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DEVELOPING THE MATURITY OF B2B SALES ANALYTICS IN AN IT CONSULTANCY COMPANY

Master's thesis
Engineering and Natural Sciences
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February 2020

ABSTRACT

Aapo Tanskanen: Developing the maturity of B2B sales analytics in an IT consultancy company
Master's thesis
Tampere University
Master's Degree Programme in Information and Knowledge Management
February 2020

Data-driven culture and more advanced analytics are continuing to get adopted more and more at organizations. However, few organizations are actually very successful at implementing analytics on business operations. Especially, B2B sales analytics is an area which is lacking research contributions and also where practitioners usually do not have tools nor guidance to realize all the benefits. This has been the situation at a medium-sized Finnish IT consultancy company where data and analytics usage have been lacking at the B2B sales. Thus, the objective of this research was to help the case company to realize benefits of the B2B sales analytics by assessing the current situation of the B2B sales analytics at the case company. Analysis and findings from the current situation can then be used as a starting point for improving the B2B sales analytics at the case company. Therefore, a research strategy of this research was a single case study.

Based on the literature review, implementing analytics includes both social and technical aspects at organizations so this research utilized a sociotechnical systems theory as the underlying research perspective. Sociotechnical systems theory emphasises a joint development of both social and technical aspects to create positive outcomes at organizations. Analytics maturity models are known as tools for assessing a relative position of an organization in relation to the different characteristics of the analytics maturity. Thus, the maturity model theory was used to build a conceptual framework for assessing the current B2B sales analytics situation at the case company. Based on the literature review, there is no single existing analytics maturity model which would be an industry standard nor directly applicable to the research problem. Therefore, a customized B2B sales analytics maturity model was created based on another model. The customized model followed the sociotechnical systems perspective by including both social and technical dimensions of the sales analytics maturity. Next, a qualitative data collection was conducted with semi-structured interviews with representatives of the case company.

The results of the research showed that the maturity of the B2B sales analytics is on the low level at the case company. Thus, the case company is on the very early stages of implementing and utilizing B2B sales analytics and there is a great potential for developing the B2B sales analytics maturity on all dimensions. The most prominent findings from the results were that the analytics culture is hindered by a lack of knowledge about B2B sales analytics possibilities, data sharing culture is missing partly due to data governance issues, analytics is not used very much in sales decision making, analytics strategy and roadmap is missing, more advanced analytics tools and techniques are not being used, and analytics is not well integrated into sales processes at the case company. These prominent issues were also commonly found from the literature so they are not unique challenges at the case company. Based on the prominent issues, it was recommended that the case company should focus development into the "Culture" and "Data & Analytics Technologies" dimensions of the maturity model. This research was able to answer all the research questions so it achieved its objectives and was successful. Findings of the research had practical contributions for the case company. For theoretical contributions, this research especially showed the relevancy of using the sociotechnical systems perspective in maturity model assessments at organizations. The research also contributed to the B2B sales analytics research gap. However, this research was a single case study using only one qualitative data collection method so that limits the wider generalizability of the results.

Keywords: data, analytics, sales analytics, B2B analytics, maturity model, analytics maturity, sociotechnical system

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TIIVISTELMÄ

Aapo Tanskanen: B2B myynnin analytiikan kypsyystason kehittäminen IT-konsultointiyrityksessä
Diplomityö
Tampereen yliopisto
Tietojohtamisen DI-tutkinto-ohjelma
Helmikuu 2020

Dataohjautuvan kulttuurin ja edistyneen analytiikan käyttö lisääntyy yhtä enenevissä määrin organisaatioissa. Vain harvat organisaatiot ovat kuitenkin todella onnistuneesti ottaneet analytiikan käyttöön liiketoiminnassaan. Erityisesti B2B myynnin analytiikka on alue, joka on saanut vähän huomiota tieteelliseltä tutkimukselta eikä sen käytännön hyödyntäminen ole helppoa organisaatioissakaan. Tämä tilanne on ollut myös keskikokoisessa suomalaisessa IT-alan konsultointiyrityksessä, jossa datan ja analytiikan hyödyntäminen on ollut heikkoa B2B myynnissä. Tämän tutkimuksen tavoite on auttaa tapausyritystä hyödyntämään paremmin B2B myynnin analytiikkaa sen nykytilan selvityksen kautta. Nykytilan selvitys ja sen tulokset voivat toimia lähtökohtana B2B myynnin analytiikan kehittämiselle tapausyrityksessä. Tutkimus toteutettiin yksittäisenä tapaustutkimuksena.

Kirjallisuuskatsauksen mukaan analytiikan kehittäminen organisaatioissa sisältää sekä sosiaalisia että teknisiä näkökohtia, joten tässä tutkimuksessa käytettiin sosio-teknistä järjestelmäteoriaa tutkimuksen teoreettisena tulokulmana. Sosio-tekninen järjestelmäteoria painottaa sekä sosiaalisten että teknisten näkökohtien yhteiskehittämistä positiivisten lopputulosten aikaansaamiseksi. Analytiikan kypsyysmallit ovat tunnettuja työkaluja organisaation tilan selvittämiseen verrattuna eri analytiikan kypsyyden näkökulmiin. Tässä tutkimuksessa kypsyysmalliteoriaa käytettiin teoreettisena viitekehyksenä, jonka kautta tapausyrityksen B2B myynnin analytiikan nykytilaa selvitettiin. Kirjallisuuskatsauksen mukaan yksikään analytiikan kypsyysmalli ei ole vielä noussut standardiasemaan eikä löydetyt mallit olleet suoraan sopivia tämän tutkimuksen ongelmaan. Tämän takia tutkimuksessa luotiin muokattu B2B myynnin analytiikan kypsyysmalli toisen mallin pohjalta tämän tutkimuksen ongelmaa varten. Muokattu kypsyysmalli sisälsi sekä sosiaalisia että teknisiä myynnin analytiikan näkökulmia sosio-teknisen järjestelmäteorian tulokulman mukaisesti. Seuraavaksi laadullisen tutkimusaineiston kerääminen toteutettiin puoliavoimilla haastatteluilla tapausyrityksen työntekijöiden kanssa.

Tutkimuksen tulosten perusteella B2B myynnin analytiikan kypsyystaso on matalalla tasolla tapausyrityksessä. Tapausyritys on vielä hyvin alkutekijöissään B2B myynnin analytiikan käyttöönotossa ja hyödyntämisessä, joten B2B myynnin analytiikan kypsyyden kehittämisessä on paljon potentiaalia jokaisella kypsyyden näkökulmalla. Merkittävimmät tulosten löydökset olivat, että tapausyrityksessä analytiikan kulttuuria heikentää B2B myynnin analytiikan mahdollisuuksien heikko tunnettuus, datan jakamisen kulttuuri on puutteellinen osittain datan hallinnan puutteiden takia, analytiikkaa käytetään vähän päätösten tukena myynnissä, analytiikan strategia ja kehityssuunnitelma puuttuvat, kehittyneempiä analytiikan työkaluja ja tekniikoita ei käytetä, ja analytiikkaa ei ole kunnolla integroitu osaksi myynnin prosesseja. Nämä merkittävimmät tulosten löydökset olivat myös havaittavissa kirjallisuuskatsauksessa, joten haasteet eivät ole yksinomaan tapausyritystä koskettavia. Merkittävimpien löydösten perusteella tapausyritystä suositeltiin kohdistamaan kehityspanoksia kypsyysmallin ”Kulttuuri” ja ”Data & Analytiikka teknologiat” dimensioihin. Tämä tutkimus kykeni vastaamaan kaikkiin tutkimuskysymyksiin, joten se saavutti tavoitteensa ja oli onnistunut. Tutkimuksen tuloksilla oli käytännön vaikuttavuutta tapausyritykselle. Teoreettisen vaikuttavuuden osalta tämä tutkimus osoitti erityisesti sosio-teknisen järjestelmäteorian olevan merkityksellinen teoreettinen tulokulma kypsyysmalleilla tehdyille selvityksille tapausyrityksissä. Lisäksi tutkimus edisti B2B myynnin analytiikan tutkimusvajetta. Tämä tutkimus oli kuitenkin yksittäinen tapaustutkimus, jossa tutkimusaineistoa kerättiin vain yhdellä laadullisella menetelmällä, mikä rajoittaa tutkimuksen tulosten yleistettävyyttä.

Avainsanat: data, analytiikka, myynnin analytiikka, B2B analytiikka, kypsyysmalli, analytiikan kypsyys, sosio-tekninen järjestelmä

PREFACE

Five years ago, I was sitting in the lecture hall at Tampere University of Technology and starting the very first courses of my university studies. Little did I know where that journey would eventually take me. Now, I can say that Information and Knowledge Management studies have proven to be really relevant and enabled me to, for example, successfully start the work life and spend one year in exchange in one of the top ranked universities in the other side of the world.

This master's thesis project has been a bit lengthy and like a graph of sine wave by sometimes going down and sometimes up. Now, it is finally finished, yay! I would like to thank professors Hannu Kärkkäinen and Leena Aarikka-Stenroos for guiding the thesis and giving feedback. I would also like to thank my colleagues Dr. Eija and Dr. Milla from the case company for their support and advices on this thesis. In addition, thanks Juho for helping me to find the thesis topic, all the colleagues who had time for my interviews, and the case company for enabling me to work and study flexibly at the same time. Last but not least, thanks to my family and friends for all the support throughout the studies and the thesis work.

Tampere, 11 February 2020

Aapo Tanskanen

CONTENTS

LIST OF SYMBOLS AND ABBREVIATIONS

BA	Business Analytics
BDA	Big Data Analytics
BI	Business Intelligence
B2B	Business to Business
B2C	Business to Consumer
CRM	Customer Relationship Management
DS	Data Science
ERP	Enterprise Resource Planning
IT	Information Technology

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1. INTRODUCTION

In this chapter, an introduction to this research is presented. At first, a background and motivation of the research are discussed. Next, a research problem with research questions and objectives of the research are defined. Lastly, a structure of this thesis is introduced.

1.1 Research background

Data and analytics are showing no signs of slowing down and more advanced analytics are continuing to spread to places where it has not existed before at organizations. More and more organizations are embracing a data-driven culture and claim that their business decisions are based on the data and analytics. However, fewer organizations are actually very successful at implementing analytics on business operations and creating competitive advantage from it. Many organizations just focus on reporting key performance metrics based on historical data and use that to justify business decisions while analytics could drive business processes by giving recommendations and even triggering actions automatically. (Sapp et al. 2018.)

Even though B2B (Business-to-Business) sales are roughly equal in the size of the economic value of transactions with the B2C (Business-to-Consumer) sales, B2B sales has only attracted a small fraction of the academic research attention. Especially, B2B sales analytics is one area where is great potential for research contributions. Also, B2B practitioners see large possible benefits of the B2B sales analytics but usually have neither the tools nor the guidance to realize those benefits. (Lilien 2016.)

Also Hallikainen et al. (2019) point out that the B2B sales analytics is a research area that is practically non-existent in the current academic literature. They also comment that there is a lack of knowledge about how the B2B sales analytics can enhance and benefit businesses, and academic research has not managed to provide information for that issue. Thus, there are clearly a research and knowledge gap in the B2B sales analytics area and in the knowledge of possibilities of the B2B sales analytics usage.

Analytics maturity models are known as tools for assessing a relative position of an organization in relation to the different characteristics of the analytics maturity. These analytics maturity characteristics can, for example, include data and analytics strategy, technical infrastructure, processes, governance, people's skills and culture. Analytics maturity models provide a framework for diagnosing the current situation of the analytics implementation at the organization, and also a guidance on how to increase analytics capabilities to the next level. Thus, analytics maturity models can be applied for guiding organizations to realize the B2B sales analytics benefits. (Menukhin et al. 2019.)

This research aims to contribute to earlier presented research and knowledge gap in the B2B sales analytics area by creating a customized B2B sales analytics maturity model to be used as a conceptual framework for assessing the current situation of the B2B sales analytics and guiding its development at organizations. Thus, results of the research can be beneficial for both the B2B academic research and the B2B practitioners.

1.2 Research problem and objectives

As mentioned, data and analytics are spreading also into the B2B sales operations at organizations but there is usually challenges in realizing benefits of analytics implementations. This has also been the situation at a medium sized Finnish IT consultancy company which embraces the data-driven culture and operations. However, data and analytics usage have been lacking behind at the B2B sales unit of the case company. Thus, this research is conducted as a case study for that company with an objective to help them realize possible benefits of the B2B sales analytics. The case company is introduced more in detail in the chapter 6.4.

This research is done to investigate what is the current B2B sales analytics maturity level at the sales unit of the case company by utilizing an analytics maturity model. The analysis and findings of the current maturity level can offer a starting point for improving the B2B sales analytics maturity at the case company. Even though maturity models could also be used to assess the desired future maturity level, that has been decided to be out of the scope of this research. In addition, this research only focuses at the Finnish sales unit of the case company. To address this research problem, research questions are derived:

- What is analytics in the B2B sales context?
- What dimensions are included in the B2B sales analytics maturity model?
- What is the current level of the B2B sales analytics maturity?

It is important to realize that implementing and developing analytics includes both social and technical aspects at the organization (Hallikainen et al. 2019). Thus, this research utilizes a sociotechnical systems theory as the underlying research perspective. On the top of that perspective, a maturity model theory is used to build a conceptual framework which is then deductively used to analyse the current B2B sales analytics maturity level at the case company with qualitative research methods.

1.3 Structure

This thesis is structured as follows. The first chapter is the introduction which presents the research background, research problem and objectives. Next, chapters from two to five cover the theoretical background with a literature review. The second chapter introduces the sociotechnical systems theory which is used as the underlying theoretical perspective in this research. The third chapter covers a review about data and analytics, B2B sales and B2B sales analytics. The fourth chapter introduces the maturity model theory, maturity model development frameworks and a comparison of analytics related maturity models. In the chapter five, customization of the B2B sales analytics maturity model for the conceptual framework of this research is explained.

The sixth chapter presents the research methodology covering from research philosophies to the chosen qualitative data analysis methods. Next, chapters from seven to eight cover the empirical part of the research. In the chapter seven, results of qualitative interviews and current maturity levels are presented. The eighth chapter discusses the most prominent findings of the research reflected with the literature and proposes ways to develop the current maturity levels to higher level. Finally, the ninth chapter summarizes the research, answers the research questions, gives managerial implications, evaluates the research, and presents its limitations and possible future research topics.

2. SOCIOTECHNICAL SYSTEMS THEORY

In this chapter, a sociotechnical systems theory is introduced. At first, a history of the sociotechnical systems theory is explained followed by a description on how the theory can be applied within knowledge work organizations. Lastly, sociotechnical systems theory's usage as a theoretical perspective in a holistic business process analysis is introduced and its selection as the theoretical perspective in this research is justified.

The sociotechnical systems theory is originated from the research by Trist & Bamforth (1951) about an introduction of new machinery in a coal mining industry. The introduction of new machinery into coal mines without an analysis of the related changes in working methods resulted in low productivity in contrary to the expected raise in the productivity. This highlighted a need for considering both the technical and social factors when seeking to promote change within an organization. The emphasis of the sociotechnical systems theory has shifted from an early focus on the heavy industry to a gradual broadening to advanced manufacturing technologies, to office-based knowledge work, to services and also to information systems research. (Appelbaum 1997; Davis et al. 2014.)

The sociotechnical system is based on the premise that an organization is a combination of social and technical parts and that it is open to its environment. The key issue is to design work so that social and technical parts yield positive outcomes. This joint optimization contrasts with the traditional methods that first design the technical component and then fit people to it. Organizations can be considered as complex systems comprising many interdependent factors. Thus, designing a change to one part of the system without really considering how the change might affect, or require change in, other aspects of the system will hinder effectiveness of the change. In addition to the joint optimization, the sociotechnical system is also concerned with the work system and its environment. This involves boundary management which is a process of protecting the work system from external disruptions and enabling an exchange of necessary information and resources. (Appelbaum 1997; Davis et al. 2014.)

Organization as a complex sociotechnical system is illustrated in the figure 1 on the next page. The organization's work system usually has a set of goals and metrics, involve people with different attitudes and skills, using a variety of technologies and tools, working within a physical infrastructure, operating with a set of cultural assumptions, and using variety of processes and working practices. The system sits within wider context including external factors like a regulatory framework, different stakeholders like customers, and a financial environment. The importance and the influence of these external factors varies with each system. For example, a particular regulatory framework could influence the goals pursued by the organization and processes in use. These all different social and technical aspects of the organization are interdependent and thus need to be analyzed together. (Davis et al. 2014.)

Figure 1. *Organizational sociotechnical system with external environment (adapted from Davis et al. 2014).*

The sociotechnical systems theory can be used as a theoretical perspective in a holistic business process analysis and in coming up with development suggestions. For example, the sociotechnical systems perspective was used to analyze company's B2B sales process and improve its knowledge creation and sharing (Bider & Klyukina 2018). Bider & Klyukina (2018) commented that the sociotechnical systems perspective was useful for the analysis of the sales process and it helped creating a holistic view on the situation and understanding the needed changes in a complex system containing both social and technical aspects of the organization.

In this research, the maturity of analytics in the case company's B2B sales unit is analyzed. As presented in the following chapter 3, analytics in B2B sales includes both social and technical aspects. Thus, the sociotechnical systems theory provides a relevant and useful theoretical perspective for this research and its analysis. The sociotechnical systems perspective is integrated in the B2B sales analytics maturity model and its dimensions presented in the chapter 5.2.

3. ANALYTICS IN B2B SALES

In this chapter, analytics, B2B sales and how analytics can be utilized in the B2B sales are introduced. At first, analytics phenomena are explained by defining the most common analytics related terms and how they are used in this research. Next, the B2B sales is described through the sales funnel concept. Lastly, analytics usage in the B2B sales is introduced with examples and also benefits of the B2B sales analytics are covered. These subjects are important for understanding the context of this research.

3.1 Analytics phenomena

Business intelligence (BI) became popular phenomenon in the business and IT communities in the 1990s. Later in the 2000s, business analytics (BA) emerged to represent the key analytical component in the BI. More recently, big data and big data analytics (BDA) have been used to characterize the data sets and analytics techniques in applications that are so large and complex that they require more advanced and unique data storage, management, analysis, and visualization technologies compared to the older BI phenomenon. (Chen et al. 2012.) In the 2010s, data science (DS) has surfaced and data scientist has even been claimed as the sexiest job of the 21st century (Cao 2017). All these terms are quite similar and sometimes even used interchangeably so next, they will be shortly defined for the scope of this thesis.

Business intelligence is a data driven process that can be seen as “an umbrella” term which covers technologies, applications and processes for gathering, storing, accessing and analysing data to help users to make better decisions. In addition to technical elements, business intelligence also requires organizational elements like management support and knowledge management to enhance decision-making processes. (Larson & Chang 2016; Olszak 2016.)

Business analytics is defined as extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport & Harris 2007). Business analytics and business intelligence have been used interchangeably in many publications but business intelligence could be seen to focus more on the measuring the past performance to guide business planning, while business analytics would include the business intelligence and go beyond it by focusing on using sophisticated modelling techniques to predict future events and discover patterns that would lead to better and more effective business decision making. (Chen & Nath 2018.)

Data analytics and big data analytics refer to the theories, technologies, tools and processes that enable in-depth understanding and a discovery of valuable insight into data. In case of big data analytics, the big data is usually described by “three V’s” volume, variety and velocity compared to the traditional data. Volume refers to the huge amount of data, variety is based on the multitude of different types of data sources and formats, and the velocity represents the high speed of data to be generated and the young age of the data. Big data analytics requires more advanced analytics techniques, like distributed data processing, compared to the traditional data analytics. Usually, there are defined three types of analytics: descriptive, predictive and prescriptive. Descriptive analyses the past, predictive uses models based on the past data to predict the future, and prescriptive uses models to specify optimal behaviours and recommends actions based on the data. (Davenport 2013, 2014; Cao 2017.) In addition, sometimes the definition of descriptive analytics is extended by “diagnostic analytics” which tries to answer the question of why did something happen in the past (Sapp et al. 2018; Lepenioti et al. 2020). Therefore, there are four types of analytics: descriptive, diagnostic, predictive and prescriptive.

Data science is the study of an advanced extraction of generalizable knowledge from data with emphasis on predictions, recommendations and discoveries. For example, advanced machine learning models are usually associated with data science. Roots of data science are in the fields of statistics and mathematics but nowadays data science is an interdisciplinary phenomenon combining fields of statistics and mathematics, computer science and business domain knowledge. Data science could be seen as “an umbrella” term which also embodies data analytics and big data analytics. (Dhar 2013; Ayankoya et al. 2014; Cao 2017.)

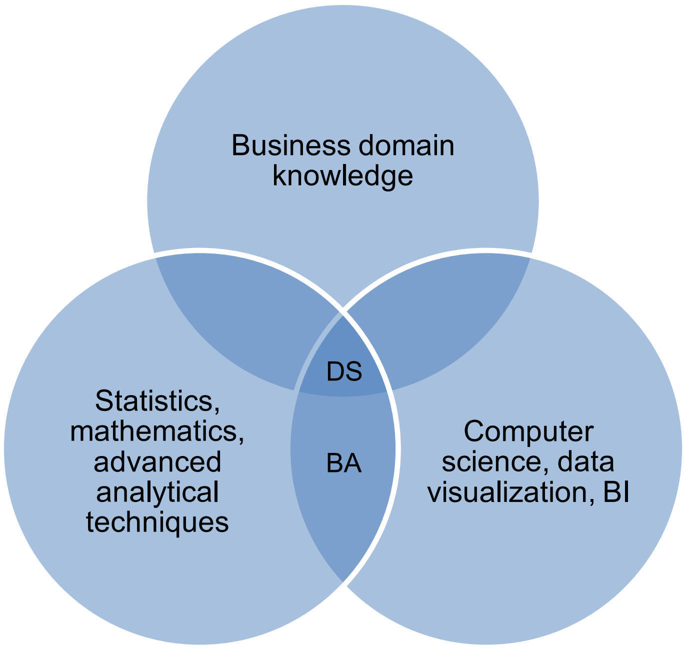

Figure 2. *Relationship between Data Science (DS), Business Intelligence (BI) and Business Analytics (BA) (adapted from Ayankoya et al. 2014).*

As seen from the definitions of business intelligence, business analytics, data and big data analytics, and data science, there are some overlapping parts especially with the business analytics and data analytics. In the scope of this research where the case organization is a medium sized IT consultancy company and the focus is in the sales unit of the company, big data analytics is not applicable since the amount of sales data is not that big. In addition, since data analytics and business analytics are defined very similarly, in this research only the word business analytics is used, and it covers the more advanced analytical methods to predict future events compared to the business intelligence. The relationship between business intelligence, business analytics and data science are also illustrated in the figure 2. In addition, in this research the word “analytics” is used to generally refer to the whole analytics related phenomena containing business intelligence, business analytics and data science.

To conclude, business intelligence has the lowest level of sophistication in terms of advanced analytics, business analytics is more sophisticated and data science is the most sophisticated and advanced analytical phenomenon. Thus, it could be said that the maturity of analytics grows from business intelligence to business analytics and finally to data science which is the highest maturity level.

3.2 B2B sales process

The case company of this research is operating in a business-to-business (B2B) market where the case company offers IT consultancy services for other businesses. B2B sales process could be treated as a production process where series of tightly coordinated activities convert raw materials (i.e. sales leads) into finished goods (i.e. closed sales) which can be illustrated by sales funnel concept (Cooper & Budd 2007).

The sales funnel concept offers a way to describe the customer acquisition process by dividing it into different stages. In other words, the sales funnel categorizes a potential customers base on their purchasing stage. Funnel's stages and their definitions vary from study to study but usually the stages are named as suspects, prospects, leads and customers. Some studies put the prospect stage before the lead and others put the lead before the prospect. (Cooper & Budd 2007; D'Haen & Van den Poel 2013; Järvinen & Taiminen 2016.)

D'Haen & Van den Poel (2013) argue that the first stage of the sales funnel is the suspects stage. Suspects are all potential new customers available. In a theory, they could be every other company in the B2B context minus the current customer base. However, in practice, suspects are a limited list of companies. The next stage is the prospects who are possible customers who meet certain predefined characteristics. The third step is the leads in the funnel. Leads are prospects which will be contacted after they have been qualified as the most likely to respond positively. The final stage of the funnel is the customers. Leads who turn into clients of the company are customers. As in a funnel, at each stage of the sales funnel the number of companies gets smaller.

Järvinen & Taiminen (2016) point out that the sales funnel concept by D'Haen & Van den Poel (2013) is purely designed for the customer acquisition and therefore it ends when the lead is turned into the customer. However, the sales funnel by Järvinen & Taiminen (2016) also includes existing customers who serve as potential targets for repurchasing, upselling and cross-selling. Thus, the sales funnel is a loop that existing customers can re-enter. Because existing customers can be in any stage of the funnel, the final stage called customers is replaced with the word "deals". The looping sales funnel is illustrated in the figure 3 on the next page.

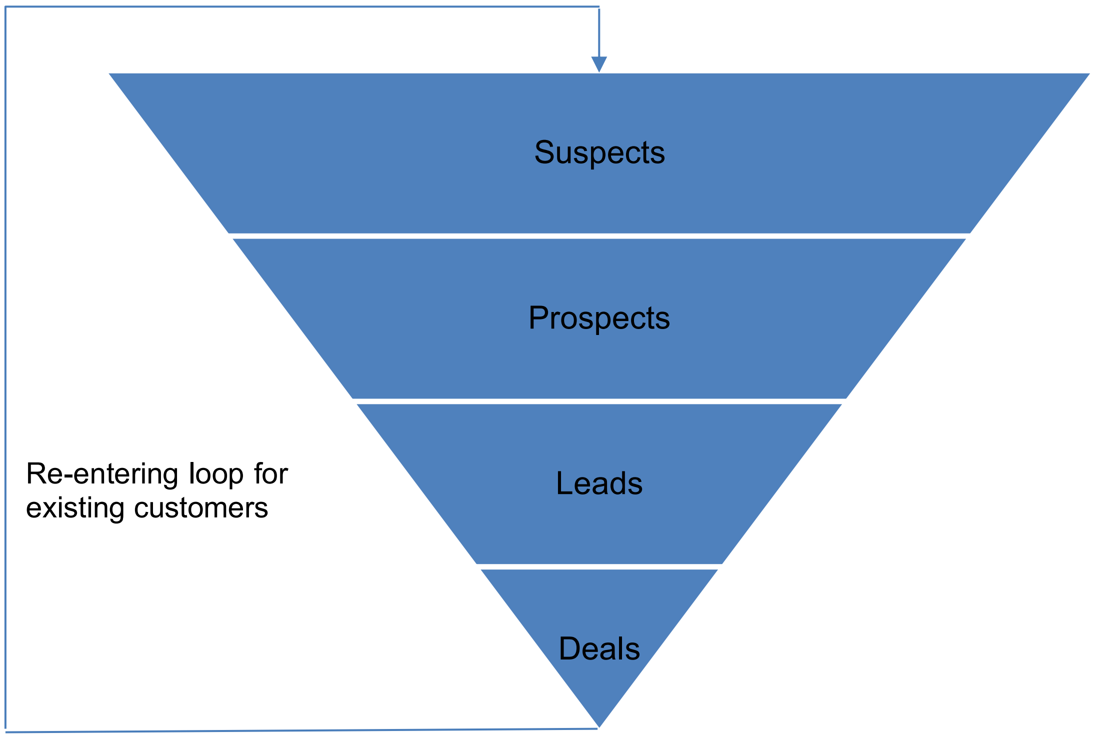

Figure 3. *The sales funnel concept (adapted from Järvinen & Taiminen 2016).*

Järvinen & Taiminen (2016) claim that the number of suspects can theoretically be very large but its size is usually limited by the firm's resources available to search for potential buyers. Also, expanding the pool of suspects excessively could be counterproductive because that complicates the task of screening and selecting prospects from suspects. Prospect selection is considered to be one of the most laborious tasks of the selling process and requires substantial human resources. Thus, B2B sellers are likely to benefit from focusing on quality over quantity in suspects.

Prospect selection is followed by the lead qualification. In this stage of the sales funnel process, the seller aims to identify prospects who offer the highest probability of profitable sales. Objectively determining which prospects are most likely to convert to deals has proven to be very challenging task in the realm of B2B sales. Thus, the lead qualification is usually based on intuition and educated guesses of sales representatives. Mistakes in the lead qualification process result in wasted resources and losses in sales revenue when sales representatives cannot focus on the most profitable leads. (Järvinen & Taiminen 2016.)

Leads are qualified prospects who are approached by the sales representatives but sometimes contacting all leads is an ideal rather than a common practice especially if leads are generated by other departments, like marketing, than the sales department itself. It is argued that several companies constantly lose sales-ready buyers because of a poor follow-up on generated leads. Especially in online leads, the momentum of sales is lost quickly, and those leads require a rapid response. This challenge can be tackled by an effective use of IT tools and by employing new processes to meet the demands of the digital age. (Järvinen & Taiminen 2016.)

3.3 B2B sales analytics

The recent explosion of available customer data has affected B2B firms and they have begun to recognize their access to far richer sources data specific to B2B customer needs, information gathering, interaction and other behaviour which was not possible earlier. Yet, B2B firms might not know what data to collect and what to do with data they have. In addition, most available commercial sales analytics applications and tools are designed to serve B2C firms which makes them difficult for B2B firms to take an advantage of because B2B markets have distinctive characteristics in terms of customers, products and marketing environments. Therefore, the usage of analytics in B2B sales has also been recognized as an emerging research area in the academic sales research. (Lilien 2016; Mora Cortez & Johnston 2017.)

Analytics can be beneficially used in all stages of the B2B sales process and the funnel presented in the previous subchapter 3.2. The presented sales process is part of the customer relationship management (CRM) process which focuses on customer acquisition, retention and expansion (Nam et al. 2019). Usually, data about the different stages of the sales funnel are recorded in a CRM information system and its underlying data warehouse, and that data can be further analysed (Stein et al. 2013; Nam et al. 2019). A common operation model in the sales funnel process with the CRM system can be described as follows: as new sales suspects (the first stage in the sales funnel in the figure 3) are identified, the seller enters these suspects into the sales opportunities in the CRM system. These suspects are further evaluated, and some are qualified into prospects and into leads. All open sales opportunities are tracked in the CRM system and ideally culminating in won deals that generate revenue. (Yan et al. 2015.) This phenomenon of B2B sales analytics with CRM system is illustrated in the figure 4 on the next page.

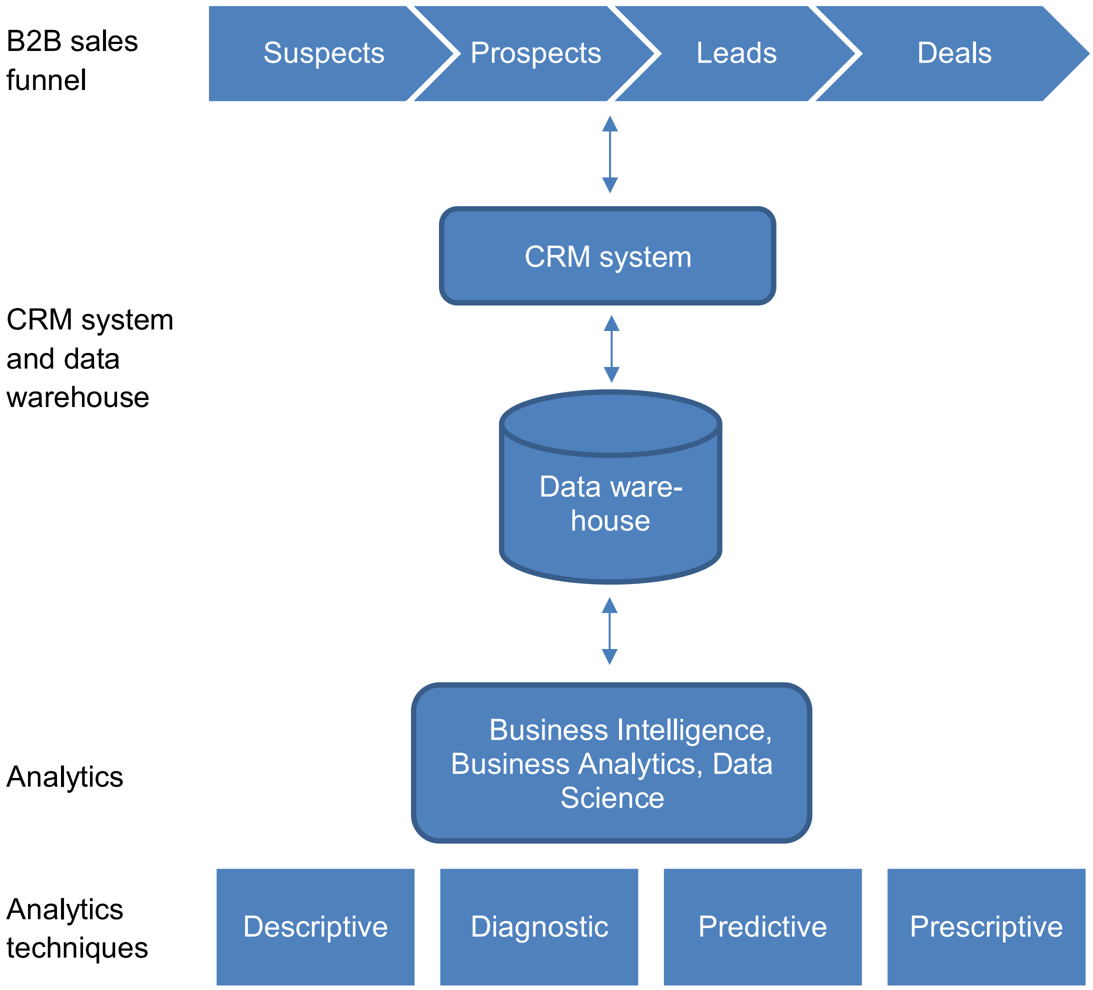

Figure 4. *Analytics in B2B sales with CRM system (adapted from Ngai et al. 2009; Pāvels 2017).*

A fundamental part of the CRM sales funnel quality analysis is the probability of the won lead. Typically, seller enters his own subjective rating towards each of the leads that he owns. However, some sellers can intentionally manipulate the ratings, for example, to avoid the competition from other sellers by underrating or to fulfil management performance targets by overrating leads. Another drawback is that different sellers may have biased personal expectations on different leads. To mitigate all these human prone errors in the lead winning prediction, for example advanced machine learning models have been developed to analyse and predict the probability of winning the lead in the different stages of the sales funnel. In addition, these models can explain which features of the leads contributed towards the predicted results which can help managers and sellers to manage the sales funnel better. (Yan et al. 2015; Eitle & Buxmann 2019.) This kind of sales analytics combines both the predictive and the prescriptive techniques of analytics presented in the figure 4.

Sales leads in the funnel are the lifeblood of the B2B companies, yet deciding which leads are likely to convert into booked meetings is often based on guesswork or intuition. This results in a loss of resources, inaccurate sales forecasts and potential loss of sales. (Monat 2011.) To mitigate these issues, for example a three-staged model containing machine learning techniques like clustering and decision trees, has been developed. (D'Haen & Van den Poel 2013). The model by D'Haen & Van den Poel (2013) outputs an automatically ranked list of prospects from available suspects. Sales representatives could then select the highest ranked prospects to qualify them further into leads. Because the model produces higher quality prospects it is easier for sales representatives to qualify them and convert them into won customers. This kind of model supports the sales representatives in the first two stages of the sales funnel where prospects are selected from the suspects which was also considered to be one of the most laborious tasks in the sales process presented in the previous subchapter 3.2.

In addition to acquiring new customers, also retention of existing customers (i.e. re-entering the sales funnel in the figure 3) is very valuable in the B2B context where selling more for existing customers is not as costly as acquiring new customers. Losing existing customers (i.e. customer churn) is therefore very costly but many companies handle customer churn ineffectively. For example, customers who are likely to churn in the near future are inaccurately analysed and thus sales campaigns and incentives are targeted for customers who do not need them and customers who would need them are missed. To overcome this analytical issue, for example a machine learning model has been developed to more accurately predict churning customers. Such model can help B2B companies to develop more effective, efficient and targeted customer retention campaigns. (Tamaddoni Jahromi et al. 2014.)

Overall, B2B sales analytics enables extraction of knowledge and gaining insights from multiple data sources for enhancing the customer relationship management. With the analytics, organization can generate better personalized product recommendations and offerings, optimize prices, understand the competitive environment and predict future trends. In addition, B2B sales analytics can be used to automatically classify and route customer interactions, and to generate more accurate view of customer behaviour through different channels. Additionally, analytics can facilitate optimization of targeted marketing activities based on real-time information in a timely manner. Thus, B2B sales analytics allows the organization to operate in a lot more customer-oriented way and to create highly personalized customer relationships. (Hallikainen et al. 2019.)

To conclude, the B2B sales allows many different possibilities for different analytics techniques. The use of analytics in the B2B sales can make the sales process more data-driven and effective by diminishing intuition and human errors from sales representatives' decision making. In addition, analytics can offer accurate insights into the past, the present and the future sales for the organization which can enhance the overall decision making and operational efficiency. Hallikainen et al. (2019) showed that B2B sales analytics positively impacts non-monetary customer relationship performance, for example customer happiness, and especially a monetary sales growth.

4. MATURITY MODELS

In this chapter, a maturity model theory, three different maturity model development models and analytics related maturity models are introduced. At first, general maturity model theory, its usage in organization's development and also the criticism of the theory are explained. Next, three different maturity model development models are introduced and compared which can be used to customize a maturity model for this research's conceptual framework. Lastly, description and comparison of existing analytics related maturity models are presented. A customized B2B sales analytics maturity model is used as the conceptual framework in this research so it is needed to understand the maturity model theory, how they can be customized and what kind of existing analytics maturity models are available.

4.1 General maturity model theory

The origins of maturity models date back to 1970's when Nolan (1973) proposed four level stage hypothesis for managing computer resources and Crosby (1979) introduced five level quality management maturity grid. Another highly cited model is the Capability Maturity Model (CMM) for software development processes (Paulk et al. 1993). Thus, the roots of maturity models are in information systems and quality management research fields even though maturity models are nowadays also used in many different fields like project management, process management, public sector and business intelligence (Wendler 2012).

The Oxford English Dictionary describes the word "maturity" generally as "the state of being complete, perfect, or ready; fullness of development" (maturity, n. 2019). Thus, from a linguistic view a model about maturity demonstrates conditions where certain examined object achieves the perfect state for its intended purpose, hence being mature. Fullness of development would imply that the maturity has the final state where further development is not possible anymore. In addition, the maturity can often be measured by object's capabilities which are the powers or abilities to fulfil specified tasks and goals. (Wendler 2012.)

The object, which maturity is examined, can for example be a person, an organization, a function of the organization, a process, a resource or basically anything of interest which is measurable (Kohlegger et al. 2009; Wendler 2012). Maturity models have been developed to assess the maturity of the chosen object based on set of criteria (de Bruin et al. 2005). This set of criteria is usually formed by qualitative or quantitative attributes which classify the assessed object into one of several distinctly defined maturity levels (Kohlegger et al. 2009). Each of these maturity levels form the foundation for the next level so they are brought into a sequential order (Paulk et al. 1993; Kohlegger et al. 2009) as demonstrated in the figure 5 below. The most maturity models have four to seven levels but five is the most common number of levels used in maturity evaluation as in five-point Likert scale (de Bruin et al. 2005; Moore 2014). The first bottom level stands for an initial state where the object is immature, and the last highest level represents the total maturity. Thus, advancing to the next maturity level increases the maturity of the object until the last final level is achieved. (Becker et al. 2009.)

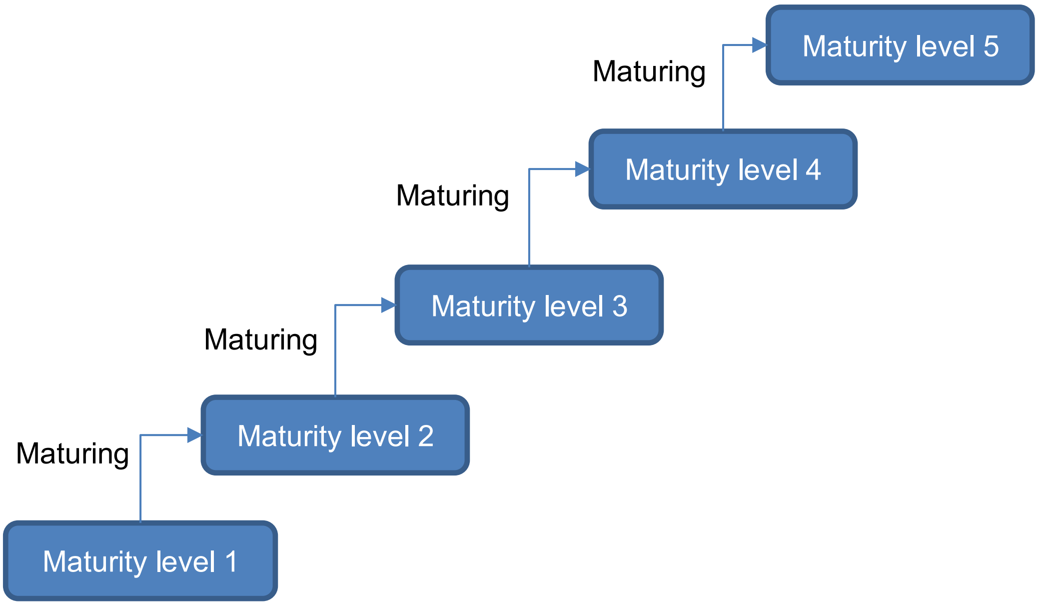

Figure 5. *Five maturity levels, each one the foundation for the next (adapted from Paulk et al. 1993).*

The set of criteria which classifies object's maturity level, can be a one-dimensional or a multi-dimensional. The defined criteria for maturity level measurement can be for example different conditions, processes, people, technologies or targets about the object. Each criteria dimension has different attributes which critically describe the requirements for the dimension's maturity levels. Nowadays, most maturity models are multi-dimensional as demonstrated in the table 1 on the next page where rows represent multi-dimensional criteria about object's maturity and columns represent maturity levels. (Wendler 2012; Van Looy et al. 2013; Moore 2014.)

Table 1. *Multi-dimensional maturity model (adapted from Menukhin et al. 2019).*

	Maturity level 1	Maturity level 2	…	Maturity level X
Criteria dimension 1	Attributes 1.1	Attributes 2.1	…	Attribute X.1
Criteria dimension 2	Attributes 1.2	Attributes 2.2	…	Attribute X.2
…	…	…	…	…
Criteria dimension Y	Attributes 1.Y	Attributes 2.Y	…	Attributes X.Y

Van Looy et al. (2013) writes that the maturity model can assess object's maturity dimensions separately and dimensions can have a different level of maturity at the prevailing time. The total overall maturity can then be determined by for example calculating the average among all different maturity dimensions.

Wendler (2012) argues that there are two different points of views about reaching the final maturity level: a life cycle perspective and a potential performance perspective. In the life cycle perspective, an organization evolves over time and therefore automatically has to go through all maturity levels thanks to organizational learning effects. On the contrary in the potential performance perspective, the maturity model rather shows the potential benefits arising of higher maturity level, but the user can decide whether it is desirable to proceed to the next level or not. According to Wendler (2012), the purpose of the maturity models in both views are principally the same but there are fine differences. The life cycle perspective has a well-defined final level of maturity which will be achieved by evolving time. Potential performance perspective focuses more on the potentially achieved improvements while moving along the maturity levels and the user has to decide by himself which level is the best for the prevailing situation. Wendler (2012) claims that nowadays the most available maturity models follow the potential performance perspective.

The usage of maturity models can be descriptive for explaining the observed changes in the chosen object, prescriptive for guiding maturing of the object to be more effective and efficient, or comparative for benchmarking the object externally or internally (de Bruin et al. 2005; Kohlegger et al. 2009; Röglinger et al. 2012). The model usually represents anticipated, desired or typical evolution path of the object and based on the results of the maturity analysis, recommendations and prioritized development road map can be derived to reach higher maturity level of the object (de Bruin et al. 2005; Becker et al. 2009). Maturity models also provide understanding of the strengths, weaknesses, opportunities, current state, importance and requirements regarding the examined object which can support organization’s decision making (Wendler 2012; Proença & Borbinha 2016). Furthermore, maturity models can serve as a reference frame to implement a systematic approach for organizational improvements, ensure quality, avoid mistakes and assess own capabilities on comparable basis (Wendler 2012).

Maturity models have been subject to criticism. They are claimed to oversimplify the reality and lack an empirical foundation. Models focus on a single maturation path and neglect the existence of multiple different paths which could lead to the same final maturation level. The characteristics of the maturity model may constrain its applicability to use as a standardized version thus requiring configuration for each use case which has led to development of multitude of similar models, sometimes even with a limited documentation. Some maturity models focus too much on the sequential order of maturity levels towards the predefined final state instead of the factors that actually affect the evolution and change. (Becker et al. 2009; Röglinger et al. 2012; Proença & Borbinha 2016.)

It has also been criticized whether the usage of maturity models and improvements in the maturity actually lead to improvements in the organizational capability and performance (Mullaly 2014). Mullaly (2014) writes that maturity models have inherent presumptions embedded into their structure and application, like the assumption that maturity is good and more maturity is better. Another issue is whether maturity models are relevant for the organizations in a sense that they might not even care about the concept of maturity. Thus, an increased organizational performance and positive outcomes of the maturity models are critical issues when investing in developing and using the maturity models.

To mitigate the criticism of maturity models, there are increase in the research from a design process (the way the maturity model is constructed) and a design product (the maturity model itself) perspectives of maturity models (Röglinger et al. 2012). From the maturity models as design products perspective, there are literature dealing with components, qualities and design principles of a good maturity model. As for the design process perspective, there are different procedure models proposed on how to properly design and develop new maturity models which is further discussed in the following subchapter 4.2.

4.2 Maturity model development

The high numbers of developed maturity models over the years have led to certain arbitrariness of the development and design process of maturity models. Thus, there are research focused on the procedures required to properly design and develop maturity models. There are three well-established development models found in the literature which all are introduced in the following subchapters 4.2.1, 4.2.2 and 4.2.3. Models are also compared in the subchapter 4.2.4. (Lahrmann et al. 2010; Röglinger et al. 2012; O'Donovan et al. 2016.)

4.2.1 General development framework by de Bruin et al. (2005)

As presented in the previous subchapter 4.1, the purpose of the maturity model can be descriptive, prescriptive or comparative in nature. De Bruin et al. (2005) writes that those model types can be seen as distinct, but they actually represent evolutionary phases of the maturity model's lifecycle. At first, the model is descriptive so that in depth understanding of the prevailing as-is domain situation is gathered. After that, the model can develop into being prescriptive since deep understanding of the prevailing situation is first needed to make substantial and repeatable improvements and suggestions. Finally, the model can be used comparatively after it has been applied in multiple different organizations to gather sufficient data for valid comparison.

De Bruin et al. (2005) proposes a standard six-step maturity model development framework which forms a sound basis to guide the development of the model through first the descriptive phase, and then the evolution of the model to become prescriptive and finally comparative. This framework and its main phases, as seen in the figure 6, can be applied across multiple disciplines even though some decisions within the phases may vary.

Figure 6. *Maturity model development phases (adapted from de Bruin et al. 2005).*

De Bruin et al. (2005) reminds that the development phases are generic but their order is important. Decisions made in the first scoping phase will impact on the research methods selected to populate the maturity model and how the model can be tested, thus the phase order is sequential. In addition, especially phases "design", "populate" and "test" can be iterative since the results of the "test" phase can indicate a need to re-visit and modify decisions made in the earlier phases.

The first phase in the maturity model development framework by de Bruin et al. (2005) is to determine the scope of the wanted model. Scoping decisions will affect all remaining phases and set outer boundaries for the application and the use of the model. The most important decision in this phase is to select a focus of the model. The focus refers to which domain the maturity model is going to be targeted and applied, and how it will distinguish from other existing models. The focus can be more general or very domain specific. Another important decision is to identify development stakeholders of the model. Stakeholders can for example include people from academia, industry and government.

The second phase is to determine a design or an architecture of the model which forms the basis for further development and application. One of most important decisions is to define an audience of the model. The audience can for example be internal executives or management, or external auditors or partners. After defining the audience, the needs of the audience are reflected in *why* they seek to apply the model, *how* the model can be applied, *who* needs to be involved in applying the model and *what* can be achieved with the application of the model. The why part can mean the driver of the model application which could be internal or external requirement. The how section indicates the method of the model application that could be a self-assessment, a third party assisted assessment or an external certified practitioner. In the who part respondents of the model application are defined who could for example be management, staff or business partners. All in all, it is important to strike an appropriate balance between a complex reality and model simplicity in the design of the maturity model. (de Bruin et al. 2005.)

The third phase is to populate and decide the content of the maturity model. In this phase it is needed to identify what needs to be measured and how that can be measured in the maturity assessment. The goal is to decide domain components and sub-components which can be used to measure the maturity. These domain components refer to dimensions presented in table 1 in chapter 4.1 and sub-components refer to attributes of the dimensions as seen in the table. Identification of the domain components can be attained by a comprehensive literature review and found components from multiple sources can be validated by interviews, for example. If the maturity domain is relatively new it might not be possible to gather sufficient material from the existing literature so other means are necessary to complement the literature review. Sub-components can also be found from the literature, but it is recommended to use exploratory research methods like case study interviews and focus groups to gather more in-depth material to form the sub-components. (de Bruin et al. 2005.)

The fourth phase includes testing both the construct and the instruments of the populated maturity model for validity, reliability and generalisability. The validity of the construct is represented by both face and content validity of the model. It can be assessed by how completely the domain has been represented in the model in terms of, for example, the extent of the literature review. The validity of the maturity assessment instruments, like an assessment survey, need the be tested for the validity and reliability so that they measure what was intended accurately and repeatably. It can be achieved by for example referencing the existing literature and conducting pilot-testing. (de Bruin et al. 2005.)

In the fifth phase, the populated and tested maturity model is deployed to be available for use and to verify the extent of the model's generalisability. The availability of the model depends on the stakeholders identified in the second phase. An initial application of the model will most likely be with the stakeholder where the model was developed and tested which is the first step in determining the critical issue of model generalisability. The generalisability will continue to be an open issue until the model has been deployed in entities independent of the model development and testing activities which is the second step of the model deployment. Model deployment in multiple independent entities can lead to standardisation and global acceptance of the developed model.

The last sixth phase is maintaining the developed maturity model. An evolution of the model will happen as the domain knowledge and model understanding expands and deepens across the users of the model. This evolution should be tracked and documented. The maintenance of the model will be the only thing ensuring the model's continued relevance and acceptance, but it depends on the available resources determined in the initial scoping of the model development. (de Bruin et al. 2005.)

4.2.2 Procedure development model by Becker et al. (2009)

Becker et al. (2009) presented a procedure development model to tackle the criticism presented in the previous subchapter 4.1 about development of multitude of similar maturity models which usually lack a proper documentation about their development procedures and methods. The procedure development model is based on catalogue of development requirements drawn from the design science guidelines in information systems research by Hevner et al. (2004). According to the development requirements, the procedure development model distinguishes eight phases in the development of maturity models which has been illustrated in the figure 7 on the next page. The development model by Becker et al. (2009) aims to provide a sound framework for the methodologically well-founded development and evaluation of maturity models.

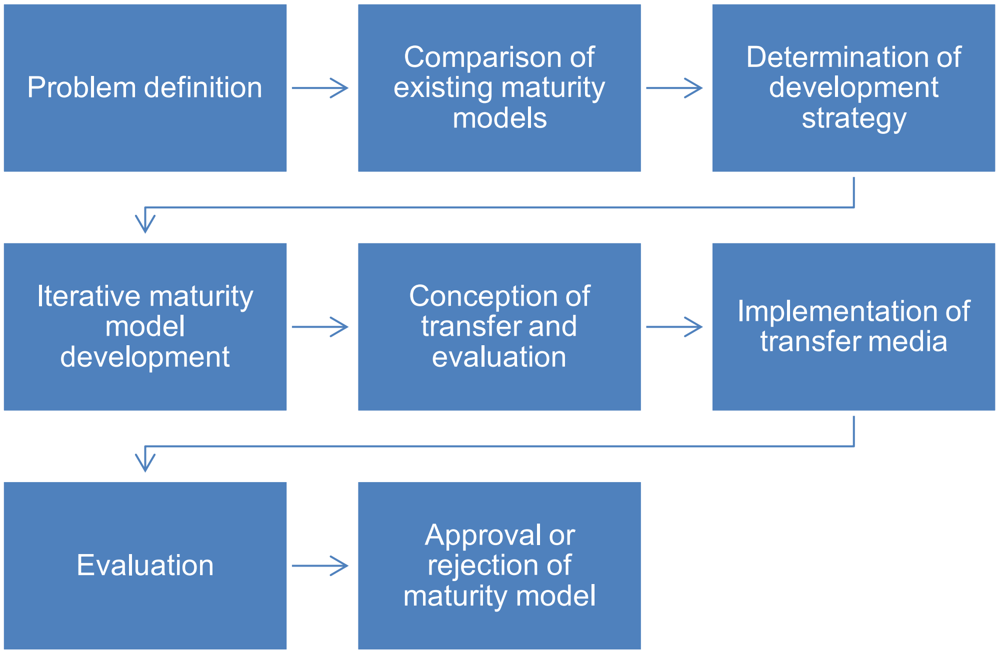

Figure 7. *Procedure development model phases (adapted from Becker et al. 2009).*

The procedure development model starts with the problem definition phase. In this phase, the targeted domain (for example sales analytics) and the targeted user group (for example internal managers or external validators) of the maturity model are defined. In addition, the actual demand for the maturity model must be clearly demonstrated and justified. (Becker et al. 2009.)

The second phase is a comparison of existing maturity models. After defined problem, already existing maturity models which address that problem should be searched. If no existing suitable models are found, then developing a new one is justified but usually shortcomings or lack of transferability of existing models motivate the development of an improved or modified model. In addition, after the development of own maturity model, a publication of new model could motivate comparison and possible incentive to further modify one's own maturity model. (Becker et al. 2009.)

The third phase is determination of the development strategy which should be documented as well. The most important basic strategies are a development of a completely new maturity model design, an enhancement of an existing model, a combination of several existing models into a new one, or a transfer of structures or contents from existing models to new model application domain. (Becker et al. 2009.)

A very central phase of the procedure model is the fourth phase called iterative maturity model development. This phase can be further divided into four different sub-phases: selecting the design level, selecting the approach, designing the model section, and testing the results. In the first selecting the design level sub-phase, the fundamental structure of the maturity model is defined. For example, the structure can be a one-dimensional sequence of discrete maturity levels or a multidimensional model. Also, individual dimensions and their attributes need the be designed. In the second sub-phase, selecting the approach, appropriate methods to design different model sections are selected. A common method is the use of literature analysis to extract maturity assessment criteria from typical developments and success factors of the application domain. Other suitable methods are for example explorative research methods like a Delphi method. In the third sub-phase, the selected model section is designed in accordance with the previously chosen approach and procedure. The last sub-phase is testing the results which means testing the comprehensiveness, consistency and problem adequacy of the designed model. The result of this evaluation will decide whether the maturity model development proceeds to the next major phase or the previous sub-phases will be iteratively performed again. (Becker et al. 2009.)

The fifth phase is conception of transfer and evaluation. In this phase, different forms of result transfer for the academic and the users of the model need to be determined. This means planning how the developed maturity model can be delivered for the end-users of the model and for the academic community. In addition, possibilities for the evaluation of the developed maturity model should be incorporated into the transfer design so that the users of the model could give feedback about the model. The model transfer can, for example, be conducted by a document publication or by some software tool. (Becker et al. 2009.)

The sixth phase, implementation of the transfer media, is meant to make the maturity model accessible in the previously planned fashion for all the defined user groups. A common implementation is a publication of voluminous reports and sometimes self-assessment questionnaires are made available. (Becker et al. 2009.)

In the seventh phase called evaluation, it is assessed whether the maturity model provides the projected benefits and an improved solution for the defined problem. A comparison of the defined goals and real-life observations should be carried out. This could be done by conducting case studies or by, for example, making the model accessible on the internet for free access to gather data for evaluation. Thus, this phase is about empirically validating the practical relevance of the developed maturity model. (Becker et al. 2009.)

The last phase is approval or rejection of the model. The outcome of the previous evaluation phase may validate the model to be relevant and be left as is to the public, or the model could be required to be re-designed so the development should be started iteratively again from the first problem definition phase, or just modified re-evaluation is needed for the model. Another possible outcome of the evaluation is that the maturity model is not relevant, and it should be rejected and be purposefully taken off the market. (Becker et al. 2009.)

4.2.3 Phase development model by Mettler (2009)

To mitigate the criticism of maturity models presented in the previous subchapter 4.1, Mettler (2009) presented a phase development model for designing theoretically sound and accepted maturity models. The model is based on the work of de Bruin et al. (2005) as presented in the earlier subchapter 4.2.1, and it also utilizes the design science research like the procedure development model by Becker et al. (2009). Mettler (2009) argues that the development and the application of the maturity model are intimately interconnected so they should not be reflected separately. Thus, Mettler proposes a phase model for both, the development and the application of the maturity models, which is illustrated in the figure 8 below.

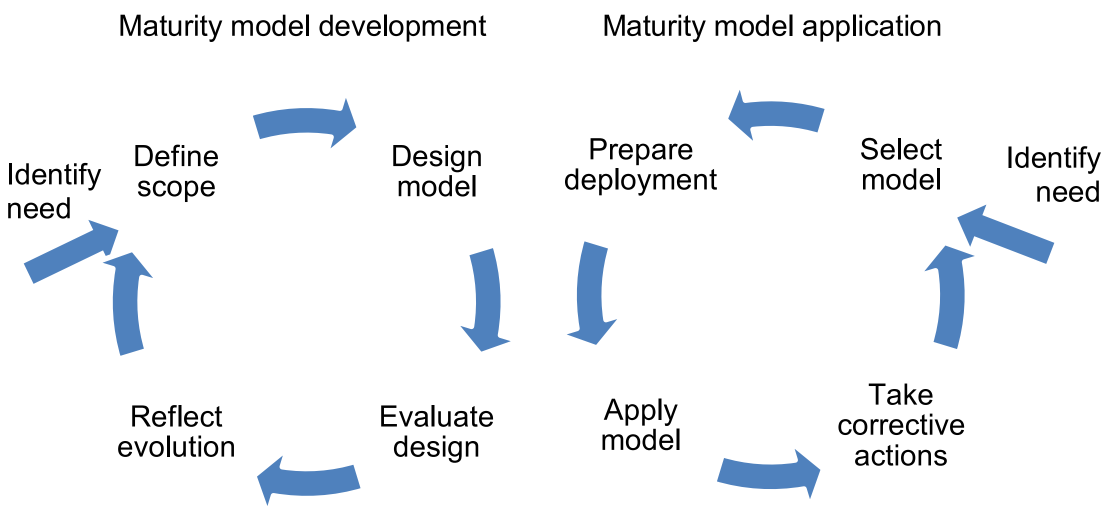

Figure 8. *Phases of maturity model development and application (adapted from Mettler 2009).*

After identified a need for developing a new maturity model, the first actual phase in the development model is defining scope where the most important design decisions are made. First, the focus of the maturity model is set. The focus can be general or more specific subject matter. Second, the level of analysis is decided whether it is done in a particular department of the organization, on the organizational level, collaboratively on the inter-organizational level, or on more global and societal level. Next, the audience of the model is considered since it can be targeted for management-oriented people, technology-oriented people or both. Also, the novelty of the subject, whose maturity is being assessed, is determined whether it is emerging, pacing, disruptive or mature which can affect the design of the maturity model and its utilization. Lastly, the dissemination of the model is decided since it can be open or exclusive access only. (Mettler 2009.)

In the second phase called design model, the actual maturity model is built. This phase is highly influenced by the choices made in the earlier made definitions, and especially by having a clear understanding of what is meant by maturity in the specified focus of the model. The model could, for example, be process-focused, object-focused or people-focused which all will have different ways how the maturity is being progressed. Also, it is important to discuss whether the progress of maturity is one-dimensional or multi-dimensional. In addition, the nature of the design process needs to be determined whether it is, for example, a theory-driven or a practitioner-based or a combination of both. This decision will also affect the choice of the research methods to be used. For example, the research method could be a literature review for theory driven design process or focus group discussions for practitioner-based design process. These choices will determine the scientific and practical quality of the resulting maturity model. (Mettler 2009.)

Third phase is the evaluate design phase which is concerned with the verification and validation of the designed maturity model. The verification is a process of determining that the maturity model represents the conceptual description and specifications with satisfactory accuracy. The validation is about the degree to which the maturity model is an accurate representation of the real world from the perspective of the planned use cases. For example, it is possible to evaluate the design process (the way the maturity model was constructed) or the design product (the maturity model itself). It is advised to do both evaluations to especially mitigate the criticism on the rigour of maturity models. (Mettler 2009.)

The last phase is called reflect evolution phase. This phase is often neglected but important for the longevity of the developed maturity model. Maturity of the focused phenomenon is usually growing and therefore the model’s solution stages and improvement activities need to be refaced from time to time. For example, there could appear a need to modify requirements for reaching a certain maturity level due to the development of new best practices and technologies. Thus, the mutability of the maturity model should be considered and determined whether the evolution is a non-recurring or continuous matter and if modifications can be openly activated by model users or exclusively by the original developer of the model. (Mettler 2009.)

Mettler's (2009) phase development model also covers the application of the maturity model which starts with the business need since application of the maturity model requires resources. The first actual phase is the select model phase which starts by searching potentially applicable maturity models with regard to the identified business need. Search criteria can include things like the origin of the model (for example academia or practice), reliability (how well the model has been evaluated), accessibility (free for use model or not) and the method of application (for example self-assessment or external certified professionals). Ultimately, all the decision criteria would yield to a suitable maturity model match.

The next phase is the prepare deployment phase. In this phase it is crucial to find a potential sponsor or responsible person for the maturity assessment with the selected model. In addition, it needs to be determined whether the assessment is rather informal or formal, corresponding application area of the organization must be decided and assessment respondents located. (Mettler 2009.)

The third phase is called apply model phase where two basic decisions are identified. First, should the maturity assessment really be conducted, and second, how many times it should be executed. After that the assessment is done by the maturity model's specifications. The final phase is the take corrective actions phase where assessment results are critically reflected. For example, it has to be decided whether the progress on maturity should be coupled or uncoupled of the regular development initiatives of the organization, and whether the implementation of the identified improvements activities can be done on the fly or a specific project is needed, and who is responsible to carry out the corrective actions in the organization. (Mettler 2009.)

4.2.4 Conclusion of development models

Maturity models have been criticized to emphasise too little the testing of the models in terms of validity, reliability and generalisability, and on the little documentation on how to develop and design maturity models. In addition, some models have lacked on proper theoretical foundations. To tackle these points of criticisms, de Bruin et al. (2005) was one of the first ones to introduce a maturity model development framework for developing sound maturity models. Since then, Mettler (2009) has built a development model based on the work of de Bruin et al. (2005) and expanded it with the design science research theories. In addition, Becker et al. (2009) proposed a development model which also utilizes design science research guidelines in information systems. Common steps in all of the development models and comparison of the individual models are presented in the table 2 on the next page.

Table 2. *Comparison of maturity model development models (adapted from Mettler 2011).*

Common steps in the development models	Model by de Bruin et al. (2005)	Model by Becker et al. (2009)	Model by Mettler (2009)
1. Identify need or new opportunity		Specify problem	Identify need and specify problem domain
		Compare existing problem solutions	
2. Define Scope	Define scope of model application and use	Define development strategy	Define scope of model application and use
3. Design model	Design model structure and deployment method	Develop model structure	Identify operationalisation measures
		Specify deployment and evaluation method	Implement deployment and evaluation method
	Populate model structure	Implement deployment measures	Apply model
4. Evaluate design	Test model structure	Evaluate deployment measures	Evaluate model structure and deployment method
5. Reflect evolution	Deploy model		Synthesis of design and continuous learning
	Maintain the model's growth and use		

As seen from the table 2, there are five common steps in the development of rigor maturity models: identifying the need for the model, defining the scope of the model, designing the model, evaluating the design of the model, and reflecting the evolution of the model.

4.3 Analytics related maturity models

Since the emergence of analytics and business intelligence, dozens of analytics related maturity models have been developed (Lahrmann et al. 2010; Olszak 2016). One of the earlier analytics related models was a data warehousing maturity model developed by Watson et al. (2001) and after that different models have been developed both by commercial organizations like SAS and Hewlett-Packard, and by academic researchers (Lahrmann et al. 2010). According to Olszak (2016) and Chen & Nath (2018), other notable analytics maturity models are TDWI's business intelligence maturity model (Eckerson 2009), Gartner's maturity model for business intelligence and performance management (Rayner & Schlegel 2008) and a model for analytical competition (Davenport & Harris 2007).

The three-level multidimensional model by Watson et al. (2001) and the TDWI's six-level multidimensional model (Eckerson 2009) are both focused on more technical aspects of the analytics. Thus, they have been criticized to neglect other softer maturity affecting aspects like people, strategy and organizational structure (Lahrmann et al. 2010). Furthermore, maturity model by Watson et al. (2001) is one of the only technologically focused models which is theory based (Lahrmann et al. 2010) but none of the technology-focused models have really been empirically validated to demonstrate the connection between analytics maturity and successful analytics outcomes for the organization (Chen & Nath 2018).

Gartner's five-level multidimensional model (Rayner & Schlegel 2008) and the five-level multidimensional model by Davenport & Harris (2007) are more organizational focused analytics maturity models. These organizational focused models emphasise the importance of identifying business drivers, developing analytics oriented organizational environment and creating strategic alignment between the analytics and the business (Chen & Nath 2018). Chen & Nath also address that organizational focused models offer higher-level assessment of the organizational analytics maturity rather than more localized or functional area of maturity assessed in the technologically focused models. However, a reliability of the Gartner's model hasn't been documented and its application needs a third-party assistance which is usually the case with practitioner developed models (Lahrmann et al. 2010).

In addition to the technologically and organizationally focused analytics maturity models, there are also notable models focused on analytics capabilities and impact. According to Chen & Nath (2018), the most notable capability focused model is the business analytics capability maturity model (BACMM) developed by Cosic et al. (2012). The five-level multidimensional model consists of four capability areas including governance, people, culture and technology. These capability dimensions are further broken down into 16 low level analytics capabilities covering widely strategic, organizational and technical issues. BACMM is based on the resource-based view theory (Cosic et al. 2012) which proposes that organizational capabilities and resources are the basis of gaining sustainable competitive advantage (Barney 1991). However, BACMM hasn't been thoroughly empirically tested to validate its claim that the presented 16 capabilities would actually lead to value and sustainable competitive advantage. Furthermore, BACMM has been criticized to be general model since it tries to be comprehensive but that has caused it to compromise its uniqueness to the area of analytics. (Chen & Nath 2018.)

Chen & Nath's (2018) justified criticism of the original BACMM (Cosic et al. 2012) did not take into account that Cosic et al. revised their original BACMM later on their newer business analytics capability framework (BACF) focusing on the criticism of the original model (Cosic et al. 2015). On the newer paper, BACF was developed in two phases. First, a conceptual framework was developed based on the resource-based view theory and a thematic content analysis of the analytics literature. Second, a Delphi study was used to refine and empirically validate the framework structure, components and capabilities. Thus, the BACF is both theoretically grounded and empirically validated to also be practically relevant analytics maturity model. (Cosic et al. 2015.)

Analytics maturity models focused on the impact emphasize more the impact of the analytics to the organizational performance and decision making (Chen & Nath 2018). Teradata's data warehouse and business intelligence maturity model by Miller et al. (2011) utilizes five maturity levels: reporting (what happened?), analyzing (why did it happen?), predicting (what will happen?), operationalizing (what is happing?), and activating (make it happen) to highlight the impact of the analytics on the business processes and organizational performance (Olszak 2016). Another notable model is the impact-oriented business intelligence maturity model by Lahrmann et al. (2011) which was empirically validated to demonstrate positive organizational impact from the deployment and the use of an analytics technology (Chen & Nath 2018). The positive impact was measured by internal process efficiency and organizational performance. The model suggested that measuring the performance of areas that are most impacted by analytics is a crucial aspect when assessing the analytics maturity of the organization. (Chen & Nath 2018.)

Another impact related analytics maturity model has been published very recently by Menukhin et al. (2019) who claim that the existing analytics maturity models tend to focus on the descriptive use of the maturity models rather than on the prescriptive use. They also emphasize the importance of an analytics-business alignment for achieving high analytics maturity. Thus, they developed an analytics maturity model which is influenced by the IT-business alignment literature and covers both the descriptive and especially the prescriptive usages of maturity models. The model was also empirically validated to be practically relevant in the case study organization and some external organizations.

Overall, analytics maturity models tend to have from three to six maturity levels yet most commonly five levels. Models usually have some focus in assessing the maturity of the analytics, for example technology, organization, capabilities or impact, rather than covering the entire domain comprehensively (Chen & Nath 2018). Models are often multidimensional and classic information technology topics like applications, data and infrastructure are highly present, while topics like costs, organizational structures, people and strategy are less addressed (Lahrmann et al. 2010). However, newer models cover also more of those organizational dimensions like strategic alignment, top level sponsorship, analytics talents, performance management and impact (Chen & Nath 2018). Different dimensions of previously introduced analytics related maturity models are compared in the table 3 below.

Table 3. *Comparison of dimensions in different analytics maturity models.*

Dimension	Watson et al. (2001)	Eckerson (2009)	Rayner & Schlegel (2008)	Davenport & Harris (2007)	Cosic et al. (2012)	Miller et al. (2011)	Lahrmann et al. (2011)	Menukhin et al. (2019)
Analytics applications and technologies	X	X	X	X	X	X	X	X
Architecture and infrastructure	X	X			X	X	X	X
Data governance	X		X		X	X	X	X

Culture		X	X	X	X			X
Impact	X	X	X			X	X	
Organizational structure			X					
Processes				X				X
Skills	X			X	X		X	X
Strategy				X	X			
Users	X				X		X	

Regards the origin of analytics maturity models, there is a mixture of models from academia, from practice, and from a grey area between. Especially, the practice originated models are not documented very well, and their development process and structure remain unclear. In addition, many models lack verification of their reliability and empirical validation of their content. Therefore, the relationship between analytics maturity and organizational success cannot be assessed effectively with some models. An important part of the reliability is the theoretical foundation of the model, but many models suffer from a poor theoretical foundation. Finally, it seems like that no single analytics maturity model has yet reached the state of an industry standard like in some other fields. (Lahrmann et al. 2010; Chen & Nath 2018.)

5. CUSTOMIZED B2B SALES ANALYTICS MATURITY MODEL AS CONCEPTUAL FRAMEWORK

In this chapter, a customization process and a customized B2B sales analytics maturity model are introduced. At first, the customization of the existing maturity model following the development model by Becker et al. (2009) is explained. Next, the final customized maturity model is described by defining its dimensions and maturity levels. This customized B2B sales analytics maturity model is used as the conceptual framework in this research so it is important to understand how it was build.

5.1 Customization process

As presented in the analytics related maturity model comparison in the previous chapter 4.3, there is no single theoretical analytics maturity model which would be an industry standard. In addition, since this research is a holistic single case study in the quite unique case organization, a customized B2B sales analytics maturity model is needed to get practically relevant results for this research.

Three well-established maturity model development models were introduced in the previous chapter 4.2 which could be used to create the customized B2B sales analytics maturity model. The development model by Becker et al. (2009) is chosen to be applicably used in the scope of this research. Next, a development process of the customized B2B sales analytics maturity model is presented following the development phases of Becker et al. (2009) as introduced in the chapter 4.2.2.

The development model by Becker et al. (2009) starts with the problem definition phase. The problem in this research is to get an analysis of the current B2B sales analytics maturity level at the case organization. Information about the current level could be then utilized to create a focused future analytics development plan to increase the sales analytics maturity at the case organization. Thus, the target domain of the needed maturity model is the B2B sales analytics, and the target user group is case organization's sales development people and the sales unit as a whole.

The second phase is the comparison of existing maturity models where already existing maturity models suitable for the defined problem need to be searched. This was already done in the previous chapter 4.3. There was not found any existing sales analytics maturity model which would really well fit the unique case organization's problem in practice. There were couple promising maturity models, like models by Menukhin et al. (2019) and Cosic et al. (2015), but as Becker et al. (2009) state, usually existing models have shortcomings and lack of transferability for specific problems which justifies the development of the customized maturity model.

The third phase is the determination of a development strategy for the maturity model. Since there were found promising existing maturity models in the previous phase, the development strategy is chosen to be an enhancement of the existing model. The analytics maturity model by Menukhin et al. (2019) is chosen to be enhanced to fit the problem of this research. The model was chosen because it is very recently published so it would be more relevant for the recent analytics developments, it also emphasizes the prescriptive usage of the maturity models in addition to the descriptive usage, and it has been originally developed to address a case organization's problem of sales analytics which is very similar with the problem of this research.

The fourth phase is the iterative maturity model development which in this case means customizing the existing maturity model. The approach for the customization had three stages. First, the author customized the existing model based on other existing models and literary in addition to the knowledge about the case organization. Next, the customized model was discussed and tested in a workshop with the case organization's sales development representatives. Lastly, final modifications to the customized model were made according to the workshop and its feedback. The customized sales analytics maturity model is introduced more in detail in the following chapter 5.2.

The fifth phase is the conception of transfer and evaluation which means determining how the developed maturity model is delivered for the end-users and for the academic community with a possibility for further evaluation. In the scope of this research, it was determined that this published thesis is the chosen transfer media to make the developed model publicly accessible. This also fulfills the following sixth phase which is the actual implementation of the transfer media.

The seventh phase is the evaluation of the developed model whether it provides valuable results for the defined problem. The evaluation can be executed, for example, by an empirical case study like in this research. The eighth phase is the approval or rejection of the developed model according to the outcome of the seventh phase. Results of both the seventh and the eighth phases are discussed more in the chapter 9.1.

5.2 Customized B2B sales analytics maturity model

The original maturity model by Menukhin et al. (2019) has five maturity levels and six different dimensions so it is a multidimensional model. Five maturity levels are named as “Initial”, “Committed”, “Focused”, “Managed” and “Optimised”. Six dimensions are “Organisation”, “IT & Analytics Infrastructure”, “Analytics Processes”, “Skills”, “Governance”, and “Data & Analytics Technologies”. Each dimension and maturity level have specific defined attributes.

The model customization started with the maturity level names. The number of levels were deemed to be relevant but their names were not so self-explanatory. Thus, names were changed to correspond to the types of analytics techniques presented in the chapter 3.1 which usually are also seen as different maturity levels of analytics. Customized maturity level names are following: “Initial”, “Descriptive”, “Diagnostic”, “Predictive”, and “Prescriptive” so that the “Initial” is the lowest level and the “Prescriptive” is the highest level.

Original dimensions of the maturity model deemed to have a good mix of both social and technical aspects which are needed according to the sociotechnical systems theory perspective of developing the B2B sales analytics maturity in this research as presented in the chapter 2. Comparison of dimensions included in different analytics maturity models in the table 3 in the chapter 4.3 also shows that the model by Menukhin et al. (2019) includes all of the most common dimensions. However, the “Analytics Processes” dimension was decided to be left out because it was not seen so relevant for the case organization and also there was a little overlapping with the “Data & Analytics Technologies” and the “IT & Analytics Infrastructure” dimensions. Thus, the process view of analytics maturity was added especially into the “Data & Analytics Technologies” dimension where integration of analytics into the sales processes and delivery process of analytics are assessed. In addition, the “Organisation” dimension was renamed into “Culture”. Otherwise, dimensions were kept as original.

In the sociotechnical systems theory perspective, customized dimensions include two clearly social dimensions: “Culture” and “Skills”, and two clearly technical dimensions: “IT & Analytics Infrastructure” and “Data & Analytics Technologies”. The dimension called “Governance” is a bit both social and technical. Thus, there is a good balance between the social and the technical aspects in the customized maturity model. Customized maturity levels and dimensions are illustrated in the table 4 on the next page.

Table 4. *Customized maturity levels and dimensions.*

	Initial	Descriptive	Diagnostic	Predictive	Prescriptive
Culture					
Skills					
Governance					
IT & Analytics Infrastructure					
Data & Analytics Technologies					

Definitions of the dimensions and attributes regards what it means to be in the certain maturity level in the certain dimension needed most customizing so that they fit with the case organization and the problem of this research. Next, those customized definitions are presented for every dimension and their maturity levels.

Culture: Defines to what extent the organisational strategy, culture, attitudes and leadership support analytics initiatives. Demonstrates the support and awareness of the benefits of the use of analytics across the organization. Is analytics used in everyday decision making?

Initial: No analytics awareness, negative attitudes towards analytics, gut decision making in sales, no data sharing culture, no shared situational awareness, organizational siloes exists.

Descriptive: Consideration of analytics benefits, ad-hoc simple analyses of past are used in sales decision making, gut feeling still mostly affects decision making.

Diagnostic: Identified problems to solve with analytics (why something happened?), more advanced reports of past used in sales decision making, data is commonly shared in the sales unit.

Predictive: Sales analytics strategy exists, growing culture and support for analytics, decisions are mostly based on data analysis, future predictions are commonly made from data analysis, data is shared in whole sales unit.

Prescriptive: Analytics is strategically critical for sales, decisions are made based on all available data and recommendations from analytics, effective data sharing across whole organization, prescriptive analytics is guiding the work in sales.

Skills: Demonstrates what level of data and analytics skills exist in the organisation to work with current and future sales analytics technologies. Assesses practices such as training and skills development as well as capability for learning. How capable are people to do and utilize sales analytics?

Initial: Beginner level, skills to do very basic graphs with Excel, no interest to learn more analytics skills.

Descriptive: Excel skills used to analyze past and visualize data effectively, willingness to learn more skills.

Diagnostic: Skills to do analytics with business intelligence applications, can create some business value from data analysis, actively learning more skills.

Predictive: Skills to do analytics reports and dashboards effectively with business intelligence applications, can create some predictive analytics for decision making.

Prescriptive: Advanced analytics skills, data science skills in addition to business intelligence application skills, can make automated dynamic reports effectively, data can be turned into very useful and guiding prescriptive information with a lot of business value, enthusiastic about learning analytics skills.

Governance: Demonstrates the level of data governance and management at the organization. Assesses needed data for sales analytics, availability of the data, usability of the data and ownership of the data. How is data governed to support sales analytics?

Initial: No data management strategy nor real governance, no easy access to data, no data ownership, very poor data quality, data management processes are not thought of.

Descriptive: Governance is fragmented, processes for data management are somewhat existing, data quality is somewhat poor and requires manual cleaning for analytics, data is accessible.

Diagnostic: Governance on sales unit level, named data ownerships, data quality good enough for diagnostic analytics with business intelligence applications, quite easy access to all data.

Predictive: Strategic data governance, processes for data management and ownership exists and are followed, data quality enables more advanced predictive analytics.

Prescriptive: Full data governance and management strategy on organizational level, governance used routinely to create value, very high data quality which enables predictions and recommendations with prescriptive analytics, all data is very easily available when needed.

IT & Analytics Infrastructure: Defines the level of suitability of the IT infrastructure, systems and their development to support sales analytics. Assesses how data is gathered into the systems, how existing systems support sales analytics and how those are being developed in the future. How do information systems and architecture support sales analytics?

Initial: IT infrastructure does not support sales analytics, existing information systems but no integrations, data is in siloes between systems, sales data is not gathered effectively, information systems and infrastructure are not being developed.

Descriptive: Information systems support basic sales analytics, data is mostly in siloes between systems but some integrations between systems, sales data gathering is mostly manual process, some plans for information system and infrastructure developments.

Diagnostic: Information systems support more advanced sales analytics, little data siloes, sales data gathering is somewhat automated, concrete plans and development of information systems and infrastructure.

Predictive: Information systems support effective predictive sales analytics, no data siloes, common data warehouse exists for sales analytics, consistent and mostly automatic sales data gathering, active development of information systems and infrastructure.

Prescriptive: Information systems support advanced prescriptive sales analytics, sales data gathering is as much fully automated as possible and part of sales processes, really strategic development of information systems and infrastructure.

Data & Analytics Technologies: Demonstrates how advanced the organization is in the use of analytics technologies, tools and techniques. Assesses what kind of analytics technologies are used, how analytics are used and delivered, and how integrated analytics is with the sales processes. How mature sales analytics technologies are utilized?

Initial: No real analytics technologies are used, not much analytics being done at all, analytics is totally separated from sales processes.

Descriptive: Mostly Excel based analytics is used with some visualizations and graphs, simple analytics about the past is being done, analytics affects little bit sales processes, analytics tools are manual.

Diagnostic: Business intelligence applications are used with analytics dashboards, no common unified analytics tools, a bit more advanced analytics is being done, analytics is somewhat integrated with the sales processes, some automated analytics tools are in use.

Predictive: Common business intelligence application is used, advanced predictive analytics is being done, analytics is mostly integrated with sales processes, automated analytics dashboards are commonly used.

Prescriptive: Advanced data science technologies are used, prescriptive analytics is being done, analytics is fully integrated and critical part of the sales processes, automated guiding and recommending analytics is used.

6. RESEARCH METHODOLOGY

In this chapter, a research methodology explaining how the research was conducted is introduced. At first, different research philosophies are presented, and the philosophy choice of this research is justified. Next, different research approaches and strategies are discussed, and the chosen approach and strategy for this research are explained and reasoned. After that, the case organization of this research is briefly introduced to give background for the later discussion of the findings of the research. Lastly, data collection and data analysis of this research are explained.

6.1 Research philosophy

The term research philosophy refers to the researcher's assumptions about the way he views the world, and a development and a nature of the knowledge in the research. These assumptions will support chosen research strategy and methods, and generally impact on all aspects of the research. The research philosophy is influenced by practical considerations but the main influence is usually the particular view on the relationships between knowledge and the process by which the knowledge is developed. One research philosophy is not better than another but can be better at doing different things. Which research philosophy is better depends on the research questions pursued to answer. However, practical reality is that particular research question rarely falls neatly into only one research philosophy so the researcher can be more flexible in adopting suitable research approaches and methods. (Saunders et al. 2009, pp. 107–109.)

Saunders et al. (2009, pp. 109–119) present four different research philosophies: positivism, realism, interpretivism and pragmatism. Important part of the philosophy of positivism is that the research is undertaken in an objective value-free way and the researcher is independent and does not affect nor get affected by the subject of the research. Positivist research usually utilizes quantitative and large sample data collection techniques and aims to produce law-like generalisations. Philosophy of realism also focuses on objective research but is not value-free since the researcher is biased by the world views and cultural experiences. Philosophy of interpretivism emphasizes the difference between conducting research among people rather than objects. Crucial to the interpretivist philosophy is that the researcher understands the world from the point of view of the research subjects thus the research is value bound and subjective. Interpretivist research usually utilizes qualitive in-depth investigations and small sample data collection techniques. Philosophy of pragmatism argues that the most important determinant of all aspects of the research is the research question. In pragmatistic view, it can be realistic in practice to work with variations of different philosophies and use mixed methods, both qualitative and quantitative, to collect data within one study.

This research utilizes pragmatism as the research philosophy. Since the goal of this research is to answer the research questions and solve a real-world problem in the case organization, the pragmatistic view for the research is appropriate. Thus, for example the goal of positivist philosophy to produce law-like generalisations from quantitative analysis is not applicable for this research because it aims to solve the problem only in one case organization. Interpretivist research would be value bound and subjective but, in this research, adopting pragmatistic both objective and subjective points of view can produce better answers to the research questions while interpreting the results. In addition, Saunders et al. (2009, p. 119) claims that pragmatistic philosophy focuses on practical applied research which fits well with the context of this research.

6.2 Research approach

The research approach refers to the use of theory in the research design. There are two main research approaches: deduction and induction. Deduction is about testing theory so that at first, theory and hypotheses are developed and then a research strategy is designed to test those hypotheses. In deductive research, also a conceptual framework can be developed instead of theory and the framework explaining some phenomenon is then tested. On the other hand, induction is about building theory by analysing the collected data and its patterns. In induction, usually qualitative and small sample data is collected with variety of methods to establish different views of research phenomena. In inductive research, the researcher is usually subjective and part of the research process, and the research is less concerned with the need to generalize results. (Saunders et al. 2009, pp. 124–127; Farquhar 2012, pp. 24–26.)

This research utilizes the deductive research approach. In this research, first a maturity model theory is used to build a conceptual framework and then the framework is tested by analysing the analytics maturity in the case organization with the framework. Thus, this research is following the deductive approach and not the inductive which would require first to collect data and then build a theory based on the data analysis.

6.3 Research strategy

Research strategy provides a framework and overall direction for the research to answer the research questions and meet research objectives. No research strategy is superior or inferior to any other and the choice of the strategy is guided by research questions, amount of time and resources and research philosophy. (Saunders et al. 2009, p. 141; Farquhar 2012, p. 30.) Saunders et al. (2009, p. 141) present seven different research strategies: experiment, survey, case study, action research, grounded theory, ethnography and archival research.

This research uses the case study as the research strategy. The case study involves an empirical investigation of a particular phenomenon within its real-life context to gain a rich understanding of the researched phenomenon. The case study strategy is particularly suitable for in-depth investigations where the research problem and questions are explored, explained, understood and described. With the case study, it is not possible to make statements about the findings that would be applicable and generalizable to a wider population. The case study strategy is relevant for this research where a very specific problem of B2B sales analytics maturity in a single case organization is assessed which requires an empirical in-depth investigation in a real-life context and results are not generalizable. (Saunders et al. 2009, pp. 145–146; Farquhar 2012, pp. 38–39.)

More precisely, this research utilizes a holistic single case strategy because the research problem is empirically investigated only in one case organization and more specifically only in the sales unit of the case organization. Thus, this research does not utilize a multiple case strategy nor an embedded case strategy where multiple sub-units within one case organization would be examined (Saunders et al. 2009, pp. 146–147; Farquhar 2012, pp. 41–42). The choice of a holistic single case study is reasoned by the research problem and available time and resources for the research. Since the problem is about investigating the maturity of B2B sales analytics in the IT consultancy company, it is not possible to do embedded case study with other than the single sales unit within the case organization. In addition, for this research, there are no time nor resources to replicate the investigation in multiple different IT consultancy companies, thus the multiple case strategy is not applicable.

6.4 The case organization

The case organization is a Finnish IT consultancy company providing B2B services covering the whole digitalization value chain from management consultancy to service design and to actual service development. The company has offices in multiple cities in

Finland and also abroad in four different countries in the Europe. In total, there are almost 600 employees and the company is a publicly listed company.

What is unique about the company is that it has grown rapidly in the 2010s while being highly profitable. In addition, the culture of the company is very open and self-determination based, and there are no traditional organizational structures like business units. Thus, the company is very flat organization without much hierarchy nor management. These things will affect the results of this research and thus they might not be generalizable to other organizations which operate with different kind of organizational structures.

The sales unit of the case organization is led by the sales director and it is internally divided into three main sales themes which all focus on different main customer segments. All three sales themes have a named lead person. In the sales themes, there are different sub-customer segments with segment owners, salespeople and account owners. In addition, there is a very small team developing the sales and its practices, for example sales analytics.

6.5 Data collection

There are three recommended data collection techniques suitable for the case study research strategy: a survey, an observation and an interview (Farquhar 2012, p. 68). Since this research features an in-depth investigation in a single case organization, a qualitative data collection is well suited for this purpose (Farquhar 2012, p. 72). Interviews are well fitting for qualitative data collection and especially semi-structured interviews which are also quite commonly used in case study research strategies (Saunders et al. 2009, pp. 321–322; Farquhar 2012, pp. 72–73). Thus, semi-structured interviews are used as the data collection technique in this research.

Semi-structured interviews give more flexibility and adaptation compared to the structured interviews but follow an interview guide containing questions and themes to be covered in the interview as opposed to the unstructured interviews without predeterminant list of questions. In semi-structured interviews, the list of questions may vary from interview to interview and the order of questions may also vary depending on the flow of the conversation. Semi-structured interviews are usually recorded with the permission of the interviewee and also notes can be written during the interview. (Saunders et al. 2009, pp. 320–321; Farquhar 2012, pp. 73–74.)

Interviewees for the semi-structured interviews were selected by using a non-probability sampling. The non-probability sampling is a widely used sampling technique in case study researches like this research (Saunders et al. 2009, p. 233). Common non-probability sampling techniques are quota sampling, purposive sampling, snowball sampling, self-selection sampling and convenience sampling (Saunders et al. 2009, p. 213). This research used the purposive sampling technique to select interviewees from the case organization. The purposive sampling is often used when the sample size is very small, like in this singe case study research, and judgement is used to select interviewees who can best enable answering to the research questions (Saunders et al. 2009, p. 237).

Interviewees were selected by asking recommendation about who should be interviewed from the sales director of the case organization. The recommendation criteria was that different interviewees should be able to offer an in-depth insight into the interview questions from different point of views. More precisely, the criteria were that selected interviewees would represent different sales themes of the case organization, there would be full-time salespeople and also other people who are involved with the sales, and people who are more technically and analytics oriented and also less technical people. In addition, the criteria also included that all interviewees were from Finland since the scope of this research included only the Finnish sales of the case organization. In the end, ten interviewees were selected and interviewed which offered enough data and insights into the research questions until data saturation. With non-probability sampling, data collection is recommended to be continued until data saturation is reached (Saunders et al. 2009, p. 235). All interviewees, reasoning of their selection and information about their interviews are presented in the table 5 below.

Table 5. *Selected interviewees, their reasonings and interview information.*

Interviewee	Job role	Reasoning	Interview method	Interview length
I1	Head of the sales development	Has in-depth knowledge about the current and the future development initiatives at the sales unit.	Face to face	1h 30 mins
I2	Head of the public government sector sales	Has in-depth knowledge about how the sales and its processes are being executed at the public sector.	Phone	1h

I3	Head of the social services and healthcare sector sales	Has long experience at the case company and knowledge about its sales.	Face to face	1h
I4	Head of the public sector procurement	Has in-depth knowledge about how the sales and its processes are being executed at the public sector.	Face to face	1h
I5	Subcontracting management and software development resourcing	Works in close cooperation with the sales unit and subcontractors and software developers.	Face to face	1h 30mins
I6	Software development resourcing	Works in close cooperation with the sales unit and software developers.	Face to face	1h
I7	Head of the cloud business	Newer employee so has also outsider perspective. Does directly sales and develops cloud business in close cooperation with the sales unit.	Face to face	1h
I8	Private sector sales theme owner	Has in-depth knowledge about how the sales and its processes are being executed at the private sector.	Phone	1h
I9	Head of the advisory business	Has long experience at the case company. Does directly sales and develops advisory business in close cooperation with the sales unit.	Face to face	1h

I10	Sales director	Has in-depth knowledge about the current and the future development initiatives at the sales unit.	Face to face	1h 30mins

All ten interviewees presented in the table 4 were interviewed as one-to-one at the case organization during two weeks in November 2019. All interviews were recorded and also notes were written down during the interviews. Interviews were structured according to the B2B sales analytics maturity model's dimensions. Each of the five different dimensions had from three to four predetermined questions.

Interview questions for each maturity model dimension were formulated by utilizing the definitions of the maturity model dimensions presented in the chapter 5.2, and also by utilizing questionnaires from online maturity model assessment tools based on the analytics maturity models by Burciaga (2013), Halper & Stodder (2014) and Vesset et al. (2015). Those analytics maturity models were used to synthesise the analytics maturity model in the research by Menukhin et al. (2019) which was used as the base maturity model and theoretical framework in this research. Interview questions were formulated so that they would create qualitative data which could be analysed to determine current maturity levels for each dimension which is the goal of this research. The interview structure and questions can be found from the appendix A.

6.6 Data analysis

After the interviews, data analysis were made using suitable qualitative data analysis methods such as summarizing and categorization (Saunders et al. 2009, p. 490). At first, all the interview recordings were listened in detail and all relevant information were summarized into documents. After summarization, all summarized information from different interviews were categorized into one document. Categorizing followed the B2B sales analytics maturity model's dimensions which was used as the theoretical framework in this research. Thus, data analysis followed deductive approach which was also the overall research approach of this research.

Next, summarized and categorized information were analyzed by reflecting it with the B2B sales analytics maturity model presented in the chapter 5.2. Information from different interviews were compared to identify both similarities and differences for each category. Finally, conclusions were made based on the interview information and current maturity level for each dimension was determined based on the information gathered from the interviews. Results of the data analysis are presented in the chapter 7.

7. RESULTS

In this chapter, results of the data analysis of this research are presented. The B2B sales analytics maturity model presented in the previous chapter 5.2 was used as the conceptual framework for analysing the current maturity level of the case organization's B2B sales analytics. Data collection for the analysis was conducted with qualitative semi-structured interviews and the interview structure was based on the maturity model. Next, analysed results from the interviews are introduced in the following subchapters which are structured based on the dimensions of the maturity model.

7.1 Current maturity level of the culture dimension

The culture dimension of the maturity model deals with subjects like the sales unit's atmosphere towards analytics, the use of analytics in decision making, analytics roadmap and strategy, and awareness of analytics benefits. These subjects were discussed by having three main questions about culture with the interviewees at the case organization.

The question of overall culture and atmosphere towards analytics at the sales unit led to mixed responses from interviewees. Around half of the interviewees responded that the sales unit has a positive and encouraging culture towards analytics. However, rest of the interviewees thought that the culture is quite neutral, and few even answered that the analytics is not really emphasised nor encouraged at the sales unit.

"Culture is welcoming for the analytics and atmosphere is encouraging for the use of analytics. The bar should even be raised in regards of the analytics". (I3)

"The use of analytics is not very emphasised at the sales and actions are often based on gut feeling." (I7)

Many interviewees pointed out that culture of data sharing is lacking at the sales unit. Especially, data about customer interactions, for example customer contacts and meetings, are not filled into the CRM system actively. This can lead into situations like two salespeople being in contact with the same customer without knowing about each other which is not very professional in the eyes of the customer. In addition, lack of data makes doing sales analytics harder or even impossible.

"Customer interaction data is not filled into CRM. Others do not know what others have been doing when there is no data. Questions are only raised afterwards that why did something happen." (I5)

Answers regards the use of analytics in decision making focused around analysing resourcing data to get insights on what to sell and when to sell. Previously, sales were usually selling resources without even knowing if needed resources were available for selling. Recently, it has been changing towards more proactive selling where predictive resourcing analytics is used to sell resources when they really are becoming available.

"We have learned to sell more accurately based on predictive resourcing analytics to know when resources are becoming free". (I5)

Some interviewees mentioned that business intelligence style of analytics dashboards have been introduced to, for example, weekly meetings, but those dashboards are not really utilized in decision making.

"Dashboards have been brought into play but they are not really used to actually lead the sales". (I7)

Few interviewees stated that there have not been that many actual actions or decisions made based on analytics. It was noted that people can notice something based on analytics but it is easy to go back to the prevailing way of doing things and not take actions based on analytics. Especially, if there are no clear benefits identified from the analytics, then decisions will not be made based on analytics or they will only be made temporarily.

The question about analytics roadmap and strategy at the sales unit resulted in unanimous answers from interviewees. There are no long-term analytics roadmap nor any concrete analytics strategy in place. Instead, some responded that there is agile analytics development happening all the time and couple dedicated people are doing agile analytics experiments, for example, with new tools and technologies. However, many interviewees said that they are not actually aware on what is really happening with that agile analytics development and the question should be asked from those couple dedicated people. Thus, information about the development is not shared very effectively among the sales unit.

"Analytics is developed in an agile way. Something new can be experimented even on weekly basis. There is no long-term development plan nor concrete sales analytics strategy". (I1)

Some interviewees mentioned that newly experimented analytics tools do not necessarily get into wider use among other salespeople. It was also noted that there could be even more agile analytics development but available human resources for sales analytics development are very limited which sets its own challenges.

"Analytics development has been lagging behind and it could be more determined." (I10)

To conclude, the overall culture towards sales analytics at the case organization seems to be mostly positive and encouraging while few interviewees did not see analytics really emphasised at the sales unit. The biggest cultural challenge looks to be data sharing about customer interactions into the CRM system. The actual use of analytics in sales decision making seems to focus mostly on just analysing available resources predictively which is still quite newly introduced way of working at the sales. Thus, gut feeling still affects the overall decision making at the sales. A strategic long-term analytics development roadmap is not really implemented at the sales unit. Instead, analytics development is done in an agile way with limited human resources but information about the development is not communicated effectively among the salespeople.

Considering the descriptions of the five different maturity levels in the culture dimension of the B2B sales analytics maturity model, it can be stated that the case organization is currently at the second "descriptive" level illustrated in the table 6 below.

Table 6. *Current maturity level of the culture dimension at the case organization.*

	Initial	Descriptive	Diagnostic	Predictive	Prescriptive
Culture					

Higher maturity levels would require more effective and active data sharing culture at the sales unit, having a sales analytics strategy in place, and most importantly that decisions would be based more on data and analytics. Overall, sales analytics is considered as positive, some use cases and benefits of the analytics are realised, and some analytics is used in decision making so that is the why the maturity level is not the lowest "initial".

7.2 Current maturity level of the skills dimension

The skills dimension of the maturity model considers subjects like current data and analytics skills at the sales unit, possible needed skills, and skills training. These subjects were discussed by having three main questions about skills with the interviewees at the case organization.

During the question about current data and analytics skills at the sales unit many interviewees pointed out that most of the salespeople have a technical information technology working background and have shifted to the sales role over the time. Thus, they have solid technical skills to do basic data processing and analytics tasks with the tools like Excel and user-friendly business intelligence applications.

“Our salespeople usually have longer technical working experience so we do not really have ‘traditional’ salespeople. Salespeople could use user-friendly analytics tools thanks to the technical backgrounds.” (I2)

“If we want to develop our sales analytics also individuals should have skills to analyse for example past actions, reflect on that and change actions if needed. This is mostly a mindset challenge since technical skills already exist.” (I3)

Some interviewees commented that there are skills to do analytics but very little analytics is actually being done and gut feeling affects many decisions at the sales. One given reason was that most likely there are not much available time to do analytics when salespeople are focused on customer interactions. In addition, a few interviewees pointed out that individual salespeople do not necessarily need to do analytics by themselves. Instead, sales theme owners could focus on doing analytics and sharing the results for other salespeople.

“There are salespeople who could do a lot more analytics but they probably do not have time to do it because they are focusing on customer contacts.” (I8)

“Individual salespeople could do analytics with, for example, BI tools but is it sensible? Maybe sales theme owners could do the analytics.” (I9)

The question about possible needed analytics skills at the sales unit disclosed one quite common theme: future sales trends. Some interviewees commented that skills on analysing future trends about customer needs would be needed. It was brought up that there are no good mutual future sales trends knowledge at the sales. In addition, skills on analysing individual customer organizations on wider scope would be beneficial according to few interviewees.

“Future sales prediction skills would be needed. For example, trends about customers’ technology needs so we would know what technological skills our consultants should have”. (I6)

The question about analytics skills training at the sales unit resulted in unanimous answers from interviewees. There have not been organized any analytics skills training for the salespeople. Some pointed out that if training was requested then it would be arranged. Since the case organization is operating with flat hierarchy and self-determination, it is not necessary to force some trainings for all of the salespeople. It was also noted that some training about the usage of the CRM system and its analytics options could be beneficial for all of the salespeople since technical tools and processes are evolving all the time.

"The basic technological tools usage training could be arranged for older and newer salespeople because those tools, processes and methods are developing all the time." (I5)

"There is no need for so called official analytics training because we operate with self-determination. Also, available time is limited and could be used for customer interaction instead". (I2)

To conclude, overall technical analytics skills seem to be in quite good shape at the sales unit thanks to the very technical backgrounds of most of the salespeople. Analytical thinking mindset might be the bigger challenge compared to technical skills since some salespeople tend to base decisions usually on gut feeling. However, not all salespeople would have to do analytics by themselves if sales theme owners and the sales development team would provide the needed shared sales analytics for others. Future sales trends analysis skills would be needed more at the sales unit. Sales analytics training has not ever been organized but training on CRM system usage and analytics could be beneficial for some. However, due to self-determinated culture at the case organization, forced trainings for all might not be the best way for enhancing analytics skills.

Considering the descriptions of the five different maturity levels in the skills dimension of the B2B sales analytics maturity model, it can be stated that the case organization is currently at the third "diagnostic" level illustrated in the table 7 below.

Table 7. *Current maturity level of the skills dimension at the case organization.*

	Initial	Descriptive	Diagnostic	Predictive	Prescriptive
Skills					

Higher maturity levels would require more advanced analytics skills like future prediction, prescriptive analytics and that individual level decisions would be based on data ana analytics instead of gut feeling. On the other hand, lower maturity levels would mean that technical skills were very limited, for example only basic Excel skills, and that there was not much capability to learn and develop skills further which is not the situation at the case organization.

7.3 Current maturity level of the governance dimension

The governance dimension of the maturity model considers subjects like needed data at the sales, accessibility of the data, quality and usability of the data, and how data is managed at the sales unit. These subjects were discussed by having four main questions about the governance with the interviewees at the case organization.

The question about needed data at the sales resulted in quite unanimous answers from interviewees. Needed data is mostly about customer interactions (demand) and available resources for selling (supply). Customer interactions data include, for example, data about customer contacts, meetings, events and needs of the customer. Available resources data include data about people's capacity, skills, location and hourly price. In addition, sales contract, reference and competitor data was mentioned.

"Sales is quite simple business in the end. The needed and collected data is somewhat simple, for example customer background, contacts and needs." (I8)

"Needed data is customer company data, contacts, references, customer demand, our people's capabilities and what capabilities we should have." (I7)

Data accessibility question disclosed unanimously that everyone has access to the needed data and it is quite easy to access. Customer interaction data is stored in the CRM system where data is open for everybody who has an account to the CRM system and all salespeople have the account. Resourcing data is stored in an internally developed system which is open for every employee so not just for salespeople. Sales contracts and offers are stored in a shared cloud storage which is also accessible by every employee. There is even a vision about an ecosystem where some data would be opened for other stakeholders, like subcontractors and customers, in the ecosystem.

"All data is open for everyone by default. If data is not accessible there must be a clear reason like a non-disclosure agreement". (I2)

"Data is accessible by everybody. There are no cultural restrictions that someone would not be allowed to see some data". (I5)

A few interviewees commented that sometimes it is not possible to access the needed data just in the right time because some people insert data with a delay to the CRM system or do not insert it at all. In addition, it was noted that sometimes data can be a bit trickier to access since the CRM system can have duplicated data, and data can be scattered between different systems and storages.

"In principle, data is accessible just in the right time but for example in the CRM system it is not so real-time since some people insert data afterwards with a delay". (I9)

"On the other hand, data is quite scattered and it would be good to get it stored into one place with an easy access". (I10)

The question about data quality and usability revealed that the overall data quality is seen as mediocre and it has quite a lot of variance. The biggest problem seems to be the CRM system data which quality varies a lot depending on individual salespeople's data inserting practises. Some salespeople insert better quality data but some might not even insert any data. The CRM system does not force people to insert all the possibly useful data so the challenge is more cultural and behavioural. Especially, data about customer contacts, meetings and messaging is usually missing or very low quality.

"Data is not very rich. Salespeople are not interested in inputting data into the CRM when they do not see the value of doing it. Because of the missing data, for example if some salesperson gets sick, we do not know what the person have been doing. We cannot do all the wanted sales analytics thanks to the missing data." (I1)

"Data is inserted into the CRM if the person is motivated for that. However, Information is usually as tacit information inside the minds of the salespeople." (I2)

"Small leads are not always inserted into the CRM which hinders the precision of sales prediction analyses." (I4)

"Data quality depends on different cases because different salespeople insert the data in different ways. Many cases lack even basic information. Data quality probably do not enable very good future prediction analyses." (I7)

The question about how data is being managed at the sales resulted in quite unanimous answers from interviewees. Data is not being officially managed that much. There are some documentations about sales processes and data management in the intranet but they might be outdated and especially not so known to even exists. It seems that couple people have taken more active role in managing and owning the data but there are no official data owners. However, couple interviewees mentioned that there would be data owners but that information is not documented nor probably communicated very effectively. In addition, it was noted that as self-determinated organization everyone is responsible for managing their own data and there is no need for top-down micromanagement.

"Data is not managed very much. Management is done in a small start-up company way even though we already are a large company." (I1)

"I have not seen data management definitions. Everyone manages data the way they want which could also result in the data quality issues". (I7)

“Data management processes have not been defined very well. There are no named data owners. Everyone is responsible for managing their own data in self-determinated way. (I9)

To conclude, the needed data at the sales is quite simple data about the demand and the supply. Everyone has access to all data without restrictions. Data is mostly easily accessible but it can be bit scattered across different systems. The biggest problem is data quality. Especially, the CRM system data is overall somewhat mediocre but sometimes there are totally missing data or low-quality data. Because of the quality issues, some wanted sales analytics have not been possible to be accomplished or the precision of analytics is not so good. Data is not managed officially very much, and management processes are not defined clearly nor communicated effectively across the sales unit which could be one reason for data quality issues. However, the self-determinated culture at the case organization shares the data management responsibility for all the individual salespeople, thus a traditional top-down management would not work so well.

Considering the descriptions of the five different maturity levels in the governance dimension of the B2B sales analytics maturity model, it can be stated that the case organization is currently at the second “descriptive” level illustrated in the table 8 below.

Table 8. *Current maturity level of the governance dimension at the case organization.*

	Initial	Descriptive	Diagnostic	Predictive	Prescriptive
Governance					

Higher maturity levels would require a lot better data quality so that for example more predictive analytics could be possible to be carried out. In addition, more systematic and codified data management operations should be in place for higher maturity levels. On the other hand, accessibility of the data is good at the sales unit so the maturity level is not the lowest “initial”.

7.4 Current maturity level of the IT & analytics infrastructure dimension

The IT & analytics infrastructure dimension of the maturity model considers subjects like sales data gathering into different information systems, integrations between the systems, out of the box analytics capabilities of the information systems, and investments into systems at the sales unit. These subjects were discussed by having three main questions about the IT & analytics infrastructure with the interviewees at the case organization.

The question about data gathering into information systems revealed that it is mostly seen as a quite manual process for salespeople. The CRM system acts as a master data for sales and data need to be manually inserted into the CRM. There is an integration between the CRM system and the internally developed resourcing system so data is automatically transferred from the CRM to the resourcing system. However, there is still some need for salespeople to insert data manually also into the resourcing system. In addition, an hour reporting system is not integrated and its data is manually exported for doing, for example, sales analytics.

“Data inputting into the CRM is manual process. We would like to get more automation and some ‘smart’ solutions so that salespeople could work more efficiently. However, would salespeople actually start using new solutions?” (I1)

“Data inserting is very manual but there are some integrations between the CRM and the resourcing system. There are still legacy things, like Excels, used. Sometimes old Excels get back into the use again even though information systems could support same tasks better.” (I5)

It was also commented that more data could be gathered but there needs to be a balance between the amount of data gathered and its additional value since the data inserting is mostly manual process for salespeople. Some interviewees noted that the CRM data gathering is quite limited even though it is easy to insert data into the CRM system.

“Even more data could be gathered but it easily brings more manual tasks and bureaucracy for salespeople.” (I8)

“It is easy to insert data into the CRM system but salespeople do not always do that because they are too busy or there is no culture of data gathering. More data should be gathered but of course not unnecessary data. Especially, customer data is gathered too little.” (I10)

The question about out of the box analytics capabilities of used information systems resulted in quite unanimous answers from the interviewees. The CRM system offers quite basic sales statistics and analytics dashboards. The CRM system lacks some wanted analytics dashboards so those needs were fulfilled by getting a third party sales analytics dashboard tool which is integrated into the CRM system. It was noted that if you want more advanced analytics, like predictive and prescriptive, data needs to be exported or integrated from the CRM system to some analytics tool like business intelligence application. However, it was also commented that CRM system’s out of the box analytics dashboards are aimed for a bit different business and sales models than the case organization's model. In addition, the CRM system probably offers even more analytics options but it should be considered how much of those adds value because there is also a risk of getting vendor lock-in with that specific commercial CRM system.

"The CRM system offers basic reports and dashboards but if you want more fancier analytics, you need to export the data into other tool like business intelligence application". (I10)

"Most likely there would be even more analytics possibilities in the CRM system which could be used to lead the sales with analytics." (I2)

"The CRM system has some out of the box analytics dashboards and also the resourcing system has some analytics views. However, there is some incoherence between the systems and they are not always synced and integrated." (I8)

The question about investments and developments into sales analytics and systems did not create much of conversation with the interviewees. Many responded that they do not know about possible investments and developments being made. This implies that if there are ongoing investments and developments they have not been communicated very well for larger audience at the case organization. A few commented that the license level of the CRM system is probably getting increased so that new features like better data integrations between the CRM system and salespeople's email and calendar can be utilized. In addition, couple interviewees noted that there is an ongoing new ERP system implementation project and that will bring changes to the current systems and processes which could also enable better sales analytics options.

"I have no idea. Are there nothing concrete planned?" (I5)

"The CRM system is getting upgraded to have an integration with Office applications". (I6)

"In the future, a new upcoming ERP system and data warehouse could also support sales analytics too? A development schedule is a bit unclear though." (I7)

"There have not been much investments and we do not even really know how much working time we have used for developments. During the next year, more investments into reporting and analytics need to be made and we are willing to do that." (I10)

To conclude, sales data is very manually gathered into the CRM system but after that the data is somewhat automatically transferred to the resourcing system with integrations. It is easy to insert data into the CRM system but especially customer data is not inserted that much. Thus, more data could be gathered but it needs to be relevant data so that the data inserting does not become too time consuming for salespeople. The CRM system offers basic sales reporting and analytics dashboards but more advanced analytics need to be done with other analytics tools. However, the CRM system's analytics offering might be a bit underused and not fully explored. Investments and developments into sales systems and analytics are not being made that much nor communicated but there is a new ERP project ongoing which will also affect the sales unit. However, there seems to be willingness to invest more into sales analytics in the future.

Considering the descriptions of the five different maturity levels in the IT & analytics infrastructure dimension of the sales analytics maturity model, it can be stated that the case organization is currently at the second "descriptive" level illustrated in the table 9 below.

Table 9. *Current maturity level of the IT & analytics infrastructure dimension at the case organization.*

	Initial	Descriptive	Diagnostic	Predictive	Prescriptive
IT & Analytics Infrastructure					

Higher maturity levels would require more automated sales data gathering and integrations between different systems in addition to a data warehouse which could be used to enable more advanced sales analytics. Also, more active investments into sales analytics and systems could be made. However, there already are some integrations between the CRM system and the resourcing system, the CRM system has some built-in analytics options and there is a willingness to make more investments so the maturity level is not the lowest "initial".

7.5 Current maturity level of the data & analytics technologies dimension

The data & analytics technologies dimension of the maturity model considers subjects like used analytics tools, the kind of analytics done, integration of analytics with sales processes and automation of analytics at the sales unit. These subjects were discussed by having four main questions about the data & analytics technologies with the interviewees at the case organization.

The question about used analytics tools at the sales unit revealed unanimously that commonly used tools are just Excel, out of the box analytics dashboards from the CRM system and the purchased third-party analytics dashboard tool connected to the CRM. Business intelligence application Tableau has been tried sometime at the sales unit but it is not actively used anymore. It was commented that some sales analysis graphs are done with Excel and then distributed with PowerPoint presentations which is very manual process and not sensible. In addition, a future sales turnover prediction analysis is done with an Excel sheet where salespeople insert their data on monthly basis and finance people add data about realized sales from their system. That Excel sheet and its formulas have sometimes got broken and there has been a rush to get it finished on time. It was noted that the future sales prediction should happen automatically by the CRM system or by some other analytics tool instead of the current manual Excel sheet.

“Excel is the most used tool. Also, out of the box analytics tools within the CRM system and the third-party analytics dashboard connected to the CRM are used. Tableau was tried sometime.” (I10)

“There are no business intelligence applications used at the sales. Business intelligence applications could be utilized a lot more in, for example, leading sales themes and the overall sales.” (I8)

“The whole sales turnover prediction is done with an Excel based on realized and possible future sales. Data is inserted manually into the Excel usually based on salespeople’s intuition.” (I9)

“The third-party analytics dashboard connected to the CRM is not utilized so often. There are Excel tables and graphs which are done manually and then exported into PowerPoint presentations. It is not sensible.” (I7)

The question about the kind of analytics done at the sales unit resulted in very similar answers from interviewees. Performed sales analytics is mostly focused on analysing the past and the present, for example an analysis about the realized sales in the past and the present in different sales themes. Some future prediction is done too, for example the future sales turnover prediction with the Excel, but it was commented that a lot more future analysis should be done. In addition, most interviewees noted that the done analytics at the sales has been valuable but it has been done very little so far. Many commented that a lot more analytics could be done at the sales and especially focused on analysing the future so that the analytics could be used to guide decisions at the sales. However, a few also reminded that a possible increase in performed analytics should be done in an agile way without large and heavy analytics projects.

“The done analytics is basic graphs about present. Quite superficial analyses. Future prediction is done very little.” (I1)

“Analytics is focused on the past and the present but a lot more future prediction should be done.” (I6)

“Analytics has been valuable at the sales. Especially sales trends analyses so we can change actions based on trends. We have not over-invested in analytics and more analytics could be done and invested in. We could use more analytics in our decision making.” (I3)

“Analytics has been useful and brought more transparency. Used time in analytics has been positive but we use very little time in that. We could use more time in analytics but first we should figure out what analytics would be valuable to try in an agile way.” (I8)

“Analytics has been really valuable. We might miss noticing some things if we did not do analytics. Of course, there are a lot more to be done in analytics and unutilized potential.” (I10)

The question about integration of analytics with sales processes created a bit mixed answers from the interviewees. The most interviewees commented that generally analytics is a little integrated with the sales processes. However, couple interviewees felt that analytics is more integrated with the sales processes but on the contrary, couple felt that analytics would be separated from the sales processes. It was noted that analytics is involved mostly in a retrospective way so that sometimes analytics is used to get information about past performance. That past performance information can then be used to steer future actions. Also, it was commented that analytics is part of the sales processes only on the very top level of the sales unit. On the other hand, it was noted that analytics is not part of the sales processes and it has not really been possible to get support for decisions from analytics so sales decisions have mostly been based on intuition.

“Analytics is somewhat separated from sales processes. Analytics guides the processes only a little bit.” (I7)

“On the upper level, analytics is guiding and integrated with the sales processes. We would need more operative and in-depth analytics and not just very upper level analytics” (I9)

“Analytics is guiding sales processes little bit but not significantly. Sales processes and made decisions are more based on intuition rather than analytics and factual information.” (I10)

“Analytics is separated from sales processes and not guiding them. Analytics is worryingly little guiding sales processes.” (I6)

“Analytics is an integrated part of the processes. However, even though analytics would give some insight, salespeople still need to figure out its reasons and do the needed actions” (I4)

The question about automation of the analytics at the sales unit revealed that it is mostly manual except couple automated things. The purchased third-party sales analytics dashboard tool connected to the CRM is an automated live dashboard so it fetches data from the CRM system and creates analytics reports automatically. In addition, the CRM system’s own out of the box analytics capabilities are automatic and some analytics related notifications and information are automatically sent to the internal communication tool Slack via bots. Otherwise, analytics is manual work at the sales unit, and for example the future sales turnover prediction analysis made with a manual Excel is good example of that. In addition, it was commented that the goal is to automate all important analyses, more automated notifications about happened sales activities could be added and also automatic data gathering from the internet for sales analytics could be utilized.

“Slack bots are creating automatic notifications for sales. Basically, everything else is manual work.” (I8)

“There is not much automation. Sure, the CRM and the third-party dashboard tool produce analytics automatically.” (I10)

“Analytics is very much manual at the moment. I utilize manual Excels myself too.” (I9)

To conclude, used analytics tools are very basic like manual Excels, some out of the box analytics graphs from the CRM system and the third-party sales analytics dashboard connected to the CRM. For example, business intelligence applications are not used at the sales unit. Performed analytics is mostly focused on the past and the present but there is also a little future oriented analysis being done too. However, overall there is not much analytics being done and a lot more could be done. Analytics is only a little integrated with the sales processes mostly in a retrospective manner and on the very upper level decision making of the sales unit. There are automated analytics with the third-party analytics dashboard and with the CRM system’s internal analytics capabilities but otherwise analytics is very manual work at the sales unit. For example, there are legacy manual Excels used for analyses but the aspiration seems to be to get better and automated analytics.

Considering the descriptions of the five different maturity levels in the data & analytics technologies dimension of the B2B sales analytics maturity model, it can be stated that the case organization is currently at the second “descriptive” level illustrated in the table 10 below.

Table 10. *Current maturity level of the data & analytics technologies dimension at the case organization.*

	Initial	Descriptive	Diagnostic	Predictive	Prescriptive
Data & Analytics Technologies					

Higher maturity levels would require more advanced analytics technologies, like business intelligence applications, to be used instead of manual Excel analyses, more predictive and prescriptive focused analytics, more automated delivery of live analytics instead of ad-hoc retrospective analytics on PowerPoint slides, and analytics would need to be more tightly integrated into the sales processes and decision making. However, there is an automated third-party sales analytics dashboard connected to the CRM system being used and analytics is a little integrated with the sales processes so the maturity level is not the lowest “initial”.

8. DISCUSSION

In this chapter, a discussion based on the results of this research is presented. At first, the current overall maturity level of the case organization's B2B sales analytics is introduced. Next, the most prominent both the social and the technical issues of the case organization's B2B sales analytics maturity are discussed and reflected with the literature. Lastly, proposals on how to develop the current maturity level to the higher level are presented taking possible bottlenecks into account, too.

8.1 Current overall level of the B2B sales analytics maturity

Based on the results of qualitative semi-structured interviews, current overall maturity level of the B2B sales analytics at the case organization is on the second "Descriptive" level. Only one dimension, "Skills", is on the third maturity level "Diagnostic" and all other dimensions are on the second "Descriptive" level. This implies that the case organization is still on the very early stages of implementing and utilizing B2B sales analytics, like one interviewee commented "*there are a lot more to be done in analytics and unutilized potential"* and another noted *"so far, analytics has been utilized very little because our sales has been operating very well but now, we should proactively develop operations to the next level"*. The current overall maturity level has been illustrated in the table 11 below.

Table 11. *Current maturity level of the B2B sales analytics at the case organization.*

	Initial	Descriptive	Diagnostic	Predictive	Prescriptive
Culture					
Skills					
Governance					
IT & Analytics Infrastructure					
Data & Analytics Technologies					

With the sociotechnical systems perspective, a joint development of both social and technical aspects is needed to create successful outcomes (Appelbaum 1997; Davis et al. 2014). Thus, all dimensions of the B2B sales maturity in the table 11 should be jointly developed because of their interdependencies. Focusing developments too much on one dimension could hinder the overall success of results. Next, the most prominent findings from both the social and the technical aspects of the results are discussed and reflected with the literature.

8.2 Issues in the social aspects of the B2B sales analytics maturity

Hallikainen et al. (2019) found out that supportive data-driven analytics culture is crucial for gaining a competitive advantage from the B2B sales analytics. The relationship between increased customer relationship performance from the usage of the B2B sales analytics was stronger for companies with a strong analytics culture than companies with weaker analytics culture. Analytics supportive culture can have a significant positive moderating influence on the paths leading from human skills and technical resources to the successful usage of the B2B sales analytics. According to Hallikainen et al. (2019), strong data-driven analytics culture seems to be one of the key characteristics for those companies who succeed in their B2B sales analytics initiatives.

At the case organization, the culture towards analytics was generally somewhat positive and encouraging. However, it seemed that especially in the public sector sales theme analytics was not seen as so important and emphasized as in private sector sales. It was commented in the interviews that it could be partly due to the very standardised selling processes set by the public sector regulations which was seen as a limiting factor for the use of sales analytics. This is an example of an external factor, like the regulatory framework, affecting the organizational sociotechnical system (Davis et al. 2014) as seen in the figure 1 in the chapter 2.

Overall, another commented limiting factor for the use of sales analytics was the business model of the case organization. The case organization offers B2B consultancy services and it was thought that in that model sales analytics cannot be utilized so effectively as in a B2B product selling business model. This is another example of the organizational sociotechnical system presented in the figure 1 when, for example, goals and processes (business model) of the organization are also affecting the culture of the organization. This cultural issue probably also stems deeper from a comparison of B2B and B2C sales analytics. Generally, sales analytics has been utilized a lot more in the B2C context and most commercial sales analytics tools are designed for the B2C context (Lilien 2016). Thus, possibilities of the B2B sales analytics are not so well known let alone sales analytics in the B2B services business model which hinders the analytics culture at the case organization.

Lismont et al. (2017) discovered that usually the most common big challenges for analytics are data management issues, such as sharing of data, at organizations. Lack of data sharing culture was also an evident issue at the case organization. CRM data is not inserted actively and its quality can be quite poor. It was commented that the CRM system is easy to use and well-functioning for its purpose so the problem is not in the technical usability aspects. However, it was noted that the data sharing has improved lately and it is going to the correct direction since the issue has been emphasised at the sales unit for a long time already. On the other hand, it was brought up that it has not been possible to do all the wanted sales analytics because of the missing data or poor data quality. One interviewee commented that "*salespeople are not interested in inputting data into the CRM when they do not see the value of doing it*". Thus, there seems to be a "chicken and egg" problem when data is not shared because its value is not known but the value cannot be realized through analytics if there is no shared data for analytics usage. This problem also probably stems from the lack of knowledge about different B2B sales analytics possibilities as explained in the previous paragraph. Therefore, a joint development of both the technical analytics tools for value realization and the social culture could be done to improve the data sharing culture.

Another way to improve the data sharing culture could be by improving the maturity of the "Governance" dimension. One of the biggest issues in the "Governance" dimension was the lack of proper data governance and management practices. It was commented that data is managed in a small start-up way even though the case company has already grown into a large company. In addition, it was noted that everyone is responsible for their own data management in a self-determinated way which is also the overall culture at the case company. Thus, a common ground between stricter management processes and self-determination should be found because the culture at the case company does not allow strict top-down management of, for example, sales data sharing. Again, the joint development of processes, management and culture is needed for successful results in the sociotechnical systems perspective.

Mikalef et al. (2019) found out that usually there is organizational inertia encountered when attempting to implement data-driven decision making at organizations. They discovered resistance to change and tendency to fall back to previous ways of making decisions. This phenomenon was also present at the case organization. In the interviews, it was commented that analytics is not used very much in decision making and mostly people's gut feeling affects decisions. In addition, it was noted that salespeople sometimes fall back to previous ways of making decisions even though they would have gotten new insights from the sales analytics. Same has happened with the technical tools when apparently legacy Excels have gotten back into use again at the times. Thus, Berndtsson et al. (2018) emphasise the importance of change management in becoming data-driven organization and proposes creating common rules like that gut feeling is not allowed to override data generated insights in decision making.

Mikalef et al. (2019) discovered that an analytics strategy was a significant contributor to achieving positive results from the usage of analytics at organizations. Discovered key aspects of the analytics strategy was for example a clear roadmap for the future. In addition, it was found that usually the analytics strategy was developed gradually at organizations by doing initial experimentations and gaining a gradual understanding of the importance of analytics. Also Vidgen et al. (2017) and Menukhin et al. (2019) emphasise the importance of well-established analytics strategy. However, at the case organization it was evident that the sales analytics strategy is missing and concrete long-term analytics roadmap is not thought of. On the other hand, it was commented that sales analytics is being developed in an agile way and heavy analytics development projects are not sensible for the case organization. Nonetheless, gradually developed sales analytics strategy and roadmap for agile developments could be beneficial for the case organization and bring more determination to the sales analytics maturity development.

8.3 Issues in the technical aspects of the B2B sales analytics maturity

Shanks & Bekmamedova (2012) propose that a high quality technology and data infrastructure is one of the important factors for achieving a long-term success and evolution of analytics usage. For example, the technology infrastructure could include a stable and mature data warehousing capability with real-time data feeds that is also well integrated with information systems. Also Berndtsson et al. (2018) argue that suitable technical analytics tools for employees are needed to enable widespread adoption of analytics and data-driven culture.

At the case organization, the technology and data infrastructure are evolving quite a lot in the very near future so issues of the current situation are not so valuable to be deeply investigated. There is an ongoing ERP system implementation project which will update the enterprise architecture and bring new data platform solutions like a date warehouse.

That should enable better technical capabilities for the usage of the B2B sales analytics, too. For example, in the interviews it was commented that there is a missing integration between the hour reporting system and the resourcing system but that issue will be solved with the ERP project.

Tools used for basic B2B sales analytics were out of the box analytics options of the CRM system and the additional third-party sales analytics dashboard tool. More advanced analytics and analytics for more specific use cases need to be done with other tools. Usually, Excel was used as the tool for analytics and static screenshots of analytics visualizations were then shared in communication channels. On the other hand, many salespeople could have technical skills to use user-friendly tools like business intelligence applications which could enable more advanced analytics and better automated live dashboard delivery of analytics. This technical issue could stem from the cultural issues presented in the previous chapter 8.2 so they both should be jointly developed. Berndtsson et al. (2018) claim that usually the first step towards data-driven culture is to develop analytics dashboards related to employee’s daily work in a self-service business intelligence way. However, according to Berndtsson et al. (2018), it is important to train the users both in the tools and the theory behind the various analytics techniques for the self-service business intelligence.

Lismont et al. (2017) discovered that usually descriptive analytics, like customer segmentation, is more popular than predictive analytics, such as customer churn prediction, in sales analytics at organizations. Focus on the descriptive analytics was also present at the case organization. It was commented in the interviews that a lot more future prediction analytics should be done and it would be valuable. However, predictive analytics is more advanced and mature than descriptive analytics so first, the data and analytics infrastructure need to get mature enough to really support advanced analytics (Sapp et al. 2018).

Davenport (2013) suggest embedding analytics into organization’s operational and decision making processes. Also, Menukhin et al. (2019) discovered that lack of clearly defined analytics processes can be a barrier to a wider usage of analytics. At the case organization, analytics has not really been integrated into the sales processes nor defined. It was commented that analytics is a little part of the sales processes mostly in a retrospective way and on the very top level of the sales management. By integrating analytics more deeply into the sales processes also in more operational level, it could enhance the decision making, guide the processes and make analytics and its benefits more visible and routine part of the daily sales work at the case organization. In the sociotechnical systems perspective, this could affect positively social issues of the B2B sales analytics maturity, but also development of those social issues, like analytics culture and strategy, is needed to make the integration of analytics into the sales processes successful.

8.4 Proposals to develop the maturity of the B2B sales analytics

Considering the findings and issues presented in the previous subchapters 8.2 and 8.3, it can be stated that the most important B2B sales analytics maturity dimensions needing development are the “Culture” and the “Data & Analytics Technologies” dimensions. At first, the development focus should mostly be on those two dimensions but also the “Governance” and the “IT & Analytics Infrastructure” dimensions need attention, too. The “Skills” dimension is already more mature compared to the other dimensions so it will not become an immediate bottleneck blocking the development of the other dimensions.

The biggest bottleneck in the “Culture” dimension was that possibilities and benefits of the B2B sales analytics were not generally well known at the sales unit. This lack of knowledge has resulted in a culture where sales data is not shared very actively, decisions are based on gut feeling and people tend to fall back into previous ways of working even though, for example, new analytics dashboard would have been introduced. Lack of knowledge about possibilities of the B2B sales analytics could be improved by creating concrete analytics demonstrations for the salespeople with more advanced analytics technologies than are currently being used at the sales unit. Thus, there is a link between the development of the “Culture” and the “Data & Analytics Technologies” dimensions.

The biggest bottlenecks in the “Data & Analytics Technologies” dimensions were that tools used for sales analytics were very basic and analytics was not really integrated into the sales processes. By taking business intelligence applications into the use, more advanced B2B sales analytics could be done and especially demonstrated for the salespeople how it could benefit their daily work. Those demonstrations could then improve the “Culture” dimension of the B2B sales analytics maturity. Also, advanced data science methods like clustering, regression and text mining based on machine learning could be demonstrated for the salespeople to increase the knowledge about analytics possibilities in the B2B sales processes. In addition, usage of analytics tools could be integrated more deeply into the sales processes. Deeper integration could demonstrate the possibilities of the sales analytics for the salespeople and make the sales analytics part of the daily work at the sales unit which could then lead into more analytics guided processes and decision making.

Previously mentioned B2B sales analytics demonstrations could possibly be done with limited sales data availability but productization of more advanced sales analytics requires a good amount of good quality sales data. Thus, if the “Culture” dimension and its issue of lacking data sharing culture will not get improved by previously presented analytics demonstrations then it could become a bottleneck hindering the implementation and the usage of more advanced sales analytics. To avoid that bottleneck, also the “Governance” dimension could be developed. Data sharing and management processes could be more clearly defined and communicated to be required to be followed at the sales unit. However, thinking of the open self-determinated culture of the case organization, there must be a balance between the management processes and people’s self-determination so that stricter data management would not backfire as a degradation of the “Culture” dimension.

There is also a link between the availability of good amount of good quality data and the “IT & Analytics Infrastructure” dimension. At the moment, the case organization is lacking solutions like data warehouse and some integrations between different information systems which hinders the availability and the usage of data. Thus, development of the “IT & Analytics Infrastructure” dimension is needed to enable better access to better sales data for the sales analytics usage. However, there is an ongoing ERP system implementation project at the case organization which will bring the needed data warehouse and system integrations which will enable better sales data availability in the near future. Thus, before the ERP implementation project is finished it is not sensible nor really possible to start actually implementing more advanced sales analytics technologies at the case organization.

9. CONCLUSIONS

In this chapter, a summarization of this research and its main findings is presented. At first, answers to the research questions are introduced followed by managerial implications and an evaluation of the research. Lastly, limitations of the research and future research possibilities are discussed.

9.1 Answers to research questions

The objective of this research was to help the case company to realize benefits of the B2B sales analytics by assessing the current maturity level of the B2B sales analytics. Analysis and findings of the current maturity level can offer a starting point for improving the maturity further at the case company. Next, answers to the research questions are presented.

What is analytics in the B2B context?

Based on the literature review, analytics is not yet so well-known and used in the B2B context compared to the B2C context. However, it was found out that analytics can be used in the whole B2B sales process. In addition to basic sales statistics and reporting, more advanced analytics can be used to for example automatically sort new sales suspects based on predictions of deal winning probability. Also, existing customers to be likely to get churned could be predicted. Overall, B2B sales analytics can generate new and better insights from multiple data sources about the competitive environment and customer relationships. These insights can be used to predict future sales trends, optimize pricing, create customer specific personalized offerings and generate targeted marketing activities. B2B sales analytics has been proven to positively impact the customer relationship performance and also monetary sales growth.

What dimensions are included in the B2B sales analytics maturity model?

This research problem was approached with a sociotechnical systems perspective so that the B2B sales analytics maturity model would be holistic covering both the social and the technical aspects of the B2B sales analytics. Based on the literature review about maturity model theory and comparison of existing analytics related maturity models, it seemed that no single analytics, let alone B2B sales analytics, maturity model had yet reached the state of an industry standard. Thus, a customized maturity model had to be created for the purpose of this research and also to fit the case company.

A maturity model development model by Becker et al. (2009) was followed in the customization process. A very recent analytics maturity model by Menukhin et al. (2019) was used as the base model for the customization. In the end, the customized B2B sales analytics maturity model had following dimensions: Culture, Skills, Governance, IT & Analytics Infrastructure and Data & Analytics Technologies. Those dimensions have a good mix of both the social and the technical aspects of the B2B sales analytics following the sociotechnical systems research perspective.

The Culture dimension analyses to what extent the organization's attitudes, strategy and decision-making support analytics. The Skills dimension evaluates the level of data and analytics skills of the employees. The Governance dimension investigates data governance and management, like availability, usability and ownership of data, at the organization. The IT & Analytics Infrastructure dimension analyses information systems, architecture and how they support analytics. The Data & Analytics Technologies dimension investigates used analytics tools and how analytics is integrated into the processes at the organization.

The customized B2B sales analytics maturity model was able to provide valuable results for the defined research problem in this case study so it could be evaluated as successful model. Based on that, the customized model could be approved. This evaluation and approval or rejection of the customized model were the last seventh and eighth phases of the maturity model development model by Becker et al. (2009) discussed more in the chapter 5.1. However, for wider generalizability of the model, a lot more validation should be done in other organizations too since now the model was only validated in one case organization.

What is the current level of the B2B sales analytics maturity?

The customized B2B sales analytics maturity model was used as a conceptual framework to analyse the current maturity level at the case company. The framework was utilized to create a qualitative semi-structured interview structure and ten interviewees from the case company were interviewed.

Based on the qualitative analysis, it can be stated that the case company is still on the very low maturity level and early stages of utilizing B2B sales analytics. At the case company, the "Skills" maturity dimension is on the third level and all other dimensions are on the second level when the B2B sales analytics maturity model has in total five different levels. Thus, there are great potential for future development to increase the maturity of all the dimensions at the case company.

Prominent findings from the analysis of the current B2B sales analytics maturity at the case company are following:

- Possibilities and benefits of the B2B sales analytics are not well-known
- Analytics culture is hindered by the lack of knowledge about analytics possibilities
- Analytics is not emphasized as much at the public sector sales
- Data sharing culture is missing partly due to data governance issues and lack of knowledge about analytics possibilities
- Analytics is not used very much in decision making
- Analytics strategy and roadmap is missing
- More advanced analytics tools and techniques are not used
- Analytics is not well integrated into the sales processes

Most of the found prominent findings at the case company are not unique since they were also commonly found issues in the literature review. The finding about the lack of knowledge about possibilities and benefits of the B2B sales analytics is in line with the research by Hallikainen et al. (2019). Hallikainen et al. (2019) also found out that a supportive analytics culture is crucial for gaining a competitive advantage from the B2B sales analytics which was one issue at the case company of this research. The finding about missing data sharing culture is in line with the research by Lismont et al. (2017). Mikalef et al. (2019) found that usually there is a tendency to fall back to previous ways of making decision and not using analytics in the decision making which was also one finding at the case company of this research. Menukhin et al. (2019) emphasize the importance of well-established analytics strategy which was found to be one issue at the case company too. The finding about lacking usage of more advanced analytics is in line with the research by Lismont et al. (2017). Davenport (2013) proposes integrating analytics into the business processes which was also found to be one issue at the case company.

However, one unique and a bit surprising finding of this research is that analytics was not as emphasized and seen as important at the public sector sales than at the private sector sales. In the interviews, it was noted that regulations of the public sector sales processes were seen as limiting factors for the usage of analytics. Even though this particular finding was not directly found in the literature review it is applicable to the sociotechnical systems perspective seen in the figure 1 in the chapter 2. In the figure 1, external factor like regulatory framework can affect the sociotechnical organization and its culture and people. This has clearly happened at the case company and the effect has been negative for the maturity of the B2B sales analytics.

9.2 Managerial implications

Based on the most prominent findings and issues presented earlier, this research proposes that the case company should start developing the B2B sales analytics maturity by focusing the development first in the “Culture” and the “Data & Analytics Technologies” dimensions. Especially, agile concrete sales analytics demonstrations with more advanced technologies than are currently being used, could be made for the salespeople. That could help them realize possibilities and benefits of the sales analytics on their daily work which could positively affect the “Culture” dimension and its prominent issues. However, there is also a link to the “IT & Analytics Infrastructure” dimension because there is an ongoing ERP system implementation project at the case company which is acting as a bottleneck since before its completion, more advanced sales analytics technologies cannot really be implemented into productised usage.

On more general level, this research emphasizes the importance of a proper data management and governance practices in quickly growing companies. When a company is growing quickly, there tend to be more prominent issues than the data management but without availability of good amount of good quality data it is not possible to implement B2B sales analytics when the need for the analytics would arise. When concrete analytics cannot be done the data and analytics driven culture will get hindered because people cannot see and realize possibilities and benefits of the analytics. If the data bottleneck gets solved later then the lacking analytics culture can become a new bottleneck hindering the analytics implementation. This a great example of a sociotechnical system where a joint development of both the social and the technical aspects of the B2B sales analytics is needed.

9.3 Research evaluation

All in all, it can be stated that this research was able to answer all the research questions presented in the previous subchapter 9.1. Earlier discussed results, prominent findings and development proposals of the current maturity level assessment have practical contributions for the case company since the assessment can provide a starting point for the future developments of the B2B sales analytics. Thus, this research achieved its objectives and was successful.

For theoretical contributions, this research showed the relevancy of the sociotechnical systems perspective for maturity model assessments at organizations. Also, the maturity model theory was seen valid for creating a conceptual framework to be used in the qualitative data collection and analysis. In addition, this research contributed to the B2B sales analytics research which has not attracted much academic research attention.

9.4 Limitations and future research

In qualitative research, reliability of the research is concerned with whether alternative researchers could reveal similar findings. With the available resources and time constraints of this research, only qualitative semi-structured interviews were used in data collection. There are different types of biases to consider with the qualitative interviews as data collection method. Interviewer bias can happen when for example comments and non-verbal behavior of the interviewer creates bias in the way the interviewees answer to the questions. Also, there can be bias in the way the interviewer interprets interviewee's answers. On the other hand, there can also be interviewee bias if the interviewee is not willing to answer openly and truthfully to interviewer's questions. (Saunders et al. 2009, pp. 326–327.)

The author of this research had been working at the case company for over year which might have caused interviewer and interviewee bias. It is possible that author's preconceptions about interviewees, who where already known colleagues, might have created bias in the interviewer's comments and in the interpretation of the answers. On the other hand, there could have been interviewee bias since the interviewees knew the interviewer beforehand. However, since the interviewees knew the interviewer beforehand there may have been more trustworthy setting in the interviews and the interviewees could have been more willing to answer and share even sensitive information about the case company. All in all, it can be stated that alternative researchers most likely would not have been able to reveal very similar research findings which hinders the reliability of this research.

In the scope of this research, a single case study research strategy was used. Thus, this choice of research strategy limits the wider generalizability and external validity of the results in this research (Saunders et al. 2009, pp. 145–146; Farquhar 2012, pp. 103–105). However, the objective of this research was not to create generalizable theoretical propositions so the lack of generalizability of the findings is acceptable in this research as usually in many case studies.

With more resources, the data collection and analysis could be complemented with a quantitative survey in a mixed methods approach in future research. This analytics maturity assessment research could also be conducted in a larger scale at the case company with an embedded case study research strategy, and not just at the sales unit with the single case study strategy. Also, the research could be replicated in multiple different case organizations with a multiple case study strategy which would also validate the customized B2B sales analytics maturity model better.

Future research could also be done to investigate different ways different companies practically utilize the B2B sales analytics and how it has benefitted them. Especially, this research could be done with companies operating in B2B consultancy services business model. It seems that there is a lack of knowledge about different possibilities of the B2B sales analytics both in the literature and in companies. Another interesting research topic would be to investigate the usage of the B2B sales analytics in public sector procurement processes because regulations of the public sector sales were seen as a limiting factor for the usage of the B2B sales analytics at the case company.

It was evident that no single analytics maturity model has yet reached a state of an industry standard. Thus, more rigorous research about analytics maturity models could be done to create research based and widely validated analytics maturity model which could be used as the standard in future research and also in practice.

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APPENDIX A: INTERVIEW STRUCTURE

What is your role at the company?

How does data and analytics show in your work?

Culture:

- How does the sales unit promote and encourage the use of analytics?
- What kind of actions have you taken based on analytics at the sales unit?
- What kind of analytics road map do you have in place at the sales unit?
    a. Analytics strategy?

Skills:

- What kind of analytics skills does salespeople have at the sales unit?
    a. Past, present, future prediction?
    b. Excel, business intelligence applications?
- What kind of analytics skills would be needed at the sales unit?
- What kind of analytics skills training does the sales unit provide for salespeople?

Governance:

- What kind of data is needed at the sales unit?
- How can salespeople access the needed data when they need it?
    a. Does all have access, easy to access, can access on time?
- How usable is the available data?
    a. Does it enable future prediction?
- How is sales data managed at the sales unit?
    a. Who manages, named owners?
    b. Management processes?

IT & Analytics Infrastructure:

- How is the sales data gathered at the sales unit?
    a. Manually, automatically?

- How do information systems support sales analytics?
- What kind of investments and developments are being made in the area of sales data and analytics?

Data & Analytics Technologies:

- What kind of analytics technologies do you utilize at the sales unit?
- What kind of analytics do you do with the available technologies?
    a. Past, present, future prediction?
    b. Has the done analytics been useful for the sales?
- How are analytics technologies integrated into the sales processes?
- How automated are the used analytics technologies?

Do you have additional comments on the topic?