problems that we have identified regarding to data are mostly master data management related but the awareness regarding to data has risen but the change takes time.”*

I4: *“It’s more important to get data available than high quality data.”*

The reasons for that difference might become from the different approaches. All the experts emphasized the importance of the business problem behind everything. For them that dictates a lot of the work that is to be done. Once the business problem is identified they can scope down the data that is used to solve it. One of the expert said “90% of the data in data warehouses are unused and thus have no value. Data that has no value is just nice to know”. So only scoped data is useful and provides insight that turns into value. From the organizations point of view they have all started to build data warehouses where data can be stored and possibly used in the future. Regardless of which approach is better or the “right” way to do analytics cannot be said but the problems that the experts have identified in their customers and the sample organizations interviewed for this thesis seem to have same issues.

Development

The problems that the organizations identified regarding their analytics have effect on the future development intentions. Mentioned development targets revolved around master data management and data ownership. The development targets can be related to the maturity levels of analytics as for example one of organization representative states that even though they understand that the organization should eventually change to become more data driven, they acknowledge their low level maturity about the issue and still focus mostly on developing the data handling.

C1: *"Future development is going to be for us mostly the development of master data management. The other development targets are reporting and doing ad hoc analytics. We are trying to think what we should do, for who and how much so that it would still reasonable in resource point of view because they are not easy to do."*

C3*:"I wish that in the future we could get rid of most of the old systems or at least get our information flows in a condition that our data would be available almost in real time and not months old. This of course is dependable of the business units as for example new business units have designed their processes in a way that data is taken into account but in old units the systems don't really support real time data usage."*

C2: *"In future I see that we should have clear ownerships for the data and information. The other development target should be architecture for the whole entity of analytics and IT so that we can see what systems we are using and how. We still have quite big volume of our data in traditional reporting systems so I'd like to see transformation to the self-service analytics."*

What is interesting about the quote is the ad hoc analytics that was seen as one of the development targets. Ad hoc working is based on the need of someone who is consuming analytics and sees a problem or need and thinks that analytics might help to bring insight to the issue. Comparing the ad hoc approach to the approach that the consultant company's experts proposed as their way to do analytics there has much similarities. Both approaches start with the need of something and then use fast development process iterations to produce insight to be used to gain value in the end. Ad hoc approach might be a good way to start agile analytics implementing for a low maturity level organization to see and learn the capabilities that are required to deliver ad hoc analytics. Based on the learnings it might be then easier to build large scale analytical capabilities.

The other issue that was raised from the answers was the use of different analytics suppliers for developing the capabilities and processes for organization. Large organizations, like the interviewed customer companies in this sample, can use multiple different suppliers that help them with the analytics. It also means multiple different approaches to the issue which can lead to problems stated earlier like communication problems or completely different solutions for different purposes.

C1: *"Developing the analytics in our domain is also supplier dependent as there are different analytics suppliers who do different things but not necessarily can take all of our organization's data and analytics related issues under their supply which makes a situation where you have to use different supplier in different situations."*

We have already reviewed agile methods and how they are considered in analytics context in the literature point of view. The experts consider it basically the only way of developing analytical capabilities and the organizations interviewed also see it as way to do it but they have more structural obstacles that do not support agile method implementations.

Problems are related to budgeting and overall investment processes that are prevailing along rigid ways of working.

C1: *"When implementing a solution, was it analytics or other IT solution, we are trying to use methods that show the value quickly but there is challenge that the solutions are usually quite unconnected from other solutions which makes it harder to implement the learnings from one solution to further in the organization. That makes a situation where people don't understand what they should use analytics for. For now our organization is a bit behind regarding to agile methods. We are moving slowly to the direction of agile but there are organization structures that don't support it like investment policy which is not designed for agile methods. For example budgeting for projects that try something new without the promise of profits is hard. Bottom line is that only investments that are calculated and have certain repayment period are being invested so something that might not enable profit is not done or tried."*

C2: *"Our organization utilizes agile methods in minor projects and usually in IT services but I see that in analytics the ownership of data and information pose a challenge to do agile method development in analytics."*

C3*:"I think that in our organization we speak about doing MVPs but in reality the projects usually are just normal projects because building the MVPs might take even years."*

Even though agile is seen as the best way to implement analytics projects, there are many obstacles and situations where organizations have to really change their ways of working. As the maturity level of analytics rises in the organizations and capabilities to handle and produce analytics increases, the agile method delivering comes more relevant according to the customer company representatives. The challenge seems to be to break the processes around the analytics to support agile development and involve relevant people to the agile process to deliver analytics that can be consumed and has a value for the end users.

7.2 Delivering analytics

This chapter introduces the main points of how the consultant company's experts see analytics and its development in organizations. All the experts agreed with each other in many cases and had same ideas about the theme that is discussed in this chapter.

Identifying performance gap

The current state of the analytics in organizations varies largely and organizations approach the subject from different perspectives based on their previous choices or paths as they were described in dynamic capabilities literature. Regardless of what is the maturity level of analytics that organizations have, delivering the value process should be uniform and take into account the long term strategic goals but also show short term benefits so that the value of the analytics is seen and understood how it affects different operations.

I3: "I*n order to be able to start with anything you need to find the performance gap*."

Delivering analytics starts, from the value perspective, always with identifying the performance gaps of the organization. This was an issue that all the experts interviewed emphasized and how they saw that analytics delivery process should start. Performance gaps can be approached slightly from different perspectives as the interviewees mentioned them in different terms varying from target picture of analytics, performance gap to business issues. Despite different terms used in interviews, all might actually mean the same thing of identifying a problem that the customer has regarding to their business. For example the one of the interviewees mentioned analytics target state that needs to be identified when starting to deliver analytics.

I1: "*What we do is to advise customer to develop a target picture of analytics and define the target state on how they should use analytics in certain settings."*

I6: *"Examples what we did in one project were customer churn to identify customers who were likely to leave the organization. The need started with the problem that bank noticed that customers were leaving and wanted to know why. So that's an example where we start with the business problem and not with a load of data."*

This statement would imply that developing analytics means that an organization should have a clear vision and understanding of analytics to be able to set the business goals for analytics. Knowledge about the different possibilities of analytics and data should be in company's resources so that those possibilities could be grasped and the requirements to achieve the future state of analytics can be achieved. In a case where organizations own analytics resources and knowledge is sufficient for this, developing the target state for analytics is possible but in a lower analytics maturity level organization it might be hard.

Different perspective to approach the performance gap was mentioned by one the interviewees who mentioned business issue as the starting point. In a business driven analytics delivery, data or technology doesn't play the main part but the business issue that drives the course of the analytical actions and insights generated from it. Differing from the viewpoint of developing analytics future state at first, the future state of the business issue should be set. Business issues and the future states of them might vary depending on what the organization wants. For example, a business issue might be simply to improve sales or reduce churn from existing customer base but the issue might also be much larger. Nevertheless the business issue and future business state dictates what kind of analytics should be developed in order to achieve that future business state.

I4: *"Everything we do is very issue based. So we will never go to a customer and ask for the data and then identify model. We always start with the business issue."*

Even though slightly different perspectives were presented in the interviews of how to approach the performance gap, the conclusion can be derived that the regardless of the terms used as analytics future state or business issue that must be identified, the performance gap is usually a problem that the organization has. To find a solution for it the business side and the analytics side must be considered. From the analytical side the current capabilities and the resources available have an effect on what can be done and what's the desired future state but the business side determines largely on how analytics approaches the problem. For example in a case of improving sales figures being the business issue it determines largely with the data available, what kind of analytical modeling could be done and should be done.

Understanding the domain

Understanding the performance gap is the main priority when delivering analytics and implementing it to the organization. There still might be issues to identify the gaps if there is no knowledge about how something can be done better or the prevailing processes are considered inadequate. As one of the interviewees stated that if there is no understanding of the domain that the organization is operating it might be hard to identify the performance gaps.

I3: "*One problem is to understand the domain of the customer. If we truly don't understand the business it is hard to answer and give answers to the performance gaps."*

I4: "*Always when we are addressing the client there is a guy who knows the client, a guy who knows the domain of the problem and then the analytics guy who can understand how to use analytics to approach this*."

Statements about the domain knowledge and the importance of it also support the idea of approaching the analytics from the business viewpoint. When the problem is understood thoroughly and the issues that have an effect to it, the modeling can be done much more efficiently as for example scoping of the data is steered by the problem but also by the domain environment. The traditional approach where data is collected and then explored to gain insight to a certain problem is in this light quite inefficient as there might be loads of data and models that can be used and explored but if the problem is not scoped resources are wasted to a futile exploring. There is also a risk of interpreting the results wrong if there is no consensus of what things affect to the model and the problem that is being solved. Understanding the domain can be a problem especially in organizations where analytics maturity level is low and the capabilities around analytics has not yet been developed. This might lead to a situation where the need of analytics is acknowledged but the possibilities and requirements to develop analytics are not sufficient.

I3: *"Many customers come and say that we lack analytics but they really don't see where they need to apply analytics."*

Developing the roadmap

After the performance gaps are identified the steps to get to the desired state must be defined.

I1: *"After developing the target state for analytics, we develop a road map on how they should get there."*

I1: *"We help customer to set up operating model to build analytical capabilities. Help them define what could their analytical capability look like, what their responsibilities should be, what type of people they need, what competencies they need, what process they should follow."*

Developing the roadmap is basically identifying the processes, resources and people that are needed to improve performance and then rearranging their work to new better processes so that the performance can be achieved. As discussed in the literature review, the mentioned actors are related to the dynamic capabilities that the organizations have as new processes cause change that needs response and adaptation. It is of course dependable on different factors like the maturity level of analytics and the prevailing dynamic capabilities how the road map is built but same issues are needed to be considered and identified.

I3: *"In order to be able to start with anything you need to find the performance gap. So when we start working with analytics you have some common things like churn or cross-sell but in order to be able to work agile you must scope the problem in to small bits. When you understand the performance gap then you can start discussing with the customer that what kind of actions it needs to be solved or make it better."*

The other thing related to the roadmap that the quote above mentioned was the scoping of the problem to the roadmap. As we discussed before there can be different size business problems or analytical gaps in organization's resources that needs to be improved. In order to find the tools and processes that build the road map, the organization must divide the main problem into a smaller pieces so that the problems are better understood but also the requirements to solve them can be identified better. Dividing the problem concretizes the problem so that the processes and changes required are not in a vague level but concrete and understandable actions. This way also the results of the changes can be measured easily as the measurement of the benefits from analytics is also a problem for most organizations.

I6: *"Most of organizations have already spent an awful lot of money to build data warehouses so obviously they have data already. Clients who start from scratch I wouldn't advice to start building data warehouse since I think that's completely wrong way of doing analytics."*

Part of the organizational transformation to become more analytics and data driven not only should the analytics related processes developed but all the processes related to the analytics value chain. As discussed in the literature review that even though organization might have analytics team and thus analytical capabilities, becoming analytics driven means transformation in all levels of operation. Analytics is about generating insight and the insight is used usually by someone who is not part of the analytics team but works in completely different business area. To find the business problems to be solved with analytics the problems must be actively assessed and communicated from the analytics users to the analytics team. People working in different business areas shouldn't just wait for analytics deliverables to use them but to actively be involved in the value chain of analytics to find business problems that can be answered with analytics and thus be part of the roadmap that is developed.

Delivery process

After the performance gaps have been identified and the road map has been developed the real process of developing analytics can begin. At this point the nature of analytics changes to agile as one interviewee stated that the analytics is always referred by him as agile analytics:

I3: *"When I talk about analytics, I put always Agile in front of it."*

I2*: "During the project we are working agile"*

I4*: "We always focus on agile principle and delivering minimum viable products to get feedback using rapid prototyping. This is so that we can move fast from idea to testing and activation."*

I5: *"Agile is the only sensible way of implementing any kind of IT solution and it implies to analytics solutions also."*

I6: *"I think that agile implementation of analytics goes hand in hand with the business problems. One important concept in agile methods is minimum viable products or prototyping which is iterative process where you get a solution that you test. When you are working with business problems you're essentially working in unknown space where there are no existing solutions available so you can't plan them ahead."*

The agile nature of analytics was also mentioned by everyone who were from the consultant company. It has to be kept in mind that the consultant company's interviewees do project like development as their job for different customers. On the other hand dividing the problem into smaller bits for the roadmap supports the agile implementation of the analytics solutions as the smaller parts of the overall solution can be completed within one iteration in agile implementation. Agile implementation enables to see quick results as the value and improvements are delivered in smart entities rather than one big project.

The feedback and development part is also quicker as the results of the solutions can be seen in short time and feedback gained based on the results.

I3: *"The usual way for companies to do the chain is to start from the data and spent millions of euros to create high quality data and modeling where as our model is the opposite, so we start with the profit and move from end to start. The process is also agile so going through the whole value chain takes about 2-4 weeks. In that time we have to understand what's the business problem that we are solving and the performance gap, and also understanding what decisions affect to it and what models we must create."*

I6: *"The role of data is essential to analytics but not all data is equal so it doesn't make sense to start by building data warehouse. You start by identifying the problems that you are trying to solve and then you need to identify the actions required to solve the problem and then what decision I need to make and what insight do I need and then thinking what models I need and what data I need to do the models. When end in the data you can start thinking where you get that data."*

The value first approach to analytics like the quotes say enables organizations to use their resources and capabilities more reasonably when they do not start from developing large technological solutions that require big resources. Starting with the business problem and identifying only related issues and data to produce quick results. On top of the short and quick development there must also be a long term plan for the organization.

I3: "*After going in to customer you need to work in 2 perspectives. In order to work in long term vision you first need to produce something to that the people see the value in it and see how analytics can benefits them. After couple of iterations you can start to discuss about the long term change with the customers."*

Long term perspective is closely related to the organizational transformation that requires changes in the capabilities of the organization to become more analytics driven. The short term working, like it is said in the quote, is to show the value and sell the idea of becoming analytics driven organization to the customer. With the small iterations when the benefits are clearly seen the change is also incremental and easier to implement especially for people that have not used analytics or were involved in processes where analytics has been used. The agile implementation allows organization to learn the required capabilities so that people get used to the process of communicating business issues and problems and consume the produced analytical solutions to decisions that in the improve the performance of the company.

Even if the analytics process is approached from the value point of view, where the beginning of the process starts from the value part of the value chain and only in the end the data comes in, there still is the basic analytics process that produces deliverables for different business units to be consumed. This implies that the value chain is not a chain from data to value like was presented in chapter 5, but rather iterative process.

I4: *"Analytic process has 3 major steps: first is explorative part where you are testing hypothesis and finding insight, then you have step 2 which is implementing the insight to business processes. It can be agile or it can be not. Then you have the maintenance of the implementation."*

So not only during one iteration the value chain of the analytics is done from the end to the beginning to understand the problem and resources required to make the change for it but it also goes from the beginning to end as it would in normal approach where the data is used for analytical modelling to produce insight that can be used for decision making. What the agile approach might miss is that after developing a model for a problem during one iteration the model and the processes related to it must be maintained. Maintaining the analytics process is understandable since as we have spoken the environment and the data used in the modelling can be highly dynamic which causes changes. The changes mean that the models and processes that have been changed because of the insights that have been gained from the models must be constantly evaluated to check if they are valid to use.

I5: *"In analytics the insights that you gain along the way are the ones that shape your journey as it's more or less impossible to know where you are going to be in the future in detailed level and what you're going to discover in doing the first analysis"*

Coming back to the long term change which has to happen along with short term changes, the long term change can affect the whole organization which means that all the factors that can be affected must be taken into account. In the interviews there were mentioned for example project management, that has not been necessarily related to analytics in any way previously but should be changed when delivering analytics.

I1: *"Implementing the road map is to the goal is about thinking organization architecture, what do you need on the business side, what do you need on the technology side and then you split that to the different capabilities which can be people, technology, data. Then you start to build the steps to get to the goal."*

I2: *"We try to restructure their project management."*

I4: "*We are very issue driven on everything that we do. So we have to focus on strategic and change part of the analytics."*

Like it was mentioned that splitting the problem and implementing the solutions in small iterations helps the large change to happen gradually as changes are not too big and there is time to adapt and develop within the iterations. In a management level more high level tools like organization architecture or decision making processes must be taken into evaluation and rebuild them in a way that they acknowledge analytics processes and capabilities and support them. In the end it is about strategic change that the companies must do in order to gain all the value from analytics and not just think of it as a technological asset that's going to improve business by itself. This was supported by one of the expert interviewees who mentioned that even though companies are usually buying analytics as only analytics there is always the element of change that should be taken considered.

I1: *"Implementing analytics is usually technological for many companies but you should try always ask how the technology is used in business and how to drive business forward."*

In the end implementing analytics in to an organization is dependent on many things that we have discussed but the value must always be shown to be able to sell it to the management and see the benefits. Business world is driven by figures so to gain resources to enable organizational transformation, the need for resources must be argued from them management like any other development project. Only by showing the value people can be committed to change their ways of working to support analytics driven decision making in all organization levels. All of the change is down to the numbers below the line and in the end that's the value that is perceived as the most important and enables the change for whole organization.

I1: *"When we are sell customer insight it's about how much we can improve the sales figures."*

7.3 Organizational transformation and value of analytics

From the delivery project to continuous development of analytics, the development requires transformation that should be started in the delivery process but maintained and cherished after it. This chapter is about the organization's needs for that transformation and how to implement value from the analytics value chain.

Organizational transformation

Delivering analytics with agile methods is just a way to enable long term transformation. The long term transformation of the organization was something that was also raised from the experts' responses as they all saw that analytics enables change. The change can happen in multiple levels. We have discussed about how processes, capabilities, people and environment affects the current situation of the analytics in companies but also how analytics delivery process is affected by them. The interviewees see the long term change also requires changes to these factors.

I1: *"Analytics becomes an enablement to business transformation."*

I2: *"Analytics is change management, changing people behavior."*

I4: "*The result of my projects is never been a new tools that have improved the client's performance. It's always about changing the way they are working and the culture like how they are communicating."*

I5: *"Analytics is an enabler for something but it depends a lot of the context whether it's the whole organization or more specific goal that you want to achieve but the main point of it is that it's not a goal in its self."*

Changing processes or people and developing new capabilities is always a process in its self. It takes time and resources that have to be allocated from the everyday work to the change process. It's also hard to make the change as it can be hard to see the vision state or know the steps that should be taken to achieve it. If the results are also vague, it can be hard to believe in the change and continue to improve working methods. It's something that the experts also emphasized that becoming data and analytics driven organization is hard and takes time and resources to make it happen.

I1:*"Difficult part of the analytics is to make the change and make it stick in the organizations."*

I3: *"Cultural change does not happen in a three month project. It might take a year or two and it is important the management of the company starts to understand that analytics is not only about making old things effectively but innovating new methods and ways to work. So the strategic aligning cannot start before let say a year has been gone because you need to show them first the value but also change for example their CIOs mind on how it should be done."*

I2: "A*nalytics is a journey for the customers."*

I6: *"Analytics is as much about the cultural change as it is organizational change and it needs top down support. For example we are working with a sales unit in a customer and with the guys who own the sales processes. With them we need to make cultural change to their processes from a situation where sales people call to people they know with products they are comfortable with to a process where they call to people based on analytics and offer products based on the insights gained from analytics."*

The reasons for change can be multiple and vary in different business environments and organizations. Companies have woken up for the need of analytics but the actual need is related to the dynamic environment that we have discussed in this thesis. New businesses are evolved, new companies who do things differently emerge in old markets and the customer behavior is changing. Those drivers are just one of the reasons why analytics has become important issue to answer to these changes as it gives insight about the changes and habits that otherwise can't be seen. Some issues that were especially risen from the responds of the experts were about the decision making processes and the human aspects of them.

I2: *"Customers are trying to improve their decision making. Companies can take the human aspect of decision making and automate it or support the human to be more efficient. Value comes from the quickness of making the decision and acting upon them. The most important thing of all is user experience which making things easier for humans."*

Changing the decision making processes can be hard and take time as people are adjusting to new ways slowly. As the processes are changing due analytics there must be a mindset that enables people to adjust and learn continuously. So not only according to the experts should the implementation of analytics be agile process but people should adjust their working ways to be more agile and adjustable.

I4: *"One of the things that we are trying to do in the client organizations is to change their ways of working to follow agile principles."*

I4: *"It's about how you work from getting from ideation to implementation that you are changing."*

I6: *"What we are for example doing is we have a sales dashboard, where we are tracking all campaigns we are running. We are tracking how many leads we are generating from the models, how many have been reacted upon, how many leads have been called to, how many customers picked up the phone and so on. So what we are doing is that we are actively tracking the whole process of sales and trying to figure how we can improve the process. We also use control groups to mirror the existing processes and see if our model is better than the existing one so we can argue why we should change something. It also helps us to show the added value to the customer."*

The factors that effect on changing the organization culture must still be taken into account when considering these statements. In the customer interviews there were mentioned especially the domain of the organization that affects to the change. If a company is operating in a field that has not changed drastically or fast there might be a bigger resistance to the new changes. The other factor that was raised from the interviews was the capability issues that the people do not really know the possibilities of analytics and thus cannot see the problems that could be solved with it. The factors mean that even more resources should be put onto dynamic capabilities and figuring what capabilities are needed to improve the business via analytics.

Value chain

Organizations transformation is steered by the value chain of analytics which dictates the steps of the process and thus shows what needs to be improved. We covered the value chain in literature and how different studies sees it. Value chain involves more or less the data and analytics phase where the modelling is done, insight generation phase where human knowledge is combined to the mix and then the decision phase where the knowledge is put into use. The value chain is also perceived similarly by the experts.

I3: "*We have our full value chain of analytics that consists of data step, modeling step, decision making step, taking action step that leads to the final step which is realized profits."*

Even though the value chain is similarly perceived in the literature and by the experts there are still one big difference on how the experts see when creating value through the chain. Where as in literature most of the researches start from the bottom of the value chain the experts approach it from top to bottom as an initial step in their delivery process. As we have discussed, they start the process from business problem and from there create a roadmap where the decision making processes and actions are evaluated to support insight generation process. The last part is to create analytical models fit to the problem. The chain of course does not go only from top to bottom or from bottom to top but rather up and down continuously as the implementation is done with agile methods.

I3: *"In the value chain you have always your loopbacks going to each stage of the chain so that you can learn effectively. You are also doing different testing to the model like A/B testing or lift calculations to make sure it works. In projects we also have deliverables which are parts of the value chain for example from data > models, that are normal reporting, or data > model > decision which is your ad hoc analytics that we are delivering to customer. Still we must keep in mind the whole chain in order to able to count the turnover of the project and point the value of the project."*

I6: *"Starting with the data and not with the business problem can only work when you have a question "what can my data tell me what I don't know" but then you are not solving a problem. That makes it hard to sell the idea to customer since they don't know what you are going to produce because customer buy solutions and not insight that might not help them."*

The answer points out almost all the matters that we have discussed already from the business need that the analytics value chain should be based on according to the experts interviewed to the agile implementation that enables learning and iteratively finding the right processes but also makes the whole organizational change easier as the change does not happen in one big leap. It also enables the measurement of the analytics that is a problem for many companies and also to see the value from deliverables. The main point of analytics from the value chain point of view is to make actions that create value for organization so that it can be measured with something like increased sales figures in short term. In long term the change can be measured by the organization's behavior so that people would start to begin thinking how to create value via analytics.

8. DISCUSSION AND CONCLUSIONS

The value creation of analytics and implementing it to organizations is not a straight forward issue. This discussion section in this thesis tries to explain and compile the factors that affect to the value creation and implementation of it. At first, all the theories that are presented in this thesis are compiled and assessed how they relate to each other. The findings are then mirrored first to the empiric findings of present state of analytics in organizations (section 7.1 in the thesis). Once the present value creation and analytics actions have been discussed, the results and findings of the value creation and implementation activities from empirical research (sections 7.2 and 7.3) are presented and discussed. The findings are mirrored and argued against the theory background to understand a new way of developing value and implementing value from analytics in organizations. After discussion, the conclusion of the study is done where the research questions are answered in chapter 8.2. A critical evaluation of the research and future implications are considered after conclusions in chapters 8.3 and 8.4.

8.1 Value creation and implementation of analytics

The value creation and implementation of analytics connect three theories: Dynamic capability –theory, analytics theory and agile implementation theory. To understand how these three theories correlate between each other in this thesis, chapter 8.1.1 explains how these theories are connected. Chapter 8.1.2 then answers to the

8.1.1 Combining theories

Approaching analytics from the business or strategic point of view requires understanding of not only the technological side of analytics but also the human and organizational factors that affect to analytics and vice versa. The theory that is related to the value creation of information systems as well as value creation of analytics is the concept of dynamic capabilities (See example Shanks & Sharma 2011, Shanks et al. 2010, Cosic et al. 2015, Corte-Real et al. 2017, Vidgen et al. 2017), which is presented in chapter 3. Linking dynamic capabilities to analytics helps to understand how different human and organizational factors affect the value creation and development of analytics in organizations and give insight what managers, for example, have to take into account when starting to develop analytical capabilities. Why dynamic capabilities and not for example resource based of view organizations is important in the value creation context can be understood when looking at the Holsapple et al.'s (2014) analytics framework where constant change and capabilities play significant part.

Relationship and correlation between analytics and dynamic capabilities can be opened through Holsapple et al.'s (2014) framework of analytics which can been seen in figure 10. Value chain concept and dynamic capabilities has been added to the figure to understand where their position in the whole framework is and what the function of them is.

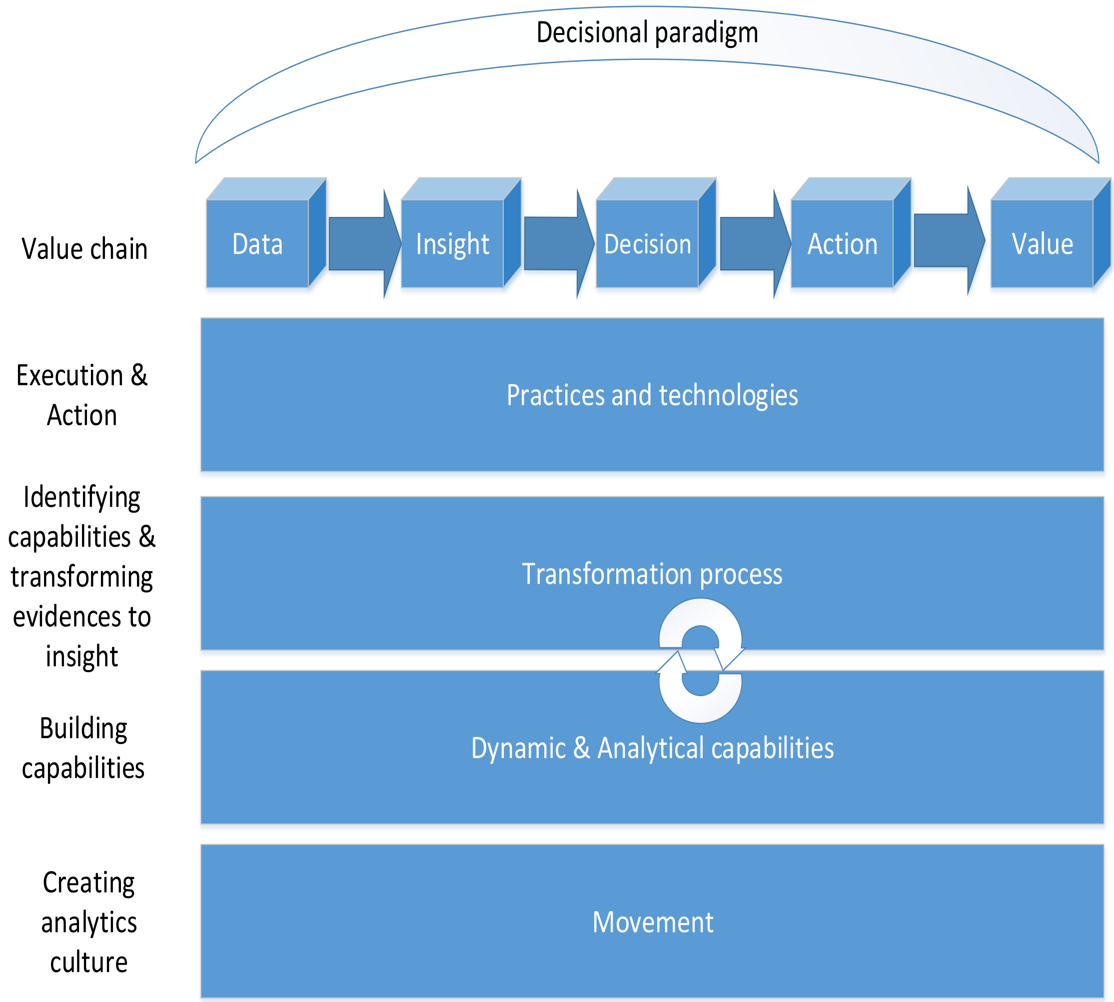

Figure 9: Depicting the relationships between analytics, the value chain of analytics and dynamic capabilities into Holsapple et al. (2014) model of analytics.

The concept of value chain has been added to the Holsapple et al. (2014) framework of analytics to show where it would be positioned. The value chain itself is only a conceptual framework which explains how value is created in analytics but it doesn't contain any rules nor clear actions to follow. In Holsapple et al.'s (2014) framework it has been positioned between conducting analytics activities and practices, and transforming process. The value chain starts with the data and modeling and from there an insight is generated to make decisions which lead to actions and in the end to value. The first two steps of the chain, data and modeling, are basically specific analytics activities which are depicted in Holsapple et al. (2014). When moving from modeling to insight and decision in the analytics value chain, the transformation process comes in. Based on the decision made by the decision makers, something should change in order to improve, for example, processes. When new insights are generated and decisions made upon them, the organization should slowly transform itself to be as efficient as possible in each market situation.

Dynamic capabilities as a part of the capability set in analytics is a much broader concept than the value chain or even analytics as a whole. Dynamic capabilities and the theory related to it were developed to improve competitive advantage on their own without any relationship to analytics in the first place. That's why dynamic capabilities cannot be something that is only related to analytics context but to everything that organizations do. Yet they provide a good theory to understand what is needed from organization to really create long term value with analytics (See example Shanks & Sharma 2011, Shanks et al. 2010, Cosic et al. 2015, Corte-Real et al. 2017, Vidgen et al. 2017).

Dynamic capability concepts, positions and paths, compared to the factors that were presented in 4.3 chapter have similarities especially with technology aspect. As Technology-category in Cosic et al. (2015) framework represents different technological capabilities related to analytics the concepts of positions and paths were defined as the choices that organization have made to be in the current position. So for example selecting analytics technology from different options takes you to a certain path in dynamic capability theory which might restrict the future choices and creating new processes as the technology might dictate or restrict them.

Cosic et al.'s (2015) three other capability areas which are governance, culture and people have closer similarity to processes in dynamic capabilities theory (see Teece et al. 1997). Although the capability areas in business analytics can't be combined to dynamic capabilities one on one as dynamic capabilities is much broader concept, they still can be compared. Dynamic capabilities were according to Teece et al. (1997) abilities to renew and adapt skills, resources and competencies accordingly based on the changes in environment. Applying this idea to the business analytics capabilities means that dynamic capabilities are in key role of building business analytics capabilities and competencies as it is quite new thing to organization and many have to build the capabilities from scratch. Analytics when implemented and acquired into organization should in the long term enable organizational transformation where ways of working change to support analytics and analytics supports decision making. This means sensing, seizing, learning and transforming continuously to find the ways to improve business with analytics. In summary building analytical capabilities does not necessarily require changes in dynamic capabilities or having high dynamic capabilities but creating value through analytics and becoming analytics driven organization requires change where dynamic capabilities come into picture. Having good dynamic capabilities enables the change in whole organization at long term.

As dynamic capabilities are related to developing analytics capabilities, agile methods and agile implementation of analytics is also part of the development and change process in organization. The use of agile methods in analytics is new as only one research was found for the thesis where some research about the topic has been made. Larson & Chang's (2016) framework (figure 9) for agile implementation of business analytics approaches the subject from technological point of view. Some similarities to value chain of analytics are in the model but mostly Larson & Chang's (2016) model focuses on the first two parts of the value chain. It's a good way to understand how deliverables in analytics can be made with agile methods but it ignores the role of insight creation and decision making in the analytics value chain. The model is not wrong but it just focuses on much smaller part of the whole analytics entity and takes technological approach only into account. When comparing it to the Holsapple et al.'s (2014) model of analytics technology is only a part of the whole entity. So there is a research gap between the value chain of analytics and agile implementation of analytics as the latter part of the analytics value chain is not considered in the implementation model.

Agile manifest on the other hand supports the value first approach to analytics. Individuals, interactions, responding to change and collaboration are actions and factors that were mentioned in the dynamic capability and analytics literature. Doing something with agile methods does not only mean fast iterations but also close interaction with all parties. For example, in the decision making process there were a problem that managers didn't believe the data but trusted their own insight as they didn't know how the data was analyzed. The answer to the problem was closer collaboration and interaction between the decision makers and analytics team which follows one on one the agile principles. In summary being agile and doing things with agile methods does not only require fast iterations but working by following the principles of agile methods.

8.1.2 Data based approach to analytics

Combining views from the literature review and from empirical research (chapter 7.1) an overall view of analytics development can be comprised. The organizations whose representatives were interviewed give an idea of how companies start to build their analytical capabilities and what kind of challenges they have had doing that. The findings from empirical research can be related to the theory in many parts. Most important findings from the customer companies' interviews are that organizations tend to develop their analytics along the value chain of analytics starting from the data and technologies. All the interviewees from those companies explained their approach on their analytics maturity level. Organizations did acknowledge the required organizational change but are not ready for it and organizations don't have capabilities or have restrictions to do the development with agile methods.

The empirical research findings derived from the customer organizations' interviewed, support the data value chain theory as the organizations had started from the data perspective to build their data capabilities. All the organizations had already developed their data capabilities and had technological tools and data warehouses to manage data. Organizations mostly did reporting as their main source of analytics as they referred to different dashboards that they produce to different business units in their organizations. Organizations' maturity level in analytics did not allow them to make more sophisticated modeling like predictive modeling. This is understandable as the organizations had yet started to build their data capabilities, and taking into account how large these organizations were and how much different systems they already had, the time that it takes to even make data capabilities is high. If we compare the customer companies viewpoints to the expert's viewpoints there is still a big gap between the approach that the experts think how analytics should be develop and the approach that the companies had taken. This difference is discussed in chapter 8.1.3 thoroughly. Comparing the interview results to the analytics theory presented in this study and especially to the Holsapple et al (2014) model of analytics, the biggest issue seem to be that analytics is not seen the way Holsapple et al. depict it but in a much narrower way. Organizations haven't yet started to see analytics as part of their culture or part of the whole organization's capabilities.

Organizational change, which has been mentioned by the consultant company's analytics experts as one of the most important things when developing analytics, was mentioned not in so many words in the customer companies' interviews but was acknowledged when asked about the problems of using analytics in the organizations. Organizational change and making it was also affected, according to the interviewees, by the maturity level of analytics that the organizations had. In the answers there was a common problem that even though reports were produced to the business units, the units used them but there were no measures or information if the data even helped the units. As we mirror these results to the analytics value chain's last parts where data should affect decision making and trigger actions that change the ways of working, the organizations interviewed were getting to the those steps of analytics value chain but felt that they couldn't derive all the value from those steps. Comparing the information from the interviews to the dynamic capabilities theory that can be considered as the base theory to follow and explain requirements to make organizational change in analytics, it seems that all the three components of dynamic capabilities (see Teece et al. 1997) play big role in the current situation of the companies. Paths that the companies have taken seem to affect largely on how the analytics is developed. Positions also seem to have an effect to the current situation but the biggest affecting factor seems to be processes around analytics. Based on the data from interviews the organizations haven't had time to develop their analytics processes in all levels required so that value could be derived from analytics.

Agile development in the organizations was also something that differed from the experts' view that were interviewed. The organizations saw that agile implementation would be something that they could do but saw many obstacles that prevented them doing that. For example investment models in organization were seen too rigid to support agile development where as in other organization agile methods were acknowledged but the time used per iteration was still even years because of the legacy systems that affected the development. Comparing the results from the customer companies interviews to the agile principles or the agile analytics implementation model that Larson & Chang (2016) present, it is hard to draw any conclusions because lack of data about the use of agile methods in the organizations. What can be said is that all the representatives wanted to do agile methods and saw advantages by doing things with agile methods but their organizations weren't able to implement the method according to them in analytics context.

8.1.3 Value based approach to analytics

Comparing the results from the empirical interviews from the client organizations and the theory approach to analytics to the statements that the analytics professionals gave, there were three main differences that are the most valuable findings in this research. The first and the most important finding is value first development of analytics that is considered better way of approaching analytics than approaching by developing data capabilities first. The second finding is the use agile development methods as a preferable way to implement analytics in organization. The third finding is the significance of organizational transformation that is part of developing analytics capabilities in organizations in order to become data driven organization and derive the most value from analytics value chain. The first finding is contradict to the value chain approach that literature presents and what was done in the organizations interviewed. The second finding supports the agile implementation of analytics which is only starting to rise in literature as a method to develop analytics. The third finding supports the scientific literature about the value creation of analytics where the investments on capabilities are not the only way to produce long term value from analytics but the organizational change is.

Value based analytics approaches analytics value chain from the opposite direction like figure 11 shows. It contradicts the normal value chain model where the development process starts with the data and modeling. Starting to develop analytics data first has problems like one the interviewed experts said that it only gives answer to the question of "what can my data tell me that I don't know". Starting to mine a data without any problem to solve can be very costly and resource intensive work as there is no guarantee to gain results in reasonable time or reasonable resources. From the interviews it came clear that it is hard to sell internally development projects to management if there are no guarantees for results or problem that can be solved. Approaching the development of analytics from value viewpoint solves the issue as there is a concrete problem and it can be predicted how much value solving it can provide. That's why the idea of value based analytics is to start the analytics development project from the value step and then move the chain from end to beginning and not from the beginning to end like literature proposes. The reason why this is done was said by all the experts interviewed for this thesis. Starting with the business problem first and foremost helps to solve a problem that a customer has and makes it easier to provide concrete value. Other benefits are for example scoping the problem and data related to it when acquiring data for the modeling, showing concrete value as fast as possible, measuring the actions that have been taken and their benefits and taking the end user of analytics into the process immediately.

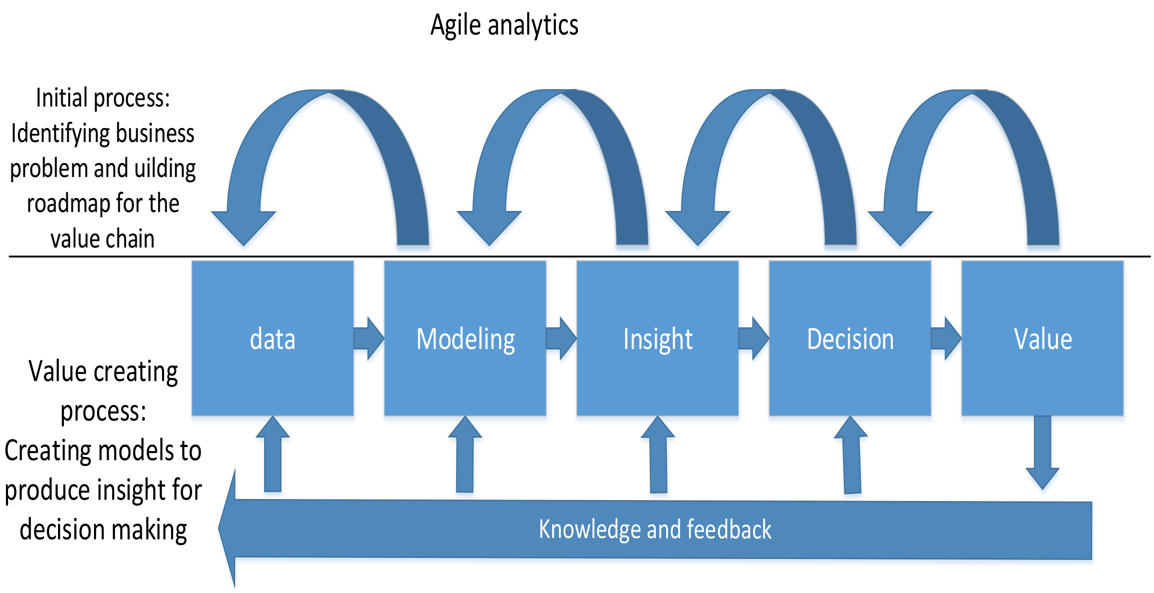

Figure 10: Value based approach on analytics value chain where the initial process starts from the value step and starts the iterative cycles back and forth along the chain.

The initial business problem can come as the interviewees stated from different business units in organization. One example was given in interview where business unit wanted to improve their sales which was their problem. After the problem is identified the next step is to identify what actions and decisions must be done in order to achieve it. After that the next step is to identify what kind of knowledge and insight is needed to do those decisions. Identifying that then scopes down the models that can provide the information to gain insight for the problem and the data that can be used for the modeling. The initial process where the value chain is defined and requirements for creating value with analytics are decided is part of the road mapping process that the experts mentioned in their interviews. It was raised from the interviews that at the same time it is important to identify the capabilities and capability gaps that the organization has in their analytics capabilities and design actions to improve those in the iterations. After the initial road mapping the implementation process can be started following the value chain from data and analytics modeling all the way through insight generation, decision making and concrete actions to creating value. Then the value creation process is evaluated and iterated again from value to data.

Approaching the value creation process from the value perspective has according to experts many benefits. Iterations in the process enable learning from previous iterations as the experts told that the end state in the delivery process is never completely clear and thus can’t be completely planned beforehand. Learning, which was one big part of the dynamic capabilities theory, also enables people to learn how to adapt to new processes or ways of working that the implementation process of analytics introduces to them. Iterative implementation also enables quick actions in a case of change in operative environment or data. Resource efficiency can be also mentioned as one benefit of the approach. Resource efficiency is related to scoping the problem and understanding what is needed in term of the project and capabilities. When the problem comes from a certain business unit, it already scopes the people who should be involved in the process along with the analytics team. Then comes the data and modeling scoping. Like one of the interviewees said that 85% of the data is same in every model so scoping down the most valuable data and not wasting resources on data mining is crucial. It means also that it might not be necessity to invest heavily on data capabilities like most organization do when they build data warehouses. The investments could also be scoped accordingly for the project which might save resources and money.

The other benefits when approaching analytics value first are, for example, showing the value concretely to people and decision makers. Showing value as soon as possible in the development project is also related to agile approach where goal is to produce working concepts as soon as possible. This helps employees to see the benefits and value from the development project and adjust working methods accordingly as the results are clearly seeable. Other benefit of the approach is including the whole analytics framework (see Holsapple et al. 2014) in implementation. Approaching value first makes organization think what actions are required to do in order to gain value and makes them think capabilities and rethink working ways. A good example was given by the last expert who was interviewed. He had helped an organization to change their working ways in a way that it supported analytics. Sales people in this example recorded everything that they had done when they were calling to a customer which, at first, added their work, but after couple of weeks they could see that the insights that were produced based on their data helped the sales people to sell over 260% more. The value from analytics was gained because the sales people started to change their ways of working to support the data and modeling. If the subject would have been approached data first, Analytics team would have produced deliverables based on the data that they got and the sales people would have either used it or not, but the change in their working ways might not have happened. One important benefit that value based approach to analytics also provides in development projects is the possibility measure the effects of analytics. Like one of the experts said that if one can't measure the effects of analytics they are approaching it wrong.

From the interviews it came very clear that analytics in its nature should be agile and iterative. Reason were argued that when starting to develop analytics and approaching it value first it is inevitable that the process will change and it needs to follow the agile principles where collaboration and communication play significant part. Larson & Chang's (2016) model of agile analytics focuses practically to the first two phases of value chain, data and modeling. The iterations according to them include only data scoping, data discovery, analyzing, modeling, validating and deploying the models. All the experts that were interviewed also agreed that the first two parts of the value chain, data and analytics modeling, are in important role when implementing analytics as the deliverables and analytics products are produced for users. One of the concept that was raised from the interviews was prototyping and building MVPs when developing new models to be used to gain insight. This was seen as essential in order to learn and see what analytics models works for the business problem stated and what data to include in the modeling.

Even though Larson & Chang (2016) acknowledge that the models need continuous reviewing because changes in operation environment might occur they still have traditional way of seeing analytics only as a technological development. Comparing Larson & Chang's (2016) view of agile analytics to the findings from interviews, the most significant difference is that the iterations do not consider only the first two parts of value chain which can be considered the most technologically intensive but iterations should be done throughout the whole value chain. This as mentioned in chapter 8.1.1 is clearly a research gap.

Iterating the whole value chain means according to findings from the interviews that the business problem, actions required to find solution to the problem, decisions that must be made to execute the actions and insight that must be generated are also iterated and continuously evaluated and re-defined along with data and analytics modeling iterations. Because Larson & Chang's (2016) representation of agile analytics focuses only to the first parts of the value chain, their model doesn't handle the capability and organizational aspects of analytics that were presented in Holsapple et al.'s (2014) framework. Approach that the interviewees presented does include these aspects. When evaluating and iterating the whole value chain, it requires to think the whole set of analytics capabilities that were discussed in chapter 4.3 and how to develop them. Capability development and cultural change doesn't happen in one or even multiple iterations but are rather on the background continuously developing as iterations modify working methods and produce new knowledge from previous actions.

The benefits of agile implementation of the whole value chain and not only the first parts of it are similar to the benefits that value based approach to analytics gives organizations. Starting with a business problem for a certain business unit for example scopes the problem, modeling and data for the project which makes the development project smaller and thus easier to manage. Organization doesn't have to produce large data warehouses in big projects that might be hard to implement with agile methods as they build a solution for smaller problem. Agile implementation helps to allocate resources and measure the results more easily than in big projects but also shows the value sooner as readymade solutions are deployed faster than in big projects.

When developing analytics and implementing value based actions to organization there were two approaches: short-term approach and long-term approach. Short-term changes can be implemented through agile implementation where most important changes are directed to changing the ways of working to support analytics. Long-term change, which is starting to be acknowledged in literature and in organizations who are leaders in analytics field, is even more important than the short-term changes that are made. Long-term change enables organization to transform into data and analytics driven organization where they are proactively used to gain competitive edge. Findings from the interviews support the idea of organizational change that needs to happen so that value can be created with analytics. Analytics must not only be new technology that is acquired to organization and expected that using it without changing working ways would provide long-term value.

Organizational change means multiple issues in organizations that affect to it. Aspects like strategy for analytics, capability and skill development, management support, changing decision making processes and working methods, innovativeness of the organization and information management (See Kiron & Shockley 2011, LaValle et al. 2011, Ransbotham et al. 2016). Same issues were mentioned in the interviews conducted to experts as they emphasized especially the strategic change, capability development and improving decision making processes when implementing analytics and creating value from it. In the literature, comparing dynamic capability literature to the analytics experts' views there is similarities between them. The experts didn't mention anything about the paths that are mentioned as a part of the dynamic capabilities. Although not mentioning the term, there were discussions about the maturity levels, which basically tell what choices different organizations have taken to be in certain point in terms of analytics. The paths also have an effect to what kind of road map should be developed to organization. Certain technologies, like legacy systems, or people that have been hired as analytics people dictate how an organization is going to start to make the transformation to become data driven organization.

Positions, which was the second concept of dynamic capabilities, was not discussed in the interviews even though for example financial position dictates also what resources and capabilities organization can put to the analytics development. On the other hand all the experts emphasized that when implementing analytics value first and with agile methods, it's not necessarily that expensive to start doing minor improvements as long as there are enough analytical capabilities to handle the data and modeling. Processes and their importance for implementation of analytics were mentioned often in the interviews. Processes also are important part of the dynamic capabilities. Findings were from the interviews that processes should always be accounted when implementing analytics and creating road map. The example that one expert gave about improving sales by changing the process of the sales men to log their actions more thoroughly is a good example of what kind of impact processes have to analytics. The process change in the example is good representation of dynamic capabilities processes like sensing, seizing, coordinating and integrating. When implementing new processes, people have to learn new ways and co-ordinate their work in new ways to succeed which is the main message of dynamic capabilities but also the experts.

8.2 Summary and conclusions

The objective of this research was to understand how value is created in analytics in organizations and how it can be implemented. In order to understand the context of the study and gain answers for the question a literature review and interviews were conducted for analytics professionals. The results from literature review and from the interviews were combined to answer the main research question:

How is the value of analytic solutions created and implemented?

Four different sub-research questions, which were derived from the main research problem, are answered first to gain insight about the main problem described above in main research question. The sub-questions help us to understand the whole entity of this research and what issues the researcher especially considered when trying to answer to the main research question. The first and the second sub-questions were derived to understand analytics and how value in analytics is seen in theory as there are multiple different terms used and definitions that vary. There is also the relationship between analytics and BI that needed clarification in order to understand how they differ from each other. The second question was relevant to understand how theory sees that what forms the value in analytics and what enables it in organization. Third question helps to understand how analytics are implemented in organizations and what the general process for doing that is. The fourth sub-question is presented in order to understand how the implementation process of analytics and the value aspect is combined to actually gain the value from analytics when implementing it.

How is analytics defined and perceived?

Analytics, having multiple different terms that are used in different contexts e.g. business analytics or big data analytics, can be defined as using data to create knowledge or insight to provide information for decision makers to enable better decision making (Holsapple et al. 2014, Elgendy & Elragal 2014, Lavalle et al. 2011, Watson 2011). The definition is quite broad and does not really explain for example the difference between BI and analytics or the different prefixes used before word analytics. The difference between analytics and BI can be said to be the modeling of the data with statistical, mathematical or with algorithmic methods. So data is not only cleaned, prepared and visualized like in business intelligence but is actually refined with different analytical models. The different prefixes like big data analytics or business analytics tell more about the context where analytics is used by using the same methods everywhere. Holsapple et al. (2014) divided analytics into domain, technique and orientation (see table 2). This division conceptualized quite well all the different aspects of analytics. Yet the division does not give enough information about the whole entity of analytics especially in organizations as it does not take all the organizational aspects into account. Figure 6 gives much broader picture of the whole analytics entity taking aspects like people and processes into account on top of the technology aspects. What figure 6 says is that analytics is not only statistical modeling methods used on top of data solutions but it's rather a part of the organization culture via decision making. Analytics is or it should be part of the processes, culture, capabilities and decisions in organizations. The methods and technologies are just part of the capabilities that the organization has but on top of that analytics should be embedded to everybody's mind as a part of the organization culture and embedded to the processes so that processes are done in a way that data can be gathered from them but also analytics results utilized in processes. Lastly analytics being part of the decisions means that the decision makers understand the results of the analytics and trust to the results and not to their own experience or intuition. This all leads to achieving the goals of analytics according to Holsapple et al. (2014): achieving competitive advantage, supporting organizations strategy, improving organization performance, improving decision making and decision making process, knowledge production, creating value from data.

How is value in analytics created?

The value in analytics is according to multiple researches closely related to the concept of dynamic capabilities in organizations. Dynamic capabilities are according to Teece et al. (1997) capabilities that enable organizations to renew competences, adapt and integrate skills, resources and competencies in order to gain competitive edge. Dynamic capabilities can be seen through three different approaches: processes, positions and paths, which all have an effect to value creation in analytics and especially have an effect in the development process of analytics.

Dynamic capabilities in themselves do not create value in analytics but rather enable it to happen. The value creation in itself happens in the value chain of analytics that is depicted in chapter 4. The value chain consists of five steps starting from the data step, including data acquisition and cleaning for example, moving to insight step where the data is refined with modeling techniques to gain insight from it. The third step is the actual decision step where the insight gained from models are presented to the decision makers and actual decision is to happen based on the presentation. Fourth step is action step that succeeds the decision and the final step is the value step where the value from the actions is finally materialized. The value creation happens in each of these steps along the chain. The differences in outcomes and gained value depend on the execution of each of the steps. The quality of the execution on the other hand is related to the dynamic capabilities of the organization and to the analytics value creation capabilities shown in table 3. Relationship between dynamic capabilities and analytics value creation capabilities is that dynamic capabilities enable organization to recognize and acquire the needed analytics capabilities.

What is analytics implementation process?

The process of implementing analytics in organizations is iterative and agile according to Larson & Chang (2016) and according to the interviewees interviewed for this thesis. All though the process is seen agile in both, literature and by the interviewees, the major difference is the content of the implementation process. Where literature tends to see the implementation process mostly on the technological side as we can see from the figure 9, the professionals interviewed for this thesis extend the scope of the implementation process by including business and organizational phases and aspects to it. Where figure 9 only sees business and IT collaboration as side process, the experts emphasize the importance of business first implementation. The business first implementation process of analytics firstly takes the whole organization into account in analytics like it is pictured in figure six and secondly the starts the whole implementation process by defining the future business state and future state of the analytics in terms of capabilities.

The analytics implementation process shouldn't be just about the data and analyses made during the process but a transformation of the organization in terms of processes and capabilities. By defining future business state where organization want to head with analytics and defining future capabilities and processes it is easier to start transforming organization to become more data driven. Agile implementation process allows organization to learn and try different analytics in different situation but also allows process changes in old processes so that the value from the changes can be seen. Seeing the value in changes again makes adapting to the transformation easier as employees can see that changes provide value and do not happen instantly or in big batches.

New analytics implementation process when comparing to the Larson & Chang's (2016) should take into account all the analytics aspects that figure six depicts but also the value chain of analytics where the technological part is only half of the process but the decisional and action parts play as important role. Iterating the whole value chain in both ways, from value to data and from data to value, is key finding as the value organization wants to achieve should be first defined with the capabilities that are required to achieve it and only then can the data and models be built.

How can value be implemented in analytics process?

The people interviewed for this thesis see the value creation of analytics much like the theory does but point out one crucial difference between their approach and the theory approach. As the normal value creation process starts with the data at first, the experts rather start the whole value chain from Value-step and move their way from value to data in the chain at first. It is a crucial initial step relative to the end result and gained value from the whole process. By starting from the Value-step, the consultants define the whole process in short term and in long term before starting the chain from data to value and actually create the value. In a long term starting from the Value-step organization can define where it wants to be in the future with analytics making them think their capabilities, people, processes and decision that they need to make in order to be there in long term. In short term, starting on the Value-step enables to scope down the value chains steps so that the resources and costs used in each step are reasonable and thus making the results as planned.

The value creation of analytics in the end can be seen from the increased revenue or happiness or whatever measure was set to measure the value in the first place. In short term value is created through solving different business problems with analytics by first defining the value and the steps to achieve it. In long term the value creation should become part of the organization like figure 6 depicts analytics but also the organization should acquire dynamic capabilities depicted in figure 4 to be able to constantly adapt themselves in the markets and use analytics as every day assets to gain competitive advantage. Only by transforming their organization, meaning that people, processes, culture and decision making is changed to support analytics value creation.

8.3 Critical evaluation of the research

This thesis has few issues that affect the results and conclusions drawn from it. These issues are related to the tight timeframe that this thesis was conducted, the subject and theme that the thesis handled, the interviewees that were available in this timeframe and the researchers experience on the subject. Taking these issues into account when reading this thesis helps reader to evaluate the results.

First issue is about the sample size that the interviews were conducted to. The interviews were conducted for two different groups where there were six experts interviewed and three organization representatives from different organizations. The six interviews conducted in Norway can be considered sample wise adequate for this thesis. Although the experts represented same company so their opinions are affected by the company policy but all of them had worked also in other companies in analytics area and still thought similarly about the subject. Therefore the participant bias is not considered as a factor that has significant effect at least on these six interviews. The validity of these interviews is also considered credible as all the interviewees spoke about the subject in same terms and emphasized same issues. Generalizability regarding to the expert interviews can be done as based on the fact that the method that the interviewees are suggesting is in use in their organization and they have used it for different domains and organizations successfully.

The other interview sample was only three persons, who represented different Finnish organizations on different domains. This sample has more issues regarding to validity, reliability and generalizability. The sample size can be considered small which affects to the conclusions that can be drawn from the interviews. The organizations represent different domains so any domain related conclusions can't be made and analytics maturity of the organizations was not mapped, so conclusions about the development of analytics can be hard to draw. Also only one representative was interviewed from each company, which means that the results are based on that one person's opinions and view of the organization. Reliability wise there might be some participant error in the results as they were asked about analytics in the whole organization yet they represented only their own teams and business units. This is why there is also a chance of observer error as some of the answers might have been generalized too much. Generalizability is also an issue that must be considered because of the reasons that were mentioned before. The organizations represent different domains so one can't say based on the answers that the all the organizations in this domain are in same state. Other thing is the nature of the organizations. All of them were big companies with thousands of employees and had long history. This means that there are old structures and for example IT-systems which affect their analytics capability. Comparing the organizations to for example medium or small size companies who don't have legacy system but adequate amount of resources to develop analytics the situation would be completely different.

Because the sample size was small in Finnish organization's sample, the results gained from the interviews are used only to map out the present analytics situation in the organization and assumptions that the organizations represent general large Finnish companies in terms of analytics is made. The main findings and conclusions of this thesis are made from the expert interviews where the sample size is bigger and material more valid and generalizable. Conclusions drawn from the other sample just support the findings of the other.

The literature review conducted in this thesis handles three different theories which are even on their own quite big entities to write about. The literature review was conducted by following Saunders et al. (2009) directions on conducting literature review. Still it can't be said that all the aspects of the theories handled would have been presented. Nevertheless the literature review shows the most relevant theory parts considering the subject of the thesis even though not all the approaches to the subject were presented. Sources cited were all scientifically reviewed or cited by other researchers in their studies. The writer also mirrored the sources contents to the other literature to make sure that the contents of the source were in line with other literature.

The results of this study can be reviewed as credible and valid when taking into account the issues that were discussed above. The main results are derived from the interviews that were conducted to the analytics experts who have tens of years of experience in their subject in different domains. They also acknowledged the approach from literature even though they saw the approach method wrong which means that they have the expertise to evaluate different approaches to analytics and the experience to see what has worked best for them

8.4 Future directions

Multiple future directions for this subject can be derived. The subject of this thesis is very broad because of the organization's and researcher's preferences. This lead to the situation where three major components, capabilities, analytics and agile theories were presented. All of those theories and their relationship to analytics could be studied in a thesis of their own. For example agile implementation of analytics is only starting to rise in scientific literature and the subject is not very well studied in theory or in case studies especially in the project point of view and not the technological point of view. Dynamic capabilities, their development and effects to analytics is another field of study that needs further studies. Especially case studies to provide insight on the concrete actions and measures that can be taken to improve dynamic capabilities would be valuable direction to study.

The importance of company's domain, analytics maturity and legacy pose also interesting opportunities to further study the field and analytics transformation of the organization. It came clear that big organizations are in complete different situations regarding to their analytics capabilities and maturity. Also the domain seemed to affect the development of analytics quite radically as some organizations tend to see their field more dynamic and had developed their capabilities further and some organizations saw their domain much less dynamic.

To take this thesis's subject further case studies could be conducted to see how value first approach to analytics changes organizations and what are the implications of it compared to more traditional approaches to analytics and data where technology and data capabilities play bigger role. The case studies' results could also be compared to the maturity levels or domains of organizations to gain more insight how they affect to this approach and what challenges they pose.

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APPENDIX A: INTERVIEW QUESTIONS

For expert interviews:

- What kind of solutions are you providing?
    - Technical?
    - Managerial solutions?
        - What kind of consulting for management are you usually doing?
        - value chain of analytics?
            - how to create the value`?
- implementing
    - roadmapping?
    - agile?
    - short term change
    - long term change
- capabilities?
    - what are required to become analytics driven organization
    - who are involved?
    - how to do the change?
- What things are you taking into consideration when you are working on an analytics project?
    - Integration to other fields in company?
    - Legal and regulations?
    - Human capital
    - Culture?
    - Management?
- Who are your dealing usually within the companies?
    - CIO?
    - Business people?
    - BI-people?
- What are the most usual problems with the customer?
- Problems on EY side in projects?
- How are you aligning analytics projects to customers strategies.
- Are you identifying different analytical maturities from the customer?
    - Predictive?
    - Prescriptive?
    - Descriptive?
    - how are you communicating these to customer?
- What kind of business challenges are you solving with analytics?
- What are the key obstacles that customers have?
- What kind of process do you have from tending an offer to starting a project?
- What are the key competences that you are providing in Norway?
- How do you differentiate yourselves from competitors in Norway?

For finnish companies interviews:

Tämän hetken tilanne:

- Miten määrittelette tällä hetkellä analytiikan?
- Minkälaisia analytiikan ratkaisuja teillä tällä hetkellä on?
- Millä tavalla organisaationne tukee analytiikan toimintoja?
- Minkälaisia haasteita ja ongelmia teillä on ollut analytiikan kanssa?
- Miten pyritte tällä hetkellä ratkaisemaan ongelmianne analytiikassa?
- Mitkä ovat suurimmat puutteet analytiikassanne tällä hetkellä?
- Onko teillä jonkunlaista analytiikkaan tai datan johtamiseen liittyvää prosessia tai governancea? Jos on niin millainen?
- Mitä asioita toivoisitte analytiikalta nyt tai tulevaisuudessa?
- Kuinka paljon hyödynnätte analytiikkaa lähteenä päätöksenteossa?
- Pystyttekö mittaamaan analytiikkaanne tai sen tuloksia jollain tavalla?

toimintaympäristö ja prosessit

- Millä tavalla näette alanne muuttuvan tulevaisuudessa analytiikan näkökulmasta?
- Minkälaisia implementaatioprosesseja organisaatiossanne käytetään?

Tarve:

- Minkälaisia tarpeita yrityksellänne on tai tulee olemaan tulevaisuudessa analytiikan osalta?
- Kuinka tärkeäksi näette analytiikan lisäksi organisaation kulttuurin ja johtamisen muutoksen data ohjaituvammaksi tulevaisuudessa?
- Minkälaisia hyötyjä tai kustannussäästöjä toivotte saavanne analytiikan kehittämisestä?
- Työkalujen ja ratkaisujen lisäksi minkälaisia muutoksia näette tulevaisuudessa tarvitsevanne organisaationne osalta esim. Johtamisessa tai osaamisessanne?
- minkälaisista asioista koette saavanne eniten arvoa analytiikan ratkaisuista?
- Millä aikataululla näette analytiikan kehityksenne liikkuvan?