Tampereen yliopisto

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ANALYSING CUSTOMER DATA FROM CUSTOMER RELATIONSHIP MANAGEMENT SYSTEM

Master's Thesis

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ABSTRACT

Nico Ylirönni: Analysing Customer Data from Customer Relationship Management System
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Organisations collect vast amounts of data from their business environment and process it in order to support their decision-making and gain benefits. Before the value is created for the organisation, the data needs to be stored and processed. Customer relationship management, or CRM, provides organisations tools to collect and store their customer data in order to create a comprehensive view of them, and this helps the organisations to build and manage long-lasting customer relationships.

To create insights of different customers and customer groups, the data needs to be analysed to offer additional information and create value, such as improved decision-making and organisational performance and more efficient processes. But organisations need different capabilities to analyse the data. They need good quality data, data-driven organisational culture, capable leadership, understanding for strategic use of analytics, competent employees, and effective tools to properly analyse the data. If some of these aspects and capabilities with them are low, the benefits are mitigated.

This study explains how to utilise data analytics with customer data from CRM, what benefits the analytics bring, and what aspects mitigate the benefits. The study explores theories from literature about CRM and data analytics, and forms a survey, to test the findings empirically. Twenty responses are analysed, and a model for data analytics and its elements is created. The model is tested with logistic regression against different benefits. Overall score of the model finds relationship between the score and improvements in decision-making, marketing capabilities, profits, and saved resources in different organisations. The most common challenges mitigating the benefits are reported to be difficulties with strategic use of analytics and data quality.

The results validate that data analytics lead to benefits and offers information on how Finnish organisations analyse their customer data from CRM and what challenges they face. The study also provides a model for others to inspect their analytical capabilities. Future research is suggested to test the model with a larger sample and to inspect the challenges organisations face with the strategic use more closely.

Keywords: CRM, customer relationship management, customer data, data analytics, data, analytics, benefits, challenges

TIIVISTELMÄ

Nico Ylirönni: Asiakasdatan Analysointi Asiakkuudenhallintajärjestelmästä
Diplomityö
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Organisaatiot keräävät suuria määriä dataa toimintaympäristöstään tukeakseen päätöksentekoaan, sekä jalostavat ja prosessoivat keräämäänsä dataa saadakseen siitä erilaisia hyötyjä toimintaansa. Ennen kuin datasta voidaan luoda lisäarvoa ja hyötyä organisaatiolle, se tulee varastoida ja prosessoida. Asiakkuudenhallintajärjestelmä, tai CRM, tarjoaa organisaatiolle työkalut datan keräämiseen ja varastointiin, ja sen avulla asiakkaista voidaan luoda organisaatiolle kokonaisvaltainen kuva, mikä helpottaa pitkäkestoisen asiakassuhteen rakentamista ja ylläpitämistä.

Jotta asiakkaista tai eri ryhmistä voidaan luoda syvää ymmärrystä, heidän datansa täytyy analysoida, jolloin siitä voidaan luoda uutta informaatiota ja lisäarvoa, kuten parantunutta päätöksentekoa ja organisaation suorituskykyä, sekä tehokkaampia prosesseja. Mutta organisaatiot tarvitsevat eri kyvykkyyksiä analysoidakseen dataansa. He tarvitsevat laadukasta dataa, datalähtöisen organisaatiokulttuurin, kyvykkäät johtajat, ymmärrystä analytiikan strategisesta hyödyntämisestä, osaavan henkilöstön, sekä tehokkaita työkaluja analysoidakseen dataansa. Jos jokin näistä kyvykkyyksistä on heikolla tasolla, analytiikasta saadut hyödyt heikkenevät.

Tämä tutkimus kertoo, kuinka analysoida ja hyödyntää asiakasdataa asiakkuudenhallintajärjestelmästä, mitä hyötyjä datan analysointi tuo organisaatiolle, sekä mitkä tekijät heikentävät mahdollisia hyötyjä. Tutkimus kartoittaa eri teorioita data analytiikan ja asiakkuudenhallintajärjestelmien kirjallisuudesta, ja muodostaa niiden perusteella kyselyn selvittääkseen tuloksia empiirisesti. Kaksikymmentä vastausta analysoidaan ja niiden perusteella data analytiikasta ja sen tekijöistä luodaan malli, ja logistisen regression avulla testataan mallin yhteyttä eri hyötyihin. Mallin kokonaistarkastelussa voidaan todeta positiivinen yhteys parannuksiin päätöksenteossa, markkinointikyvykkyyksissä, tuotoissa, sekä säästetyissä resursseissa eri organisaatioissa. Haasteellisimmaksi data analytiikan tekijöiksi, jotka heikentävät positiivisia tuloksia, kerrotaan analytiikan strateginen hyödyntäminen ja datan heikko laatu.

Tulokset vahvistavat, että data analytiikka johtaa hyötyihin, sekä ne tarjoavat tietoa, kuinka suomalaiset yritykset analysoivat asiakasdataansa asiakkuudenhallintajärjestelmistään, ja mitä haasteita analytiikassa kohdataan. Tutkimus tarjoaa myös data analytiikan mallia, jonka avulla voidaan tarkastella organisaatioiden analyyttistä kyvykkyyttä eri tekijöiden perusteella. Jatkotutkimuksina suositellaan mallin testaamista suuremmalla otannalla ja tarkempaa tutkimusta, siitä kuinka datan strateginen hyödyntäminen vaikuttaa organisaatioiden data analytiikkaa.

Avainsanat: CRM, asiakkuudenhallintajärjestelmä, asiakasdata, data analytiikka, data, analytiikka, hyödyt, haasteet

PREFACE

I started studying at Tampere University (at the time Technical University of Tampere) in 2015. It feels like a lifetime ago, but also somehow like only a few moments have passed since then. The time has passed quickly, and I remember having no idea, what I was getting into when I walked into the university for the first time. The environment was strange, the degree programme was unclear, and the studies sounded as a tremendous task, as there were lectures, reports, exercises, project works individually and in teams, exams, theses, and so on. Sometimes they felt like a never-ending journey, filled with stress and long nights.

And yet here I am, on the brink of graduation. After twenty-odd years, I have passed through elementary school, upper secondary school, and university. Finally my studies are done (for the moment at least). I’ve learned a lot, and eagerly wait for chances and opportunities to share and implement my knowledge and skills with others in practise, hopeful to make an impact. The journey, whilst long and hard, was worth it. I have many good memories and experiences from my time at Tampere University, and I have left my mark in the teekkari culture.

I want to thank professor Samuli Pekkola for his guidance, and Knowit for offering me an opportunity to write a thesis for them. Thanks to the Guild of Information and Knowledge Management, Man@ger, for raising me to be a proper teekkari, and Sportuni for keeping me healthy and offering me ways to relax. A special thank-you is in place for TEA-club and its members for providing good memories, support, joy, and laughter for many years. May these memories last long.

And finally, a heartfelt thank you for my parents, brothers, sister and her family, and to my darling. Thank you for believing in me and making me strive to be better.

So long, and thanks for all the fish.

Tampere, 07.03.2022

Nico Ylirönni

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1. INTRODUCTION

Data is being created in staggering amounts. According to Reinsel, Gantz, and Rydning (2018) the amount of data created, captured, or replicated in 2018 is 33 zettabytes and the amount could grow to 175 zettabytes by 2025. This data is created by humans interacting with different websites and services, or by different sensors communicating with other sensors. Available data is diverse, and it can be refined to offer insight to the environment it is collected from, or to create new products and services. These possibilities inspire organisations to invest in data analytics and to develop their culture to be more data-driven, so their decisions would be guided by information refined from data. Ali-Yrkkö *et al.* (2019) write that utilisation of big data and its analysis saw an increase from 10 to 13 percentage in two years, when measuring organisations employing over 10 people in EU15 countries and Gartner (2020) predicts that data utilisation and different types of analysis from it will become more common and important, especially after a global pandemic. Many an organisation see data as an opportunity to gain competitive advantage over others by having a unique and valuable resource that others do not have (Barney, 1991). One such unique resource is organisation's customer data, that can be collected with proper IT systems, such as CRM.

Customer relationship management (CRM) systems are a group of information systems enabling organisations to contact customers and collect, store, and analyse customer data to provide a comprehensive view of their customers (Khodakarami and Chan, 2014). CRM offers information that can be used as a basis for a strategy to build, manage, and strengthen loyal and long-lasting customer relationships. This information can also be analysed to provide new insight of customers, possibly leading to personalised interactions with the customers and increase in their satisfaction (Chorianopoulos, 2016). CRM helps organisations by creating a 360° view of customers, allowing them to see the comprehensive picture of customer interactions. Forming this view requires proper management of technologies, processes, information resources, and people, but the comprehensive customer data leads to improved marketing capabilities and enhanced organisational performance. (Galbreath and Rogers, 1999; Chang, Park and Chaiy, 2010; Khodakarami and Chan, 2014) CRM customer data offers organisations a remarkable opportunity to process the data for strategic and operational purposes, to find new insights, patterns, and trends of customer behaviour that they can utilise to improve their offerings and services. Customers could be grouped together to see the big picture behind their behaviour in organisation's environment, allowing the organisation to focus more relevant marketing to them or figure how to fulfil their needs better. Customer purchases could be inspected to find out similarities, so new products could be recommended to customers with similar profiles, who do not regularly buy the products. CRM offers vast amounts of customer data, ready to be processed for insights, to improve the organisation on the long term.

Data alone is not enough to create insight and improvements, but it needs to be processed by analysing it. Koohang and Nord (2021) define data analytics as the process of examining and analysing raw data (from small data sources to extremely large data sets, or big data) to obtain trends, insights, and correlations between variables of the information the data holds and use it for improving decision-making in organisations. Analytics as a process is holistic, as it combines information systems, data, and people's skills available to foster growth and to gain business value (Ji-fan Ren *et al.*, 2017). McAfee and Brynjolfsson (2012) summarised analytics as "seeking to glean intelligence from data and translate that into business advantage". Literature has many terms for data analytics, such as business intelligence and analytics, big data and analytics, business analytics, and big data analytics. This thesis will use the term data analytics of them all, as the principle behind them is the same.

Data analytics can lead to many improvements in organisational performance (Mithas, Ramasubbu and Sambamurthy, 2011; McKinsey & Company, 2016; Kitchens *et al.*, 2018; Müller, Fay and Brocke, 2018; Barnes *et al.*, 2020; Koohang and Nord, 2021), marketing and customer experience (Khodakarami and Chan, 2014; Chorianopoulos, 2016; Grover *et al.*, 2018; Kelleher and Tierney, 2018; Anshari *et al.*, 2019), and decision-making (Brynjolfsson, Hitt and Kim, 2011; Davenport, 2013; Chiang *et al.*, 2018). Data analytics allow organisations to improve their internal and external processes and offerings, and benefits can vary between tangible and intangible benefits, e.g. monetary profits or improved customer satisfaction. To gain these benefits organisations need different resources. Data is given, but it is not the only obstacle in the way of benefits. Analytics is also dependent on organisation's leadership and culture, technology and skilled personnel. (LaValle *et al.*, 2011; McAfee and Brynjolfsson, 2012; Davenport, 2013; Gillon *et al.*, 2014; Ji-fan Ren *et al.*, 2017; Kitchens *et al.*, 2018; Koohang and Nord, 2021). To succeed in analytics, all the previously mentioned elements need to work seamlessly together. Figure 1 displays the connection between data analytics, CRM, and possible benefits from an organisation's point of view, summarising and simplifying the subject of this thesis.

Figure 1. *CRM and data analytics.*

As can be seen from Figure 1, CRM offers data to be analysed and gains refined data, or information, in return. Data analytics can result to benefits, but they are possibly mitigated or prevented by different challenges organisations face regarding the requirements for data analytics and CRM usage. Benefits can also be realised from CRM and the information within it, but to simplify the figure, benefits are provided by data analytics.

CRM offers many possibilities for organisations to improve themselves with the help of data analytics, but are they utilised effectively? Are analytics treated as strategic assets or as ad hoc solutions to current operational problems? Neither utilisation is wrong, both can be effective use cases for analytics and lead to benefits. For example, data visualisations, that can be seen supporting mainly operational functions, would help users to explore and understand the data, presenting it in a clear and understandable way, helping organisations to get answers to current questions fast (Kelleher and Tierney, 2018). Or analytics can be used strategically to figure out the most profitable customer groups and find a successful marketing campaign for them, as an example. Organisations can utilise analytics and business intelligence platforms for data analytics, such as Tableau or Microsoft Power BI, that support a full analytic workflow from data preparation to visual exploration and insight generation (Richardson *et al.*, 2021). But on the long term it would be beneficial to integrate analytics into organisation's strategy and decision-making.

If organisations want to utilise data analytics for customer data effectively, how could it be done and what challenges do they face? Are the current solutions offered by aforementioned platforms enough? And importantly, can organisations perceive benefits of customer data analytics? And if not, are there detectable factors preventing them? This thesis aims to answer and offer insight to these questions by inspecting how organisations utilise data analytics in the context of customer data available from CRM.

1.1 Research problem, objective, and questions

This master's thesis is a research conducted for Knowit Solution's Data Driven Services (later data unit) and their possible customers. The aim of the research is to offer insight to customers' challenges with data analytics from CRM systems, reflect possible solutions to these problems, and inform possible customers about benefits of solving these problems. To reach this aim, this thesis will cover theory of CRM systems, data quality and its effects on data analytics, common challenges with data analytics processes, solutions to these problems and the effects of efficient data analytics in an organisation. The thesis will achieve this by relying on current literature of these subjects, combining the information gained to form a framework, that will be used to inspect different organisations' status, and conduct a quantitative case study.

The data unit is moving towards new offerings utilising data within a CRM system, and this research will offer them instructions on utilising customer data available from a CRM system. The data unit has experience and skills in offering data solutions for customers, but as this is a new offering, they want to verify that they understand customer needs and their problems correctly. This research offers them insight about customers and their challenges with data analytics, aiming to inform the data unit about challenges customers face, while analysing and utilising comprehensive customer data available from a CRM system, and reflect solutions to these problems. When the benefits of these solutions are explained to potential customers, then the data unit gains valuable information to be utilised for marketing purposes to justify the services of the data unit to customers. The research can also prove valuable for other data solutions within the data unit by offering them current information of customer needs in data analytics and possible insights of current trends of data analytics within their environment.

Problem, the data unit is facing, is that how organisations utilise and analyse customer data from a CRM and what challenges are they facing while doing so? Especially as Salesforce bought Tableau and now offers seamless data analysis of data within Salesforce (Tableau, 2019), Knowit Solution aims to offer excellent data analytics and data solutions with Salesforce data. To achieve this, they need to inspect possible problems with the data analytics in order to prepare instructions on solving them, so they can offer customers effective and professional service. This inspection includes studying current what data customers collect, how do they analyse it, what benefits they gain, and what challenges they face in analytics.

This research aims to answer the research problem with the help of one main research question and three sub-questions supporting the main research question, forming a coherent and comprehensive entity. The main research question is:

How to utilise data analytics in the context of CRM customer data?

The sub-questions supporting the main research questions are:

1. **What data is collected to different CRM systems?**
2. **What are the challenges of analysing customer data from a CRM system?**
3. **What benefits successful analytics bring or what prevents the benefits from realising?**

With the help of the first sub-question, the scope and the subject are made clear with the help of literature, introducing readers to CRM systems and the types of data they can store. Requirements of data suitable for analytics, such as quality and timeliness, are considered. Based on the literature, applications of data in organisations are evaluated to discover any discrepancies, possibly leading to challenges or ineffective use of the data.

The second sub-question offers a literature-based introduction to data analytics, its benefits and a view to aspects affecting data analytics, that could make it more challenging for organisations to gain benefit of the data. These aspects include technical, organisational, and managerial views. The third sub-question aims to create insight to realised benefits of data analytics and offer knowledge to the question of why the benefits do not realise, offering valuable information to stakeholders. Empirical research is conducted about these sub-questions to find out the common problems existing in organisations. Possible reasons and solutions for these problems are discussed, and the final result is answers and insights from business environment to the challenges, solutions, and possible benefits of customer data analytics.

In addition to knowledge brought to the data unit, this research offers scientific value, especially for data analytics in Finnish organisations. This research will delve into current challenges organisations are facing with data analytics and inspect solutions to them, which can prove useful for other stakeholders and organisations. This research could help others to understand what aspects are needed for gaining benefits of data analytics. Data-driven stakeholders can read the research and implement changes to their processes with the knowledge gained of the research.

1.2 Research methodology

Research methodology guides how the research will be conducted, but first a few words about research philosophy to make the premises of the research clear. Research philosophy refers to a system of beliefs and assumptions about the development of knowledge, which will shape how research questions are understood, methods are used, and findings are interpreted (Crotty, 1998; Saunders, Lewis and Thornhill, 2019). Research methodology in its entirety containing philosophical assumptions, methodological choices, and research strategy is summarised in Figure 2.

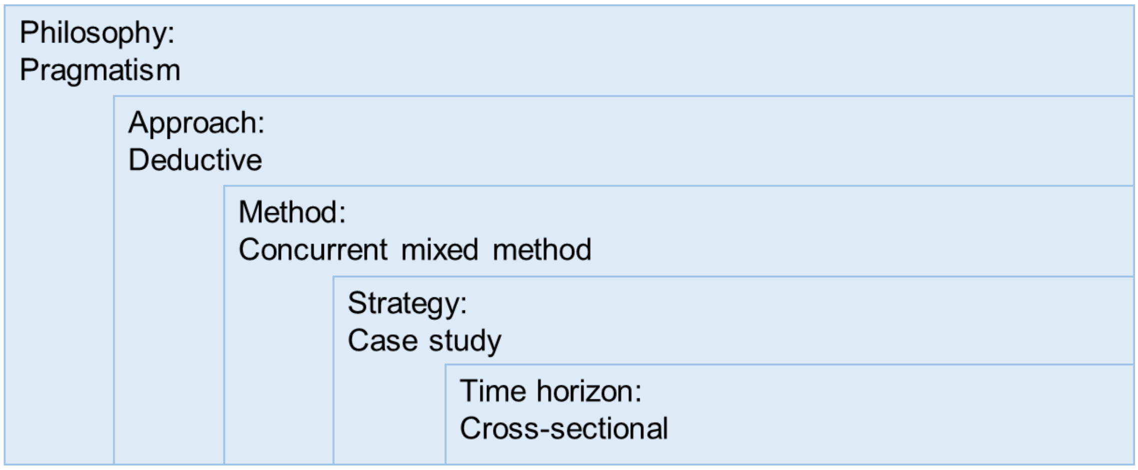

Figure 2. *Summary of the research methodology.*

As shown in Figure 2, research philosophy offers guidance for the entirety of the research focusing on the whole scope of the research, while other dimensions offer guidance for more specific sections of the research.

This research will inspect reality through pragmatism, which values practical experience and dialogue while interpreting the environment and it aims to generate knowledge that makes a positive difference and contributes to better practise, using the data and understandings available at the time (Kelemen and Rumens, 2008). The research starts with defining a problem and the result aims to form a practical solution answering it. This is done by formulating a research question that is answered with the help of literature and studies of the subject, and the result is validated by empirical research. Because of this structure, theory for the research is developed using deductive approach.

Deduction begins with the intent to explain causal relationships between concepts and variables, which are explained using academic literature. A theory is formed to explain the relationship, and this theory is evaluated by collecting quantitative data and analysing it. Deductive researches aim to generalise specific situations into a theory holding true under similar situations. (Saunders, Lewis and Thornhill, 2019)

This research will collect data and test the theory through a concurrent mixed method, which involves using qualitative and quantitative methods simultaneously while collecting and analysing data. Data collection will be focused on quantitative but this method allows collection of qualitative and quantitative data to be interpreted together to provide a comprehensive answer to the research question. (Saunders, Lewis and Thornhill, 2019) This methodology is chosen because it allows a respondent to supplement one’s answers to offer additional information, which could prove useful for answering the research question.

Research strategy, which can be thought as a plan to answer the research question, for this research is a case study (Saunders, Lewis and Thornhill, 2019). A case study is an empirical method investigating theory within its real-world context, trying to understand the dynamics present within a single settings (Eisenhardt, 1989; Yin, 2017). A case study for this research is natural, as the research is done for a particular organisation, so the context is limited to the organisation's environment. Another limitation that comes to the research as a part of research methodology, is time horizon. This research will be cross-sectional, which involves studying particular phenomenon at a particular time (Saunders, Lewis and Thornhill, 2019), which for this research is current time.

The research will be conducted by forming a survey, aiming to answer the research question. For the survey, multiple organisations utilising data analytics with CRM systems will be charted out and approached. Focus will be on CRM by Salesforce, but other systems are considered if the sample size of the research is low, as a specific CRM system and utilising data analytics with its data might restrict the research too much. Organisations will be sent a survey to validate if the findings from theories and literature support real-life scenarios and to answer the research question from realistic environment empirically. The answers will be analysed and discussed. Findings and discrepancies will be explained, and the research summarised, reviewed, and concluded.

1.3 Research structure

This chapter provides a brief introduction to the structure of the research. The structure is divided into four sections: introduction, literature research, empirical research, and discussion and conclusion. Structure is presented below.

1. Introduction
   1.1. Research problem, objective, and questions
   1.2. Research methodology
   1.3. Research structure
2. Literature research
   2.1. CRM, value creation, requirements.
   2.2. Data analytics, value creation, requirements.

3. Empirical research
    3.1. Data collection
    3.2. Survey results
    3.3. Analysis
4. Discussion and conclusion

Introduction explains, what this research is about, why is it relevant, how the research will be conducted and what benefits does it bring. Research problems, questions, and methodologies are formulated and explained in this section, and the structure of the research is introduced.

Literature research section delves into literature of subjects relevant to the research, exploring recent literature of CRM systems, data, and data analytics. This section aims to answer the sub-questions from literature point of view, explaining what customer data in CRM is, what are the challenges of analysing customer data from a CRM system, and how to overcome these challenges to gain benefits. Literature will be searched mainly from Andor and Google Scholar, but knowledge and recommendations of other parties involved are utilised. While searching for source material, focus will be in recent articles and studies from fields of business, management, and information technology. Literature research section will help in understanding the subject and it forms a base for a framework to be tested empirically in realistic business environment.

Empirical research section forms and presents the creation of the survey used to collect research data. The purpose of the survey will be explained to a small group of experts and based on their feedback the questionnaire will be updated to fulfil its purpose better. In addition to the survey, methods for data collection and analysis are explained, and the collected research data is presented and analysed to introduce the results.

In the last section, the results based on empirical research are reflected against the finding for literature and results are discussed. The research is evaluated, and possible future research subjects are proposed.

2. CUSTOMER RELATIONSHIP MANAGEMENT

Customer relationship management, or **CRM**, is about managing organisation's relations to its customers, as the name suggests. It has many definitions in literature depending on the context, and it can be seen as a tool or strategic asset. Customer relationship management can be thought as a strategic approach focusing on creation of improved value for the organisation through the development of profitable and long-term relationships with key customers and customer segments. This is enabled by integrating people, operations, processes, and marketing capabilities, and by utilising data and information, so organisations can understand customers better and implement relationship marketing strategies. (Payne, 2006, Chapter 1) Or it can be described as "a philosophy and a strategy supported by a system and a technology designed to improve human interaction in a business environment" (Greenberg, 2010). Table 1 presents different definitions for CRM throughout the years in addition to the previous definitions. Even though the context ranges from managerial studies to technical studies, the core idea and purpose of the CRM remains the same.

Table 1. *Customer relationship management definitions.*

Author(s)	Definition
Galbreath and Rogers (1999)	"Activities a business performs to identify, qualify, acquire, develop, and retain increasingly loyal and profitable customers by delivering the right product or service, to the right customer, through the right channel, at the right time and the right cost. It integrates sales, marketing, service, enterprise resource planning and supply chain management functions through business process automation, technology solutions and information resources to maximise each customer contact".
Khodakarami and Chan (2014)	"CRM systems are a group of information systems enabling organisations to contact customers and collect, store, and analyse customer data to provide a comprehensive view of their customers".
Chorianopoulos (2016)	"CRM is the strategy for building, managing, and strengthening loyal and long-lasting customer relationships".
Anshari *et al.* (2019)	"CRM consists of sales, marketing, and customer service activities. The aims are to find, attract new customers, nurture and retain them for future business. Organisations use CRM in meeting customers' expectations and aligning them with the organisation's mission and objectives in order to bring about a sustainable performance and effective customer relationships".
Buttle and Maklan (2019, p. 17)	"CRM is the core business strategy that aims to create and maintain profitable relationships with customers, by designing and delivering superior value propositions. It is grounded on high-quality customer-related data and enabled by information technology".

Table 1 indicates that CRM is about fostering profitable long-term relationships with customers, and this is enabled by comprehensive customer data and information systems. CRM helps organisations to manage customers throughout their lifecycle, from identifying and attracting potential customers to customer retention and development (Gončarovs, 2017). CRM offers organisations broad support on strategic and operational processes in sales, marketing, and service functions, bringing relevant information to relevant environment to support decision-making. Strategically this means that organisations can prepare for the future and identify changing customer landscape. On operational level CRM supports different functions and departments, making their tasks easier, e.g. marketing persons can get a list of current customers to approach effortlessly, service managers can view information of previous customer interactions, and salespersons can get leads on possible customers. Organisations can create a comprehensive view of the customers or create customer segments of similar customers with the help of CRM and combine this information with their processes to create value for them and their customers. CRM encompasses and impacts organisations on different fronts, such as customer-facing level, where they communicate with their customers, and company-wide level, where they develop their offerings to better suit future needs (Kumar and Reinartz, 2012).

CRM is about customers and the relationship organisations want to build with them, requiring active management of the processes and resources of an organisation to gain mutual benefits (Buttle and Maklan, 2019, p. 17). Organisations want to understand customers and make practical use of their data (Xu and Walton, 2005), aiming at two main objectives: customer retention through customer satisfaction and customer development (Chorianopoulos, 2016). Customer retention leads to increasing profits so it is beneficial for organisations to keep their customers satisfied (Reichheld and Sasser, 1990). CRM also helps organisations to understand which customers have untapped potential and which should be abandoned by analysing customer interactions with the organisation and turn that information into intelligent business knowledge (Galbreath and Rogers, 1999).

Data in CRM consists of data from, about, and for customers (Khodakarami and Chan, 2014). The data from the customers is data generated of their actions towards the organisation, such clicks on their websites, given feedback, and social media data. Data about the customers is data useful to identify individual customers and the data contains information of them, such as name, email, and last purchases. Data for customers is information about organisation meant for customers to inform them about products, services, or solutions the organisation provide for them (Buttle and Maklan, 2019, p. 340).

The customer data in CRM is diverse and contains not only transactional data from customers, but also general inquiries, feedbacks and comments, social media texts, and available metadata, such as time of activity and number of support contacts, which offer valuable insights to customer behaviour (Xu and Walton, 2005; Greenberg, 2010).

Customer data in organisations' CRM systems can be classified into three different categories: personal data, action data, and reaction data (Reimer and Becker, 2015). Personal data consists of person's personal data, such as demographic (i.e. age, gender), geographic (i.e. location, address), and psychographic (i.e. interests, attitude), allowing organisations to identify and contact them accurately. Action data consists of organisation's actions towards the customers, such as time, frequency, intensity, and costs of processes towards the customers, whereas reaction data is data of the customer's response to actions done by the organisation. (Reimer and Becker, 2015)

Information and knowledge gained from CRM can lead to multiple benefits. One way to divide net benefits gained from implementation of CRM systems is to divide them into two categories: tangible and intangible (Chen and Chen, 2004). Tangible benefits include increased revenues and profitability, reduced internal costs, higher employee productivity, reduced marketing costs, higher customer retention rates and protected marketing investment with maximised returns. Intangible benefits include increased customer satisfaction and customer service, streamlined business processes, acute targeting and profiling of customers, and better understanding of customer requirements. (Chen and Chen, 2004) Benefits are not limited to the organisation utilising CRM, but it also includes the customers and how they perceive the benefits. When an organisation utilises CRM to support sales activities, the benefits are salesperson's professionalism, customer interaction frequency, salesperson responsiveness, and salesperson – customer relationship quality (Boujena, Johnston and Merunka, 2009). The customers perceive that salesperson understand them well and answer their needs better, communicate more clearly with them and the interaction between them is frequent and satisfying.

In contemporary competitive business environment, it is important for organisations to utilise CRM to develop and implement more efficient and effective customer strategies leading to aforementioned benefits (Chang, Park and Chaiy, 2010). But the benefits do not appear on their own. CRM demands a successful business/IT alignment (Galbreath and Rogers, 1999) Effective use of CRM is supported by organisational culture, management of organisation's people, relevant data, competent employees, and IT infrastructure (King and Burgess, 2008; The Customer Framework, 2016; Buttle and Maklan, 2019, pp. 22–24). Data and IT infrastructure form a platform, where organisations can store, process, and analyse the data to create insight of it. These require defined processes so employees would act in the same way and communicate clearly with each other. This allows for example data being in the right place and in correct form to be analysed, and analytics to be in a form that provides necessary information to support decision-making. Organisations need skilled and competent employees to handle the processes. And on the other hand, employees need the organisational support and management to realise long-term customer strategy and develop their skills and organisation's processes to be more efficient.

Summarised, CRM unites the potential of IT and customer data to deliver profitable, long-term relationships with customers. It provides enhanced opportunities to use data and information both to understand customers and implements relationship marketing strategies better (Payne, 2006, Chapter 1). It provides support for organisations on strategical and operational level, allowing them to prepare for the future.

2.1 Types of CRM

Literature presents different types of CRM depending on their purpose. CRM can be divided into strategic, operational, collaborative, social, and analytical CRM (Xu and Walton, 2005; Payne, 2006, Chapter 1; Greenberg, 2010; Buttle and Maklan, 2019, pp. 3–24). Figure 3 presents and summarises each type of CRM.

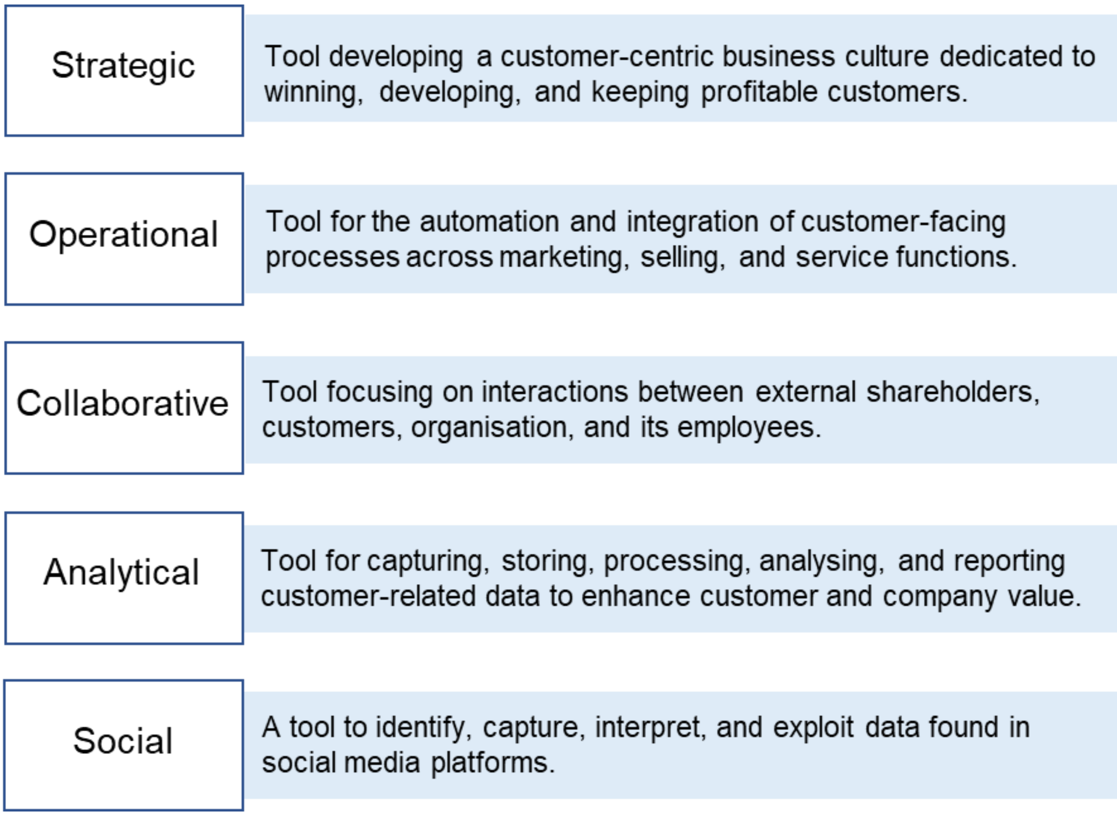

Figure 3. *Types of CRM (Paraphrased from Buttle and Maklan, 2019, pp. 3–24).*

In addition to the categorisation by type presented in Figure 3, CRM can be inspected by the perspective of its functions, which target and impact three different levels: functional, customer-facing, and organisation-wide (Kumar and Reinartz, 2012). On the functional level CRM consists of the processes supporting marketing and sales functions, such as sales force automation. On the customer-facing level CRM provides a single view of the customer making the information available for all functions that are customer-facing, such as the support services of an organisation. When the information of the customers has implications on the whole organisation, the perspective is company-wide. (Kumar and Reinartz, 2012) This kind of information is for example behaviour of customer segments, or predictions of the development of sales, useful information for strategic planning of an organisation.

Not all regard social CRM as a fundamental type of CRM as presented in Figure 3 (e.g. Buttle and Maklan, 2019, pp. 14–15). Although social CRM focuses on data from social media, that is valuable for organisations and not necessary available for them normally, the data is used for the same strategic and operational purposes as conventional siloed organisational data (Buttle and Maklan, 2019, pp. 14–15). Some regard it as “CRM 2.0” which allows organisations to engage in customer interactions in new, transparent environments, making the relationship collaborative and bi-directional effort and providing mutually beneficial value for both (Greenberg, 2010). It is brough to attention but not discussed about thoroughly, as the rapid accumulation of data in diverse forms and from various sources, such as social media, drive an increasing interest in big data analytics (Chiang *et al.*, 2018; Reinsel, Gantz and Rydning, 2018). Social CRM allows organisations to identify, capture, interpret, and exploit data found in social media platforms, and integrate it with organisation's internal data of the customer to create a comprehensive view of the customer (Buttle and Maklan, 2019, pp. 14–15). Personal information and knowledge of persons network of friends can be harvested from social media and used to profile them for marketing purposes. This profiling can be used to influence their habits, sometimes even nefariously (Cadwalladr and Graham-Harrison, 2018). Social CRM supports other business functions and types of CRM by monitoring and filtering available data from social media, integrating it with CRM, creating new insight of the customer, and supporting different methods to engage with the customer on the platform they prefer (Goldenberg, 2015). Employees can find timely data of social trends and messages for the organisation from social media integrated to the CRM, allowing them to view the messages, pick important ones to be processed, and handle customers' problems or questions from one platform, making their work more streamlined.

2.1.1 Strategic CRM

Strategic CRM focuses on developing a customer-centric business culture, aiming at winning, developing, and keeping profitable customers by creating and delivering better value propositions and customer experiences than competitors (Buttle and Maklan, 2019, p. 6). This customer-centric culture is developed by combining business strategy to a focus on developing the customer relationships towards long-term value creation (Payne, 2006, Chapter 1). When customer data and competitive information from an organisation's environment is transformed and combined, it can be actively used to shape the interactions between a customer and the organisation. These interactions allow the organisation to develop better value propositions for the customers by inspecting customers' perceived value, and the interactions enhance customers' experience while maximising lifetime value of the customer in strategic CRM. (Kumar and Reinartz, 2012; Buttle and Maklan, 2019, p. 164)

An important part of strategic CRM is customer portfolio management that allows organisations to group customers into different segments on the basis of one or more strategically important factors (Buttle and Maklan, 2019, p. 164). Customers in different segments are offered a different value proposition depending on the organisation's strategy for that segment. For example, new customers can get a discount for their order, if they give their contact information for the organisation, so the organisation can use it for marketing purposes later. This way the organisation gains information for marketing purposes, as they have an address to send marketing campaigns that encourage customers to buy their products.

Successful strategic CRM requires four components to form a basis for competitive advantage: (1) a customer management orientation, (2) the integration and alignment of organisational processes, (3) information capture and the alignment of technology, and (4) CRM strategy implementation (Kumar and Reinartz, 2012). Organisations need the support and instructions from the management when creating a strategy for CRM and its usage. It is the duty of the management to set up the organisational values, beliefs, and strategic actions regarding the CRM (Kumar and Reinartz, 2012). Organisation needs to define and synchronise their processes and focus on working cross-functional systems that allow them to build a comprehensive view of the customer, that the entire organisation can utilise to be of help in their processes and in creating long-term value.

2.1.2 Collaborative CRM

Collaborative CRM focuses on creating mutual benefits to its users, which are organisation and its internal or external stakeholders, such as users, customers, suppliers, manufacturers, and governments. It uses different services and infrastructures to enable interactions between the organisation and different stakeholders on multiple channels, offering users similar experience with the organisation regardless of the platform used for interactions (Payne, 2006, Chapter 1). Collaborative CRM systems integrate and manage the available data from customer touchpoints, such as organisation’s websites, e-mail, and customer portals, and the data can be integrated with enterprise-wide systems for greater responsiveness to customers (Xu and Walton, 2005; Khodakarami and Chan, 2014).

Organisations can use collaborative CRM systems to externalise knowledge within individuals, meaning that individuals document their tacit knowledge, making it available for others to process (Nonaka and Takeuchi, 1995). Collaborative CRM systems can be used to facilitate collaboration inside the organisations, using the systems to externalise knowledge about their customers and to support their decision-making by externalising knowledge about the customers (Khodakarami and Chan, 2014). In addition to externalisation of knowledge, collaborative CRM systems provided opportunities for internalisation of knowledge, where individuals process external knowledge into tacit knowledge by learning (Nonaka and Takeuchi, 1995; Khodakarami and Chan, 2014). Collaborative CRM can be thought as a wiki portal, where users can access, document or read information.

This information sharing can be used to create combined competitive advantage between a retailer and a manufacturer (Cuthbertson and Messenger, 2008). While the financial benefits might not be mutual and long-term, the information sharing allows participating organisations to form a more complete view of the customer in their combined environment, offering them learning opportunities and change to grow (Cuthbertson and Messenger, 2008). Summarised, collaborative CRM helps organisations to support cross-functional processes, which are dependent on comprehensive customer data, by allowing access to comprehensive data for multiple functions of organisation.

2.1.3 Operational CRM

Operational CRM is a supporting system for organisations focusing on automation and integration of customer-facing processes, such as customer service, marketing, and sales (Xu and Walton, 2005; Payne, 2006, Chapter 1; Buttle and Maklan, 2019, p. 229). Data about customers is collected via multiple touchpoints and it is stored and distributed to organisation's customer-centric database, ready to be utilised in different customer-facing functions (Xu and Walton, 2005). These functions are customer service, marketing, and sales force, which operational CRM aims to support and automate (Payne, 2006, Chapter 1; Khodakarami and Chan, 2014; Buttle and Maklan, 2019, p. 229).

Customer service automation focuses on supporting service staff and management in achieving their objectives of good quality customer service (Buttle and Maklan, 2019, p. 291). To offer good quality and effective customer support, customer data across the organisation requires integration to form a comprehensive view of the customer, the data must be accurate, and relevant functions need access to it (Payne, 2006, Chapter 1). If utilised correctly, operational CRM can enhance customer service effectiveness and efficiency, improve productivity and customer engagement, and offer improved customer experience (Buttle and Maklan, 2019, p. 298).

Marketing automation regards executing marketing processes automatically based on defined rules and algorithms, aiming to support organisation's marketing functions (Buttle and Maklan, 2019, p. 316). It allows organisation to publish marketing campaigns, allows marketing persons to calculate costs and returns for it in different scenarios, and enables monitoring customer's activities and behaviours (Payne, 2006, Chapter 1). Marketing automation can be summarised by two factors: a customised object and a trigger (Heimbach, Kostyra and Hinz, 2015). The customised object is formed of the publishing medium and the content, structures, and attributes of an object, that customer receives, and the trigger is the action or information that triggers the customised object. The trigger can be current or stored information of the customer, such as behaviour and actions on website, used keywords, purchase history or shared content. This information triggers a set of rules, defined and operated by management, which in turn are applied to customised objects. (Heimbach, Kostyra and Hinz, 2015) Marketing automation helps organisations to improve marketing intelligence and effectiveness of marketing and enhance responsiveness from customers.(Buttle and Maklan, 2019, p. 316).

Sales force automation, or SFA, refers to services used to automate and support selling, sales management tasks and workflows. SFA supports salespersons by capturing, storing, analysing, and distributing customer data to them, making them more efficient. (Buttle and Maklan, 2019, p. 270) SFA brings timely data about customers and products combined with market information to salespeople, allowing them to respond to customer leads and inquiries with good quality information (Kumar and Reinartz, 2012). SFA tools allow forecasting and analysing sales, developing workflows and manage documents, leading to improved productivity and profitability for salespeople and managers (Buttle and Maklan, 2019, p. 298). The benefits of SFA can be divided into two categories: efficiency and effectiveness. Efficiency contains improvements to sales processes and functions, while effectiveness regards improved understanding of customers and improved relations with them. Combined they lead to increased sales revenue. (Kumar and Reinartz, 2012)

Summarised, operational CRM focuses on improving customer-facing processes of an organisations, mainly customer service, marketing, and selling, by automating processes and offering relevant and timely data for users to utilise, supporting decision-making, and making users more effective and efficient.

2.1.4 Analytical CRM

Analytical CRM focuses on capturing, storing, extracting, organising, integrating, processing, interpreting, distributing, using and reporting customer-related data to support organisation and users in generating value (Payne, 2006, Chapter 1; Buttle and Maklan, 2019, pp. 13–14). Customer-related data, such as sales, financial, marketing, and service data, can be combined with external data sources and analysed to generate customer profiles and customer segments, determine customer satisfaction, and identify behavioural patterns and key segments to serve (Xu and Walton, 2005; Buttle and Maklan, 2019, pp. 13–14).

Analytical CRM can be used to enhance operational CRM functions, as it can be used to improve customer segmentation, recognise potential leads and opportunities in customers, and define behaviour patterns to be used in operational CRM's triggers. Analytical CRM enables targeting customers with appropriate, customised, and timely solutions to their needs, as organisations can form a comprehensive view of the customer and act based on analysed information (Payne, 2006, Chapter 1; Buttle and Maklan, 2019, p. 345). Analytical CRM offers organisations multiple benefits, such as possibility to improve customer retention and acquisition, and enhance cross-selling and up-selling programs, offering customers additional and supporting or more powerful applications (Buttle and Maklan, 2019, p. 345).

Analytical CRM allows organisations to inspect and analyse data to find meaningful insights to customers and different customer segments, without the need of a data science team to provide information. Users can utilise the system's tools to support their needs in the spirit of self-service, allowing them to solve their problems without the need to involve other parties possibly making the process faster, as there is no need for communication.

Analytical CRM is seldom the only CRM an organisation has, it is usually supporting other systems. An integrated solution, combining strategic, operational, and analytical CRM, is referred to as a marketing cloud (Buttle and Maklan, 2019, p. 230). These solutions combine different CRM systems and marketing, sales, and service functions under one cloud-based system, offering organisations horizontal, vertical, data, and intelligence integrations. Data integration is self-explanatory and intelligence integration refers to analytical support functions. Horizontal integration focuses on making customer experience similar across all touchpoints to the organisation and vertical integration focuses on making the sequence of actions and processes of customers clear and understandable. (Buttle and Maklan, 2019, pp. 230–231) This kind of integrated CRM supporting cross-functional processes allows employees to effectively manage their tasks from one system that has all the necessary information available for them. This simplifies their tasks as they can work on one platform and they don't need to switch from one application to another, breaking their concentration.

2.2 Value creation

Organisations use CRM to meet the expectations of their customers and to align the expectations with the organisation's mission and objectives to create a sustainable and effective relationships with the customers (Anshari *et al.,* 2019). CRM allows organisations to find and attract new customers and helps to nurture and retain these customers for the future. They are turned into profitable and loyal business partners by developing suitable value propositions meeting customers' expectations. These propositions that can be a combination of products, services, processes, prices, or interactions customers experience during the relationship with the organisations are communicated and delivered to the customers, (Kumar and Reinartz, 2012; Anshari *et al.*, 2019). This creates value for the organisation, as customers continues to purchase products or services from them, rendering income for the organisation. Customers also benefit of CRM, as they receive more relevant offers and information of products, that might be of interest to them, and organisation’s service towards them is efficient, as the organisation has the relevant information at hand.

Value creation with CRM is a process, where in order for organisations to gain value from customers, organisations need to create and deliver perceivable value to customers (Buttle and Maklan, 2019, pp. 167–172). Value from this process can be divided into two categories: value that customers receive and value that organisations receive (Payne, 2006, Chapter 3). Customers can experience the value in three different ways: value-in-exchange (value is embedded to the products and it realises as the customer gains the product), value-in-use (customer gains value and benefits from using the product), and value-in-experience (the interactions between the customer and the organisation brings value to the customer) (Buttle and Maklan, 2019, pp. 167–172).

From the point of view of the customers, they gain value in the experience, as the organisation utilises CRM to offer them more relevant services and to appear professional to them because the organisation has all the necessary information available. Customers are satisfied to the service they experience and feel like it adds value to the service. Organisations on the other hand gain value in usage of CRM, as it allows them to improve their customer-facing processes by automating and streamlining them, improve the segmentation of their customers to offer them more relevant service, and find new insights from customer data.

Organisations can create value for their customers in three different ways: by offering operational excellence, superior products, or customer intimacy (Buttle and Maklan, 2019, p. 174). Superior products (especially services in the context of CRM) offer customers some new features or highly improved processes to help their actions to be effortless, taking up less resources than before, allowing customers to be more productive. With operational excellence customers are offered reliable and cost-effective solutions, aiming to solve specific problems in a streamlined fashion. Customer intimacy means that an organisation offers individualised service to their customers based on their needs. To offer individualised service, it is important to maintain the customer data as relevant and timely to preserve good relationships with the customers and to keep up with the possible changes with them. CRM enables customer intimacy by creating an environment where an organisation can identify their key customers, offer them what they need, and deepen their relationship throughout the customer's lifecycle (Galbreath and Rogers, 1999). Customers appreciate a good and personal relationship with an organisation, as it builds trust and loyalty, offering both satisfaction (Galbreath and Rogers, 1999; Payne, 2006, Chapter 3). In addition to the quality of the relationship and the frequency of interactions, customers also value the professionalism and responsiveness of salespersons, while communicating with the customers (Boujena, Johnston and Merunka, 2009). These aspects are made possible by CRM enabling information management, where the organisations have the ability to offer its users accurate, timely, reliable, and secure data, and the ability to tailor a response for different customers and different needs (Mithas, Ramasubbu and Sambamurthy, 2011). Especially in customer-centric organisations, the use of CRM lead to enhance organisational performance because of improved marketing capabilities enabled by CRM (Chang, Park and Chaiy, 2010).

Maintaining good relationships with the customers is important, as it helps to transform them into loyal long-term partners committed to the organisation. This creates value to the organisation over a long-time frame better than acquisition of new customers, as customer retention leads to increasing profits, declining operating costs, customers' willingness to pay higher prices, and free advertisement from the customers (Reichheld and Sasser, 1990). As the organisation interacts with its customers, both parties involved learn how the other behaves leading to greater mutual understanding and collaboration from where the decline in operating costs comes. The longer the customer is a customer, the easier it becomes to cross-sell and upsell more products and services, or possibly increase the prices of existing services, leading to increasing profits. The longevity may lead to customer loyalty, which makes the customer less likely to defect and possibly recommend the organisation for others.

A model of value co-creation has been proposed between an organisation and a customer, where customer satisfaction and trust strengthen the relationships between them, impacting positively on loyalty and leading into customer engagement and value co-creation (Banyte and Dovaliene, 2014). This value co-creation benefits both parties, e.g. the organisation gains competitive advantage and increased customer retention and the customer gets more satisfying service (Banyte and Dovaliene, 2014). Organisations can pursue customer satisfaction as a primary objective with CRM, but it can be a secondary objective in value creation, or a by-product generated while interacting with the customers. For example, different marketing activities, such as customer segmentation and market basket analyses, lead to personalised interactions with the customers, increasing customer satisfaction (Chorianopoulos, 2016). Many an organisation still highly values the potential of CRM to improve customer satisfaction level and define it to be an important reason to implement CRM. Other reasons to implement CRM, in order from most important to least, are retaining existing customers, improving customer lifetime value, providing better strategic information, attracting new customers, and cost savings (Xu and Walton, 2005). These aspects indicate that organisations seek to build profitable long-term relationships with their customers, and not only settle for quickly achieved profits. Especially with the growing amounts of data of customers, organisations will understand customers, their lifecycle and behaviour in a more comprehensive way, offering more insights and validated measures to sustain good relations to the customers (Anshari *et al.*, 2019). Organisations try to strive towards a high customer lifetime value, or CLV, that is the net present value of future profits flowing to the organisation during the lifetime of customer relationship (Payne, 2006, Chapter 3). Broad customer base and good relations to the customers are of no use, if the customers or their associates do not bring profits to the organisation. CLV is a good measure to find out the expected profits of customers and customer segments for an organisation. When CLV is known, the organisation can focus on the profitable customers, try to attract similar customers and abandon unprofitable customers to stay as a profitable business.

In addition to the customer attraction, retention, and interactions, CRM creates value for organisations by improving their internal processes. Information management capability, that is the ability to provide users accurate, reliable, and timely data which users have the ability to modify and refine, improves organisation’s performance through customer management, process management, and performance management (Mithas, Ramasubbu and Sambamurthy, 2011). Customer management capability is the ability to develop long-term relationships with the customers, possibly transforming them into innovation partners that co-create value. Organisation’s performance increases appear in customer-focused performance, financial and marketing performance, human resource performance, and organisational effectiveness. (Mithas, Ramasubbu and Sambamurthy, 2011) It can be argued that CRM does not affect directly organisation’s performance but is rather mediated by differentiation and cost leadership, which improve performance outcomes, such as customer satisfaction, market effectiveness, and profitability (Reimann, Schilke and Thomas, 2010).

Many organisations have gained clear value from CRM and the benefits can be divided into tangible and intangible benefits. Tangible benefits were increased revenues and profitability, quicker turnaround time, reduced internal and marketing costs, and higher employee productivity and customer retention rates. Intangible benefits were increased customer satisfaction, positive image of organisation, improved customer service, better customer segmentation and profiling, and better understanding of customer requirements. (Chen and Chen, 2004) It is clear that CRM offers organisations and its customers great value and many benefits on operational and strategic levels, if it is utilised properly.

2.3 Requirements

CRM systems do not generate aforementioned value for organisations or its customers automatically, as the systems require strategic and operational utilisation. Many organisations fail to gain benefits as they see CRM only as a software application, and not as a strategic, customer-oriented approach for long-term management of customer relationships (Reichheld, Schefter and Rigby, 2002). For organisations to utilise CRM systems successfully towards their goals, they need successful business-IT alignment (Galbreath and Rogers, 1999), which means that they systemically apply IT systems towards their business strategies, goals, and needs, integrating the systems to be a part of the strategy and value creation (Luftman and McLean, 2004).

Effective use of CRM requires different resources. Customer data is given, but other important resources needed for building sustainable profitability are IT infrastructure, leadership and culture, data and information technology, people and their skills, and processes (The Customer Framework, 2016; Buttle and Maklan, 2019). Proficient employees and supporting IT infrastructure, including suitable hardware and software for the task at hand, are needed to collect, modify, combine, analyse, and store the customer data. If the hardware cannot store all the necessary data, software is painful to use, or the employees do not have necessary skills to process the data, benefits gained from CRM are less impactful. Because of different cloud services, storing of data is not a significant challenge at the present time, but other IT infrastructure, such as internet connections and sufficient processing power, are needed. As organisations can collect more and more data, the design of the data warehouse is also emphasised, as the model of the data warehouse impacts directly on the organisations' abilities to utilise and specifically analyse the data in CRM (Cunningham, Song and Chen, 2006). When the data is used to facilitate decision-making, small mistakes in the logic of data warehouse can cause errors in the information, wrong data to be seen, or produce no data at all, hindering decision-making.

The impact of technology in successful use of CRM is highlighted during the use of analytical tools and CRM (Sebjan, Bobek and Tominc, 2016), and during the implementation process of CRM (Meyliana, Hidayanto and Budiardjo, 2016). Critical success factors for CRM include technological readiness, system integration capability, and data sharing

(King and Burgess, 2008). There are no signs of significant impact of technological readiness, that is the organisation's technological infrastructure and the ability to use them effectively, on CRM directly, but the relation between technological readiness and knowledge management capabilities was significant, as knowledge management relies on technology to capture, manage, and analyse customer data to improve processes and provide information for decision-making (Croteau and Li, 2003). Technology selection and adaption are one of the most dominant factor necessary for successful implementation of CRM but also support, commitment, and involvement of top management plays an important role in the success of CRM (Reichheld, Schefter and Rigby, 2002; King and Burgess, 2008; Meyliana, Hidayanto and Budiardjo, 2016; Buttle and Maklan, 2019).

One of the main reasons why CRM fails to deliver value for organisations is the lack of commitment and support from the top management (Reichheld, Schefter and Rigby, 2002; Croteau and Li, 2003; Edinger, 2018). Managers fail to implement CRM properly as they do not fully understand what they are implementing, thinking CRM only as a software and not as a strategy, underestimating the time and the costs it takes (Reichheld, Schefter and Rigby, 2002). Common mistakes leading to failure of CRM, especially during the implementation, are not creating suitable strategies for utilisation of CRM, failing to understand what kind of relationships to create with different customers, failing to develop or implement innovative and data-driven organisational culture, problems in change management and communicating benefits of CRM to employees, and not utilising cross-functional processes in CRM (Reichheld, Schefter and Rigby, 2002). Also CRM can fail because it is misused as a possibility for executives to inspect data, and not for cross-functional and collaborative processes to increase revenue (Edinger, 2018). Data inspection is important, but the possibilities in CRM lay in creating a comprehensive view of the customer and streamline the customer experience to create value. Organisation should think through which processes to improve with the help of CRM and use it strategically and appropriately with those processes in mind. The processes, that are customer-facing, such as marketing, sales, and services, are important parts of CRM, as they refine data, information, and knowledge into value for the organisation and create long-term relationships with the customers (Mendoza *et al.*, 2007). The impact of management should not be mitigated as value cannot be created with CRM without managing and understanding its effects on the employees and the processes they undertake. Managers should prioritise solving human issues, especially change resistance, and offer them necessary information, motivation, and training of the CRM to combat the change resistance (Kumar and Reinartz, 2012). The management plays an important part in encouraging employees to use CRM, as if they do not lead by example and use it, or they fail to explain the benefits of using it to the employees, the employees might avoid using the system. It might seem unnecessary, difficult to use, or it increases the workload and they do not see the gains of CRM. If the management fails to involve themselves with the processes, the employees will not believe in them and will tend to resist them (Croteau and Li, 2003).

In addition to good leadership and necessary IT infrastructure, an organisation needs skilled employees to execute value creating processes and customer strategies. It is difficult for organisations create value for anybody, if they have no skilled employees refining ideas, processes, or information into value. Skilled and trained employees are required for an organisation to be flexible and to meet changing business environment and customer demands (Manna, 2008). Employees possess the skills, knowledge, and relationships to different stakeholders necessary to perform value creating tasks in an exemplary fashion. Employees innovate and generate new ideas and insights for organisations to benefit off, leading to competitive advantage and long-term profitability. Drucker (1999) has even stated that skilled employees and their productivity are the most important assets for organisations in 21st century. The use of CRM, and especially its analytical tools, requires appropriate technology and software, but also new ideas and approaches, and the knowledge and skills to utilise the systems to create new information, factors depending on the employees and their skills (Sebjan, Bobek and Tominc, 2016). It is the task of the organisation to manage and direct the skills of their employees towards the processes they are needed. While managing the human resources, it is an important task for the organisation to create an environment, where the employees enjoy working and want to work. Employee retention is as important as customer retention (Mendoza *et al.*, 2007), as employees show increasing loyalty towards the organisation the longer they stay, and because of the intangible assets employees possess, e.g. tacit knowledge of processes, customers, and business environment, social capital, and relationships to the customers. If the employees leave the organisation, most of these assets are lost to the organisation.

Critical success factors of CRM strategy can be divided into three key aspects: human factor, processes, and technology (Mendoza *et al.,* 2007). Processes in this context are customer-facing processes interacting with customers, such as marketing or sales, and technology is the integrated information systems facilitating these processes and offering a platform to understand the customers and deepen the relationships with them (Mendoza *et al.,* 2007). The human factor can be divided into two aspects: those relating to the customers and those relating to the organisation. Organisational aspects refer to the environment and culture of the organisation, such as management's support and commitment, organisational culture, effective leadership, and good internal communication. In an organisation's culture, supportive culture, involvement of the employees and sharing the mission play an important role in the success of CRM, especially during the implementation (Rahimi, 2017). Also consistency is of paramount importance for the human factor of the organisation and the processes of CRM during the implementation, and adaptability is highly important for the technology aspect (Mendoza *et al.*, 2007; Rahimi, 2017). Consistency is important for employees as they will learn to be better at tasks as time goes by. They will be able to utilise IT systems more efficiently and faster, improving their productivity. If some parts of the processes change, it creates resistance as employees are not sure how do the changes affect and alter their habits and work customs. Aspects relating to the customers are factors focusing on creating long-term relationships with the customers, and this requires the organisation knowing how the customers define value (Mendoza *et al.*, 2007). The organisation must have a good customer understanding, and they must be able to satisfy the customers based on their needs and value criteria, and the organisation must work continuously towards customer retention and loyalty in order to gain benefits of them.

Organisations need well defined processes, practical IT infrastructure, and effective personnel, including employees and managers, and adequate interactions and relations between them forming up organisational culture, in order to utilise CRM effectively (Mendoza *et al.*, 2007; Buttle and Maklan, 2019, pp. 22–24). The IT infrastructure must be practical for the use cases it is purposed, and it must be able to handle the processes it is used for without major issues to enable efficient working. Efficient working requires well specified processes which execute organisation's strategy for value creation with CRM in a consistent and deliberated fashion. Responsible for the creation and usage of both IT infrastructure and processes, are employees, who are required to be able to utilise the systems and processes. It is also important to document and communicate about these to other employees. The communication is especially a responsibility of the management, who should orientate the employees to the systems and processes used. Motivating the employees as to why the systems are used, so the employees understand the consequences of their actions, is also an important task for the management. Not to forget about creating an open organisational culture, where employees can interact and communicate with each other freely, giving feedback and possibly come up with suggestions for improvements. An open and data-driven organisational culture encourages to experiment to form new ideas and to learn from mistakes, improving the working environment. Many sources define e.g. senior management's commitment, communication, cross-functional teams, knowledge management capabilities, skills of the employees, and technological readiness to be critical factors for the success of a CRM system (Mendoza *et al.*, 2007; King and Burgess, 2008; Sebjan, Bobek and Tominc, 2016; Buttle and Maklan, 2019, pp. 22–24). But in the end, CRM is a combination of human factors, processes, and technology, each interacting with the other factors to deliver value for the organisation.

3. DATA ANALYTICS

Data analytics is becoming more common, driven by the shift to cloud-based applications, the rapid accumulation and the growing amounts of diverse data from various sources (Chiang *et al.*, 2018; Reinsel, Gantz and Rydning, 2018; Gartner, 2019, 2020). Data analytics is becoming more essential for decision-making in organisations, and this is due to the versatile data being easy to gather, store, and analyse in order to be utilised in improving organisation's processes or decision-making (Power *et al.,* 2018). And this is the essence of data analytics. It is utilisation of data, searching it for insights and correlations between variables, and using this knowledge to improve some aspects of an organisation, ranging from product recommendations for customers based on their purchase history to product delivery route optimisation. As McAfee and Brynjolfsson (2012) said, "analytics seeks to glean intelligence from data and translate that into business advantage".

Closely related to data analytics are data science, big data analytics, business analytics, and business intelligence, which could be thought as sub-sections of data analytics that are inspecting analytics through specific lenses. Business intelligence and analytics focus more on the business environment and the terms refer to the techniques, technologies, systems, practices, methodologies, and applications helping organisations to understand their business environment by analysing available data and supporting decision-making by providing timely data (Chen, Chiang and Storey, 2012). Big data analytics focuses on analysing vast amounts of data, and data science focuses more on statistical analyses. But in the end, they are data analytics, which processes data, be it a small collection or big data, to obtain trends and patterns about the information they hold, which is used to improve different processes in the organisations, such as decision-making (Koohang and Nord, 2021). The analytics process is holistic, combining information available from the organisation's environment, be it tacit or explicit information, and systems to provide value for the organisation and to foster growth (Ji-fan Ren *et al.,* 2017). It involves extensive use of data, analysing it in statistical, qualitative, and quantitative methods to form explanatory and predictive models, that support management in decision-making and making actions based on facts (Davenport and Harris, 2017; Power *et al.*, 2018).

The use of analytics is not only limited to improve processes and operations of organisations, but data analytics are also applied to organisation's offerings as embedded data services in products and services provided for customers (Davenport, 2013). The analytics process should be an ecosystem for generating new insights enabled by information sharing to facilitate decision-making to create an innovative and data-driven environment (Ji-fan Ren *et al.*, 2017). Organisations mainly seek to improve process efficiency, enhance customer experience, and develop new products with the help of data analytics (Gartner, 2018).

When organisations use data analytics to produce information to support their processes, analytics can be used to inspect the data on different scopes, helping them to support strategic or operational processes. Analytics can be divided into four categories: descriptive, diagnostic, predictive, and prescriptive analytics (Banerjee, Bandyopadhyay and Acharya, 2013). Descriptive analytics focuses on historical and current data to describe a phenomenon though relevant measures, trying to explain what has happened and alert the organisation to the phenomenon and offer a chance to inspect it (Banerjee, Bandyopadhyay and Acharya, 2013; Davenport and Harris, 2017). An example of descriptive analytics is a line chart of monthly sales where users can explore the sales of different products and see the profits generated. Diagnostic analytics are a bit more sophisticated methods, seeking answers to why some phenomenon has happened and try to explain causes of the problem with existing data (Banerjee, Bandyopadhyay and Acharya, 2013). If continued from the example of descriptive analytics, diagnostic analytics would be exploring the effect of different locations or salespersons on the sales and allowing users to drill down on some dimension of the data to explore it more specifically. When an organisation uses past and current data to predict future possibilities and developments, it is known as predictive analytics. Predictive analytics use different statistical methods and technologies, such as segmentation, models, and rule-based systems, to predict outcomes and estimate financial trends (Banerjee, Bandyopadhyay and Acharya, 2013; Davenport and Harris, 2017). In the monthly sales example, predictive analytics could involve predicting sales for the coming month or quarter. The final type of analytics is prescriptive, where organisations focus on creating optimal solutions for future problems. They use advanced statistical models and technologies, such as machine learning, to optimise and simulate different scenarios to find optimal behaviours and actions towards the organisation's goals. (Banerjee, Bandyopadhyay and Acharya, 2013; Davenport and Harris, 2017) An example of prescriptive analytics would be pricing products based on prediction of demand, available stock, prices of competitors, and resource costs.

The four categories can be thought as a maturity model, describing organisation's analytical capabilities and the capabilities to utilise them to support their processes. As organisation's analytical maturity develops, they move from descriptive analytics towards prescriptive analytics, their analytics becoming more sophisticated and decision-making transforming from reactive into proactive (Banerjee, Bandyopadhyay and Acharya, 2013). This should not be used as only measure to indicate organisation's analytical sophistication, as the majority of organisation's analytics might be descriptive analytics in the form of different dashboards and reports, because it is not always feasible or sensible to use prescriptive analytics even though organisations would have the capabilities to do so. Organisation's analytical maturity can also be defined based on their ability to utilise analytics for deriving competitive advantage and innovating new products (Ransbotham, Kiron and Prentice, 2015). The organisations are divided into three groups based on their analytical maturity: (1) analytically challenged, (2) analytical practitioners, and (3) analytical innovators. The first group, analytically challenged, seldom use sophisticated analytics to support their businesses as they lack the skills and data, and they tend to rely on managerial experience in decision-making, whereas the second group, analytical practitioners, use analytics for operational purposes, have the necessary skills and data, and aim to develop their analytical capabilities further (Ransbotham, Kiron and Prentice, 2015). When organisations use data analytics strategically, seeking long-term benefits, own high data management and analytical skills, and value data highly, they are analytical innovators. As organisation's analytical maturity develops, the less sophisticated analytical methods are not replaced by the more sophisticated, and organisations utilise all types analytics more on their processes, not only more sophisticated methods (Banerjee, Bandyopadhyay and Acharya, 2013; Ransbotham, Kiron and Prentice, 2015). Descriptive and diagnostic analytics are well suited for operative processes and ad hoc needs, while predictive and prescriptive are better suited for strategic planning, so the less sophisticated methods have plenty of use cases for organisations.

Models described previously focus intensively on analytical sophistication using the type of analytics as a reference, but reality is more complicated, and many other factors influence organisation's ability to utilise data analytics. Data analytical maturity can be inspected more thoroughly, taking into account different organisational aspects, such as data management, organisational culture, analytical skills, and management capabilities (Gartner, 2018). Organisations can be divided into five levels depending on how an organisation utilises data and analytics, the levels being (1) basic, (2) opportunistic, (3) systematic, (4) differentiating, and (5) transformational (Gartner, 2018). Or as another model similarly divides the organisations into five stages that are from the highest to lowest: analytical competitors, analytical companies, analytical aspirations, localised analytics, and analytically impaired (Davenport and Harris, 2007, pp. 58–64). Models inspect how suitable organisation's management, culture, and practises are for data-driven decision-making enabled by data analytics (Gartner, 2018), and how well they can utilise analytics systematically throughout the organisation to succeed (Davenport and Harris, 2007, pp. 58–64). On the lower levels, where majority of organisations are, data management is fragmented, the data being in silos and its format is inconsistent, and the organisation might lack necessary leadership and management of skills to implement agile and data-driven culture into the organisation (Gartner, 2018). As an organisation develops, the importance of data analytics increases, becoming more central to organisation's strategic and operational processes, and they monitor and supervise the systematic and consistent data management practices. On the highest levels organisations have adopted analytics well as a part of their culture, leadership, and processes, and they are competing with other similar organisations how well they can utilise data and analytics as a part of their business.

There are four attributes supporting the success of analytical competition (Davenport and Harris, 2007, pp. 45–64). (1) Organisations need to have a distinct capability, a unique product, service or process, differentiating them from their competitors, and they use analytics to monitor and improve this capability even further (Barney, 1991; Davenport and Harris, 2007, pp. 45–64). (2) Analytical thinking, methods, and processes extend through the entire organisation and are not focused solely on one problem, business function, or person, but the analytics and data are led and managed centrally (Davenport and Harris, 2007, pp. 45–64; McAfee and Brynjolfsson, 2012). (3) Management is committed to analytics and are passionate of it, aiming to develop their own skills and their employees' skills (Davenport and Harris, 2007, pp. 45–64; Grover *et al.*, 2018; Koohang and Nord, 2021). This is especially emphasised in organisations that do not have analytical culture and ways of working beforehand, as creating a data-driven and analytical organisation requires a change in culture, practices, processes, and skills; and leaders to guide the organisation through these changes. Leaders themselves are not required to be highly sophisticated in analytics, but they must be able to communicate about them in a clear and understandable way to encourage others into using analytics. And in addition to aforementioned, (4) the organisation needs a target to focus their analytical efforts and measure its development, so they can monitor whether they are successfully applying analytics into their processes (Davenport and Harris, 2007; Grover *et al.*, 2018; Koohang and Nord, 2021).

Organisation's data analytics maturity can be measured through multiple items, that could be categorised into three main groups. The main analytical maturity factors are data analytics integration and management support, process-level benefits, and capabilities with technology and data analytics (Chen and Nath, 2018). Integration and management factor describes organisation’s capabilities to integrate analytics as into their processes, creating cross-functionality, and the ability of executives and management to use analytics as a strategic asset and encouraging employees to use and find possible use cases for analytics. When employees use analytics and analytical tools to identify market trends, segment customers, improve operational effectiveness or services, it is categorised as process-level benefits. Capabilities with technology and data analytics include necessary human and technological resources for the analytical processes. (Chen and Nath, 2018) It would seem that similarly to the requirements of successful utilisation of CRM, also data analytics needs proper managing of processes, technology, and human factors, including skills and working culture among them.

Based on these models created by Davenport and Harris (2007), Ransbotham and Kiron (2017), Chen and Nath (2018) and Gartner (2018) top performers utilise analytics strategically, focusing on analysing historical problems, current situation, and forecasting the future, to be able to adjust themselves correctly to succeed in changing environment and aiming for success in the long run. Management supports analytics and encourages employees to develop their skills and to experiment with new processes and measures to create competitive advantage. The top performers in analytics have skilled employees and necessary technological resources at their disposal. Hardware used to run analytical applications is effective and powerful and software is capable of analysing vast amounts of data and has plethora of methods for it.

A positive relationship can be found between data analytics maturity and organisation’s overall data analytics success, specifying that especially support from the management and process-level improvements supported by data analytics lead to successful data analytics in organisation (Chen and Nath, 2018). Organisations should focus on these, as data analytics can bring many benefits to an organisation and more mature organisation, from the viewpoint of data analytics, can utilise data analytics more effectively. Organisations can use data analytics to gain understanding of their customers and improve their experience, optimise and improve their internal and external processes, and differentiate their offerings to gain competitive value (McKinsey & Company, 2016; Kitchens *et al.*, 2018). Measurable benefits are also found as data analytics helped IT-intensive industries reach over 6 percent gains in productivity (Müller, Fay and Brocke, 2018), and similar increases were found in output and productivity of organisations embracing data-driven decision-making enabled by data analytics (Brynjolfsson, Hitt and Kim, 2011). Organisation’s productivity improves, as they improve their ability to observe their performance and seek processes to improve (Mithas, Ramasubbu and Sambamurthy, 2011).

As analytics are utilised more broadly within organisations, they become more aware of the possibilities with analytics, and many organisations are reporting competitive advantage due to multiple factors (Ransbotham and Kiron, 2017). Organisations apply and utilise analytics to help in many different sectors, from strategic planning to operational tasks, ad hoc processes and needs. As new technological advances arise, such as cloud computing and storages, organisations are improving their offerings due to data-driven innovation (Ransbotham and Kiron, 2017). Especially if the organisation has skilled and innovative employees, it can find many processes to be improved with the help of analytics. Even though not all experimentations with data might lead to benefits, they offer valuable insights for the organisation, at the very least information that the experiment conducted does not lead to benefits.

But as is the case with CRM and other IT systems, benefits do not realise from thin air. Analytics need to be systematically utilised to gain benefits, and to utilise analytics, organisation needs to fulfil few requirements. Similarly to CRM, analytics require organisation and its processes to be suitable for analytics, human talent in analytics and employees eager to develop their skills, suitable and effective technology to handle analytical processes, from storing data to visualise multivariate analyses with it, and good quality data to be analysed (Davenport and Harris, 2007, pp. 144–148; Gillon *et al.*, 2014; Grover *et al.*, 2018).

Sources differ when discussing on which aspect should the organisation focus the most regarding analytics, i.e. where the greatest challenges of analytics are. Chiang *et al.* (2018) say it is business understanding and knowing how to transform analytics into competitive advantage and strategic value; McAfee and Brynjolfsson (2012) say it is leadership and management; LaValle *et al.* (2011) say it is cultural aspects of the organisation. This thesis will not take a stand on which is the most important factor but supports a comprehensive view, similar to thoughts from Davenport and Harris (2007, pp. 144–148), Gillon *et al.* (2014), and Grover *et al.* (2018), that analytics need multiple factors (e.g. organisational culture, processes, management, human capital, technology) working together to create value and to be successful in analytics. Organisation can be analytical with some of the factors lacking, but analytics won't bring significant benefits. That being said, this thesis will examine one factor of analytics more deeply, and that is data. This is due to the nature of this thesis, as it aims to study how to utilise data analytics in the context of CRM customer data. It is important to understand what kind of data is suitable for analytics, how the quality of data affects analytics and how can CRM mitigate possible risks with data and analytics.

3.1 Data

Organisations value data highly and they have awoken to the diversity and possibilities of data as the amount of available data grows (Ali-Yrkkö *et al.*, 2019). British mathematician Clive Humby has allegedly coined the term “data is the new oil” in 2006 and Falck and Koenen (2020) correct this by saying that data has become more valuable than oil. Like oil, data can be used to produce different products and benefits, but it requires initial resources in order to be processed to create value. Data itself has little value (unless organisation sells large sets of data to others), but it can be used to produce benefits for organisations (e.g. Wilder-James, 2016; Ji-fan Ren *et al.*, 2017; Ransbotham and Kiron, 2017; Grover *et al.*, 2018; Falck and Koenen, 2020). Organisations collect and store data in vast amounts, and not necessarily for some specific purpose, because it is inexpensive and it can help them improve their processes in the future (Agarwal and Dhar, 2014).

Data can be defined to be individual measurements, values, or statistics from the observed environment. Data is sometimes used interchangeably with information, which is processed data to be specific; data that has been extracted, transformed, and loaded into a context. For example, a point of data, 100, offers little value itself, but when given a context of length it transforms into information (100 kilometres) and one knows that it is a quite a journey to travel. It can be understood, put into a perspective, compared with other information of a subject, and one can make decisions based on it. Data is usually in information systems as information, as it is stored in tables with context or key-value pairs, but it could still be “raw” or unprocessed. While it is beneficial for some, for example a salesperson can find customer’s phone number from CRM, not all benefit of this data. Until processed further, it does not offer any new information. For example, from phone numbers, customer’s countries could be extracted from country code, and this could help to segment them into correct country and offer them services in their native language.

There are multiple data types and multiple ways to categorise data types. Programming languages have data types indicating whether the data is e.g. integer, floating-point number, string, list, or Boolean. Data can be distinguished by its source of origin and content to public data, automatically generated data, internal IT system data, and user and transaction data (Falck and Koenen, 2020). Suitable categorisation in the context of CRM is to distinguish data into transaction data, master data, metadata, and reference data.

Transaction data contains data points of different transactions between the parties involved, usually an organisation and a customer, describing an event such as a purchase of an item. An example of this kind of data can be found from a receipt. It informs what has been bought and when, how many items, what did they cost, who served the customer, etc. Closely related to transaction data is master data, which provides context for transactions on the business entity level, containing and describing data about people, places, products, and other things involved in organisation's processes (Mosley and Brackett, 2010, p. 176). For example, master data of a customer might contain data of full name, marital status, phone number, email, address, customer category, and order identifiers referencing to another master data table.

Often confused with master data, reference data is data classifying or categorising other data. It contains sets of allowed data values or schemas for the data, focusing on standardising the data (Mosley and Brackett, 2010, p. 174). For example, organisation can classify support cases by customer based on case's status (e.g. new, in progress, closed) or organisation can standardise location data referencing a country (FI – Suomi – Finland). The last data type, metadata, is defined as data about the data (Mosley and Brackett, 2010, p. 259). It labels and describes the data and informs of possible changes to it, telling for example who created the data and when, in what form is the data, who can access it and who has recently accessed it. It offers an audit trail, useful for those managing the data. In addition to these data types, unstructured data is worth of mentioning in CRM context. Unstructured data is data without a specific format, e.g. images, videos, audio, documents, or social media data. Useful data for organisations but in challenging format, at least to process in large quantities. For example, an organisation could store in a database their contracts with customers in PDF or videos of instructions on using some product.

These data types are useful for organisations as they can be processed and analysed to offer new insights. But regardless of analysis methods, the processing can prove difficult because data can have multiple errors in it or associated with it. Accessing the data can be hard, the data can be divided into multiple different locations, it can be of poor quality or not suitable for processing because it is old, erroneous, missing units, etc. Up to 80 % of data workers time goes into preparation of the data for analytics (Press, 2016).

Organisations need good quality data to gain benefits via analytics (Ji-fan Ren *et al.*, 2017). Bad quality data not only hinders analytics but also causes other problems in organisations. It wastes precious time of analysts, weakens decision-making, leads to customer dissatisfaction, reduces ability to execute data strategies, and lowers employee morale (Redman, 1998, 2016; Nagle, Redman and Sammon, 2017). Data quality matters. Even though data provides little value, the impacts of poor data quality are notable, so organisations should pay attention to data quality. The costs of poor data accumulates as it is processed further, which can create a “hidden data factory”, where workers need to check, prepare, and correct data as they begin to process it (Redman, 2016). As the data is processed and passed onto different function, the workers check and prepare the data again, creating unnecessary steps that could be eliminated if the organisation would have clear requirements for data quality.

To help inspect data quality, a framework for inspecting data quality in organisation’s environment is summarised in Figure 4.

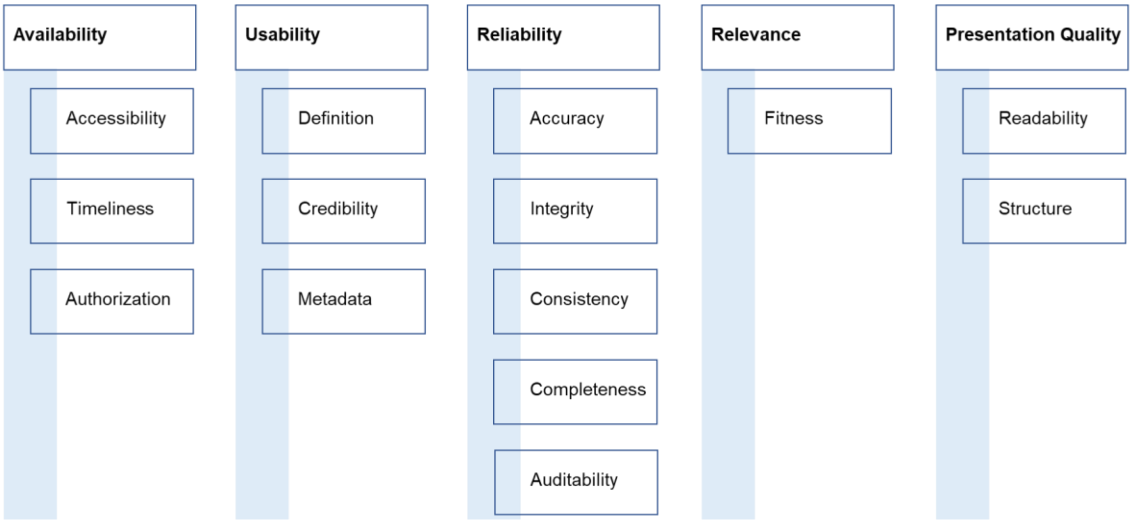

Figure 4. *Data quality dimensions and their elements (Cai and Zhu, 2015).*

Figure 4 presents dimensions, and their elements, affecting data quality. It inspects data quality comprehensively through different processes in organisation, starting from availability and ending to results or utilisation of the data.

Availability inspects whether the data can be accessed, and if the analyst has proper authorisation for current or timely data. Timely data is up-to-date and can be accessed within a suitable time. Usability contains elements affecting and related to the usage of the data, inspecting that it is from credible source and in correct format, and it contains definitions or documentation for the data. Reliability tells how erroneous the data itself is, inspecting elements telling if the data is accurately describing a measured event and is the data set whole, containing valid and reasonable measure. Whether the data is suitable for some process, relevancy examines it through fitness element. The usefulness of the data depends on the context, e.g. it is difficult to analyse customer reviews with sales data, as the sales data is not relevant in this context. And finally, presentation quality concerns itself with how understandable the data is, and elements affecting it are readability and structure. Together these dimensions and their elements form a comprehensive view of the data quality and organisations can use the framework to examine their status.

In order to achieve good quality data, it needs proper governance. If an organisation can implement policies and schemas aiming to improve data quality, it makes data preparation much easier as workers can access clear, timely, relevant, and understandable data. Organisations with strong data governance practices often engage in active data sharing, that fosters innovation and helps the organisations in catching erroneous data and already attempted analytics (Ransbotham and Kiron, 2017). There are three clear roles in data governance, ensuring data quality and enable its effective use. Executive decision makers are in the charge of the data, making strategic decisions about the data, defining what information needs defining and what data needs to be collected and managed in the organisation at minimum (Davenport, Harris and Morison, 2010, pp. 35–38). Data owners (or stewards) are responsible for collecting and maintaining the data through its lifecycle, and the last role, analytical data advocates, ensure that the data is accessible and suitable for analytics (Davenport, Harris and Morison, 2010, pp. 35–38). Despite these roles, it is best to keep in mind that ensuring data quality is dependent on the actions of every worker and data governance policies should be clear to everyone. It is easy to create a local copy of a data source for one’s own needs but when multiple persons do it, the data quality starts to deteriorate as workers might update their local copy but not the original data.

Another similar problem affecting data quality as a whole is data silos, that are segregated data sets across an organisation, where data is stored in raw and processed form in various applications (Patel, 2019). Data silos form often around business functions, e.g. marketing, sales, and product development, limiting their ability to see a comprehensive view of the organisation and possibly making poor decisions based on inadequate data. Data silos originate because of structural and political reasons, organisational growth, and vendor lock-in (Wilder-James, 2016). Different business functions have different data needs, and they accumulate their own data sets, creating a data silo that they do not share to others because it seems unnecessary, or data sharing is not a priority for them. These reasons are examples of structural reasons for data silos. Political reasons are similar but the main reasons behind them is that groups do not want to share their data for some reason, for example internal competition or negative organisational culture. Vendor lock-in is rather self-explanatory, organisation is forced to use one vendor because the application vendors making it difficult to export data out of their systems. Data silos due to organisational growth form organically, similar to structural reasons. Organisations experience with different strategies, applications, and data policies during their lifecycle and these form data silos due to incompatible systems or because the integration of data takes too many resources needed elsewhere. (Wilder-James, 2016)

One way of integrating available data and break data silos is to implement an organisation-wide data warehouse, helping organisations to store their data organised reasonably in a single place. This does not automatically solve the problem of data quality, but data schemas can be implemented into data warehouses, so they do not accept clearly erroneous data. There are no standardised rules for the model of the data warehouse supporting CRM but the data model behind CRM contributes directly to the performance of the CRM (Cunningham, Song and Chen, 2006). The organisations should plan carefully what they want to achieve with the CRM as it is used to query data to support decision-making.

Common way to implement a data model for data warehouse is to create fact and dimension tables into databases in a star schema. Fact tables forms of individual transactions containing data, that can be identified and described further with the help of dimension tables that contain more data of individual products, locations, persons, etc. With the dimension tables, transactions from fact table can be expanded to show more information, and the transactions can be grouped by an element of some dimension. This allows an organisation to analyse and improve the element, for example fact table contains customer ID and dimension table related to the fact table contains name, address, and phone number in addition to the customer ID from the fact table. Databases are storages for similar data, containing data about transactions or explanations for database entries. A commonly used categorisation for databases in CRM is division into customer, prospect, cluster, and enhancement databases (Kumar and Reinartz, 2012). Customer and prospect databases contain basic, demographic, psychographic, and transaction data of customers and prospects, and cluster database contains similar data, but of grouped data entries. Enhancement databases complement data found in other databases. (Kumar and Reinartz, 2012) Customer, prospect, and cluster databases can be thought as fact tables and enhancement databases as dimension tables, from which organisations can load and transform data into other applications to be refined into information helping decision-making.

As organisations load data in tremendous amounts into a data warehouse, it forms a comprehensive view of the organisation and its environment, but it will become cumbersome to process the data within. Because of the amount of data, a reverse ETL process is needed, which is a process of copying a part of the data from the data warehouse to operational systems (Manohar, 2021). This allows organisations to process the relevant data fast, as they have only a part of the data possibly making the process more effective because data calculations are done faster. Also, high amount of data can weaken workers' ability to translate data into business value (Ransbotham and Kiron, 2017). It is worth not to clutter the employees with data and process only the relevant data to form meaningful analyses of it.

So, for data to be useful for organisations, it should be plentiful, of good quality, and managed well. Data needs to be available, usable, reliable, relevant, and presentable to be of good quality and each one of these dimensions are important for the success of data quality. As Davenport, Harris and Morison (2010, p. 22) have stated "you can't be analytical without data, and you can't be really analytical without really good data". In the current business environment, many and more organisations collect data, so the competition favours those how can make the most of the analytics. In order to create competitive advantage of customer data the value should be high and lasting, and the information refined of it and improvements made to processes or products should be inimitable, or at least hard to copy (Hagiu and Wright, 2020). To create such improvements, organisations need not only data, but also supportive and motivated leadership, data-driven organisational culture, and skilled employees. But it is important that the premises are in good condition. For that to be realised, organisations need to have good quality data, policies for handling the data, and strategies for utilising the data.

3.2 Value creation

For organisations to succeed in data analytics, they need not only data but also skills to transform and combine different data across the organisation; capable management and leadership to define strategies and targets; and the necessary human capital and skills to achieve the defined targets (Gillon *et al.*, 2014). Data analytics need a combination of skills, technologies, processes, and understanding of the business environment to offer meaningful insights that are possible to realise. If the analytics process is successful, organisations can improve their performance (Brynjolfsson, Hitt and Kim, 2011; Müller, Fay and Brocke, 2018; Barnes *et al.*, 2020). But there are multiple challenges in the way; need of skillful analysts, leadership not understanding the possibilities of analytics, bad quality data, unfit organisational culture, and challenges extracting information from analytics (DiFranza, 2019; University of York, 2019).

As data analytics is becoming more common among organisations (Gartner, 2020), it becomes harder for organisations to compete with analytics and generate value of data analytics without strategically improving their analytical processes (Kitchens *et al.*, 2018). There are three central ways to create value from data and its analysis: (1) data analytics create insights improving business processes and decision-making, (2) data processing enables organisations to develop new products, and (3) data analytics potentially highlights or solves information problems, reducing information asymmetries (Falck and Koenen, 2020). The value seldom comes from the data itself, but through the value-adding processes and insights gained from it. As competitors have access to same, or at least similar, data, the importance of analytics is emphasised. Data analytics does not create lasting competitive advantage, as competitors can imitate the end result (Davenport and Harris, 2007, pp. 73–74), but organisations can utilise the data or process it in an innovative way to create competitive advantage. The value of data analytics come from the transparency and experimentation with the data; prediction, optimisation, customisation, and targeting of processes; organisational learning; and continuous monitoring and proactive adaptation of the analytical processes and culture (Grover *et al.,* 2018). Value creation of data analytics seems to focus on producing more information to organisations that they can use to improve themselves, their processes, or customer experience.

The value data analytics create for organisations appears as benefits organisations gain. These benefits are often immaterial and not clearly detectable, which might cause analytics to be hard to sell. Commonly referred benefit of data analytics is improved decision-making (e.g. Davenport, 2013; Chiang *et al.*, 2018; Grover *et al.*, 2018; Koohang and Nord, 2021). Improved decision-making means that organisations can access relevant data consistently to gain more information supporting them in decision-making by allowing them to assess the situation and environment in a more comprehensive way, e.g. based on forecasts supplier notices that a product sells well in the summer, so they prepare for coming summer by making sure they have enough products to meet the forecasted demand. Organisations emphasising decision-making based on data analytics show higher performance and productivity than those who do not utilise data analytics in decision-making (Brynjolfsson, Hitt and Kim, 2011).

Organisations can also achieve specific benefits with the help of data analytics. Combined with CRM and its data, they can combine internal and external customer data to form a comprehensive view of the customer, categorise customers in different segments, recognise profitable or possibly churning customers, analyse pricing to match the demand, simulate different scenarios for customers, and measure the effectiveness of marketing (Davenport and Harris, 2007, pp. 115–116). The available customer data also allows organisations to analyse customers’ purchases and make personalised recommendations for them, understand the customer experience based on analysing their contacts with the organisations, observe reasons for failures with products or services, and develop automatic and timely responses for service or product failures (Grover *et al.*, 2018). The opportunities for data analytics with customer data are endless and dependent on organisations ability to innovate new measures and use cases for the data.

Even if an organisation does not use data analytics for decision-making or to improve some parts of their business, even the ownership of data analytics assets (e.g. technologies, processes, skills) help organisations to gain benefits and improve their productivity (Müller, Fay and Brocke, 2018). The more organisations feel comfortable with the assets, the more data-driven they are, leading to performance improvements measured on financial and operational results (McAfee and Brynjolfsson, 2012). Organisations are also reporting gaining competitive advantage of data analytics and innovating new products or services due to the same capabilities, allowing them to succeed in analytics (Ransbotham and Kiron, 2017). In addition to these, organisations can also use data analytics to improve customer experience by analysing reviews to find out any shortcomings in customers' experiences (Barnes *et al.*, 2020), or optimise their processes and improve their performance (McKinsey & Company, 2016). The aim of data analytics is to deliver the right information of some specific case to the right person at the right time and in correct form to help the person to make informed decisions about the course of action.

This means, that to succeed in analytics, organisation needs to have multiple assets in good order. Data is given and it needs to have good quality so it can offer accurate and meaningful insights. Other assets include elements such as skilled people to conduct analyses and leadership that is committed to analytics, technology to enable data queries and transformations, processes informing what transformations or calculations to be done, and flexible data-driven organisational culture basing their actions on data and allowing experimentation and focusing on innovative thinking (Davenport and Harris, 2007, pp. 144–148). Others also stress the importance of leadership capability, management capability, and talent quality, describing them as critical components of data analytics (Koohang and Nord, 2021). Leadership capability consists of an organisation's ability to include data analytics into strategic decision-making and to communicate a data-driven strategy to the whole organisation, along with targets and objectives for analytics processes. Management capabilities refer to the ability of an organisation to monitor the performance of analytics, coordination and management of people and their skills, and innovating opportunities for data analytics. And lastly, talent quality is about people's personal skills to use data analytics, learning capabilities, and understanding of business environment. (Koohang and Nord, 2021)

A more comprehensive model of data analytics requirements is DELTA-model that inspects capabilities and assets an organisation needs to succeed with data analytics and it consists of data, enterprise, leadership, targets, and analysts (Davenport, Harris and

Morison, 2010, pp. 19–21). The importance of data and its quality has been presented many times in the context of data analytics, so it is sufficient to say that it needs to be accessible and high-quality. Enterprise dimension refers to the orientation of the data analytics within the organisation and the relationship between data analytics and the organisation. Organisations should create a common view of analytics for the whole organisation, aiming to develop a singular, comprehensive and holistic view to analytical processes. This helps organisations to see the global trends in their business environment and allocate resources better where they are needed to support value-creating, cross-functional processes befitting the organisation's strategy. (Davenport and Harris, 2007, pp. 21–44; Davenport, Harris and Morison, 2010) This common view also reduces complexity, as the analytics approach is coordinated and centrally managed, starting from integrating data and applications, defining analytical processes, and making employees understand how data analytics fits the organisation's strategy (Davenport and Harris, 2007, pp. 150–153; Davenport, Harris and Morison, 2010). Analytics and analytical thinking are integrated into the organisation; failures are not critical mistakes, innovative thinking and experimentations are rewarded, and decisions are based on data, not only on intuition or experience. Although these can and should be used to find new opportunities and evolving possibilities, data should be prioritised when making decisions.

Forming a unified enterprise-wide view of analytics requires analytical leadership to form and steer the organisation towards becoming more data-driven. Managers and leaders in an organisation have the necessary influence and resources to mobilise money, people, and time needed to make organisation more analytical (Davenport, Harris and Morison, 2010, pp. 57–72; Grover *et al.*, 2018; Koohang and Nord, 2021). Managers should lead by example and require analytical thinking also from employees. It is not required that managers know all of the analytical processes done in an organisation, but they should know enough to have conversations about the processes and share some ideas regarding them. Managers should hire smart people or allow people to develop their skills, and teach others, guiding them towards more data-driven way of thinking. It is important for the leadership not to focus solely on integrating analytics into processes and produce information to support decision-making, but they should also focus on transforming the organisation as a whole towards more data-driven and analytical environment (Davenport and Harris, 2007, pp. 21–44; Davenport, Harris and Morison, 2010, pp. 57–72; Grover *et al.*, 2018; Kitchens *et al.*, 2018). In the end, leaders are responsible for the success of analytics and defining what is successful analytics. They implement the strategy and a roadmap how to get there and what assets the organisation requires to do so. This is an important part in analytics because without well-defined targets, analytics can be thought as experiments, possibly leading to benefits, but not sustainable on the long-term because analytics are not managed properly and purposefully.

Organisations aim for long-term profitability and to reach that, they need to have positive results from their experiments. To know, whether they have succeeded or not, they rely on targets that can be measured and monitored; they give a point of reference that can be compared to others. This allows the organisation to compare results and focus on processes having the most impactful results by allocating more results to them. Targets and goals are important part of data analytics and they need to be measured and monitored to be improved (Davenport, Harris and Morison, 2010, pp. 73–90; Mithas, Ramasubbu and Sambamurthy, 2011; McKinsey & Company, 2016; Grover *et al.*, 2018; Koohang and Nord, 2021). A good target, especially in the context of analytics, is one that engages the business area's management, has specific goals and metrics to monitor, is feasible with usable resources, and aims at a specific, distinct capability, that has the possibility to make a difference in performance, profitability, or competitiveness (Davenport, Harris and Morison, 2010, pp. 73–90). Targets should be kept realistic and focused. For example, increasing profitability is a common target, but it can be improved by breaking it down to components. In this case, organisations could analyse specific products and their sales in different locations in different times to see which products underperform in relation to others and begin to explore reasons for it. Perhaps a competitor has opened a store selling similar products or organisation's store's customer satisfaction has lowered drastically, and these are the reasons for the decrease in the underperformance. Organisations should keep in mind that they can set the targets on large scope, but they should break the target down and analyse the components to find out where they can make an impact. Although, they should also keep in mind their resources and capabilities (Davenport and Harris, 2007; Gillon *et al.*, 2014; Koohang and Nord, 2021). Analytically less sophisticated should start low and focus on local targets and singular business areas, such as visualising sales or customer satisfaction, and as they grow more sophisticated analytically, they should begin implementing analytics into broader targets, e.g. business strategy or developing business function (Davenport, Harris and Morison, 2010, pp. 73–90).

The last piece of DELTA-model is analysts, or the employees doing value-adding processes to the data. It is important for organisations to hire or develop skilled persons in analytics to manage the analytical processes and innovate new possible solutions and insights to problems (Davenport and Harris, 2007, pp. 144–148; Davenport, Harris and Morison, 2010, pp. 19–21; Gillon *et al.*, 2014; Koohang and Nord, 2021). Analysts have two main functions: building and maintaining analytics processes that help organisations to reach their targets; and informing and spreading the analytical ways to the organisation, helping the organisations to become more analytical and develop their skills (Davenport, Harris and Morison, 2010, pp. 19–21). In addition to analytical skills, other valuable skills for analysts are communication, consulting, teaching, technical skills, and business understanding. This allows employees not only to be analytically proficient but also share their knowledge by teaching others in understandable way, present their findings and results in clear form, use multiple different applications to process the data and visualise results, and understand the connections between the analysis and organisation's business environment.

The DELTA-model (Davenport, Harris and Morison, 2010) is not perfect but it offers a comprehensive view of the organisation's analytical maturity and capabilities to compete with analytics. It supplements the findings from McAfee and Brynjolfsson (2012), Gillon *et al.* (2014), Chen and Nath (2018), Grover *et al.* (2018), and Koohang and Nord (2021), and discloses accurately, how different factors of data analytics work together in creating value for organisations. All dimension of the DELTA-model are dependent on each other and to succeed in analytics, the dimensions need to work together in harmony, as lack of one or more elements can lead to wasted resources or failure (Davenport, Harris and Morison, 2010, pp. 19–21). It does not directly consider different technologies and applications used for analytics, such as self-service analytics tools Power BI and Tableau or programming languages R and Python, but it inspects the skills of employees to utilise these tools. It is an important dimension, as not all technologies are suitable for all analytics processes, e.g. SQL is popular and broadly used tool in analytics but it supports data queries, not visualisations. Technologies would make an excellent addition to the DELTA-model, as it interacts with other dimensions in the model, e.g. technologies can be used to measure and monitor targets, data-driven organisational culture encourages self-service analytics and innovating new use cases for technologies, different technologies need good quality data to process it, and employees need to be skilled in using them (Davenport and Harris, 2007, pp. 144–148; McAfee and Brynjolfsson, 2012; Gillon *et al.*, 2014; Chiang *et al.*, 2018).

Data analytics has many requirements and lack of one, or more, can explain why organisations do not gain benefits of data analytics. Data can diverse, located in different silos, not well documented, or bad quality, making it challenging for many organisations to collect and combine into an integrated data source to be utilised by analysing it (Kitchens *et al.*, 2018; DiFranza, 2019; University of York, 2019). The organisation culture might not be as data-driven as it could be, the management not realising the benefits of data analytics and making decisions based on the opinion of the highest paid person rather than based on data (McAfee and Brynjolfsson, 2012; University of York, 2019). If the management does not take necessary actions to develop analytical processes and practises in the organisation by creating cross-functional teams utilising integrated data, that originates from all around the organisation and its environment, organisations fail to become data-driven and reach the benefits (McAfee and Brynjolfsson, 2012). Challenges can also arise in the organisation if they fail to develop or hire skilled employees; lack common terms and definitions for data analytics and its processes, causing confusion; or not specifying targets and goals of analytics well, causing possibly unnecessary work (Gillon *et al.*, 2014; McKinsey & Company, 2016; Kitchens *et al.*, 2018; DiFranza, 2019; University of York, 2019).

Data analytics is a combination of many elements, requiring many resources from an organisation and its leadership, but it has much to offer. Organisations gain competitive advantage as they gain insights and new information relating to their offerings, and they can use this new information to improve the offerings or to support decision-making. Data analytical organisations, especially when they are analytically sophisticated, have a data-driven culture that encourages employees to learn, innovate, and experiment new products or processes, allowing organisations to improve themselves in addition to their offerings. But it is a long road to become analytically sophisticated, and there are many challenges, e.g. management not committed to analytics, technologies not integrating or communicating with each other, organisational culture not supporting data-driven thinking, and organisation not defining clear strategy or targets for data utilisation. And importantly, organisation needs good quality data that is available, usable, reliable, relevant, and presentable for users to process. If organisations use CRM, the data aspect can succeed easier, as CRM collects the data into a single system, in clear and structured form, from where it can be transformed into meaningful insights that are relevant to the organisation. Organisations still need to take care of the other requirements, but the changes are that prerequisites are in good shape, if an organisation uses CRM systems, as they might have some data-driven activity ongoing.

4. THEORY SUMMARY

This chapter summarises and combines theoretical chapters, customer relationship management and data analytics, to form a comprehensive and logical view of this thesis. The purpose of theoretical chapters was to find good quality information and theories of the subjects, CRM and data analytics, that can be inspected and used to form new conclusion of their utilisations in current business environment, allowing investigation empirically. The objective of this research is to find how organisations utilised data analytics in the context of CRM customer data. To answer it, the theoretical chapters inspected what the subjects are, what kind of data they require, what benefits do they bring to organisations, and what could mitigate or prevent these benefits. Figure 5 presents the view of how these aspects are connected to each other.

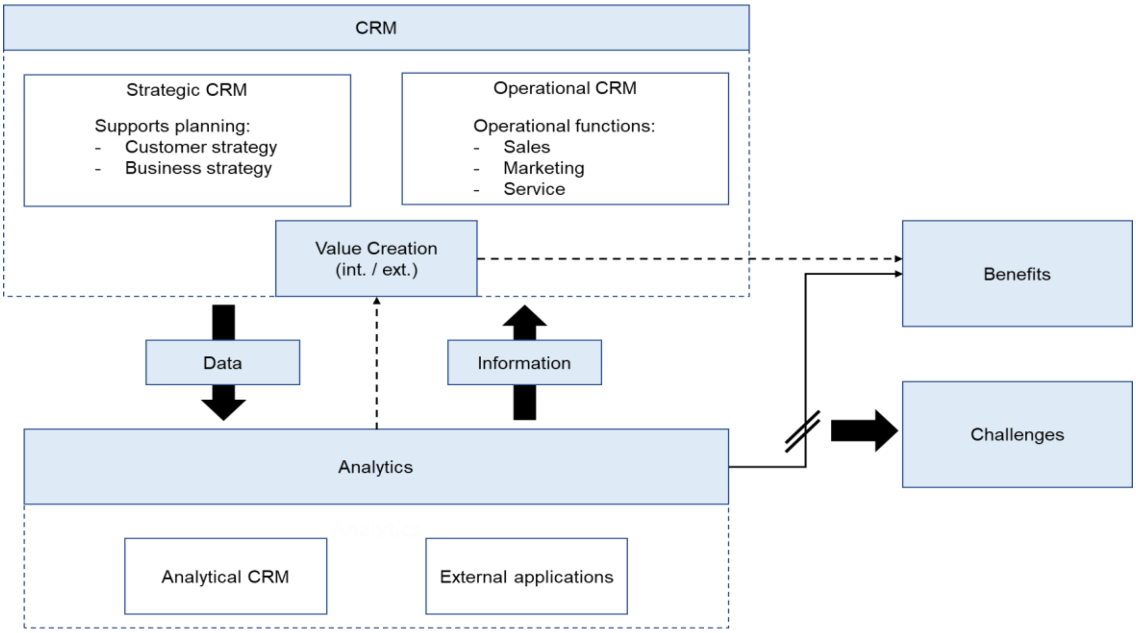

Figure 5. *Utilising analytics with CRM.*

Figure 5 summarises the thesis and its subject well. In this thesis, CRM is divided mainly into two independent systems based on their processes and scope: strategic CRM and operational CRM. Third type of CRM, analytical CRM, is also recognised, but can be seen mainly as a supporting function to the other two types, and as it analyses the data available from the other CRM types, it is placed into the analytics dimension. Strategic CRM focuses on creating lasting advantages for an organisation such as maintaining low customer churn, while operational CRM is concerned with everyday value creating processes of an organisation such as communicating with relevant customers.

Organisations can collect data from their business environment and of their customers based on their orders and contacts, surveys, and information they have given. The customer data organisations collect include, but is not limited to transaction, feedback, demographic, geographic, psychographic, and social media data. These data contain e.g. information about transactions customers have made, information of the customer as an individual, location information, and information of the behaviour and interests of the customer. The diverse data is stored into CRM, where it forms a comprehensive view of the organisation’s offerings and their customers. Organisations can utilise this data inside their CRM in different value creating processes, creating internal value for the organisation or external value for the customers and different stakeholders (Payne, 2006, Chapter 3). External value creation can provide value-in-exchange, value-in-use, or value-in-experience for customers, where benefits can realise to them as they gain or use the product the organisation offers (Buttle and Maklan, 2019, pp. 167–172). In the context of CRM this value for customers realises as intangible value, such as increased satisfaction, more relevant offering and timely assistance. Internal value provides benefits for the organisation in tangible and intangible forms, such as increased profits, saved resources and increased efficiency of employees, and customer retention.

If the organisations were to analyse the data available from CRM, they could refine it into meaningful information and use it to improve their value creating processes. With the help of analytics, organisations can make more informed decisions, find new insights, and discover (dis)similarities from the data, leading to improved benefits. Data analytics can be performed in analytical CRM or external applications, such as Python, Power BI, or Tableau. Analytical CRM might not have all the functions external applications have, but it offers easy contextual analytics inside CRM, giving the users the convenience to have the data and information in the same place, even in the same view, so they do not have to stop their working disturbing their flow, as they move to another application. Organisations can utilise data analytics to group similar customers into segments, to improve marketing by targeting similar customers; conduct market basket analysis to offer additional services or products relevant to the customer; or analyse customer happiness to figure out how to serve them well.

Data analytics allows organisations to gain improved understanding of their customers and improve their experience; to optimise and to improve their internal and external processes, and to differentiate their offerings to gain competitive value (McKinsey & Company, 2016; Kitchens *et al.*, 2018). Data analytics help data-driven organisations to improve their productivity, by improving their ability to monitor their performance and allowing them to make decisions based on data (Brynjolfsson, Hitt and Kim, 2011; Mithas, Ramasubbu and Sambamurthy, 2011; Müller, Fay and Brocke, 2018). Especially when data analytics are combined with rich customer data CRM provides, the possibilities are endless and only dependent on the organisation's ability to innovate measurements and information they need to improve their services. Data analytics can also be used to refine the data and feed it back to the CRM, to offer additional information for its users, such as a possibility to close a deal on different customers or predicting the customers' ability to pay their bills on time. This helps to monitor the status of the customers and with the help of machine learning, analytics can even provide suggestion how to improve the customer relationship.

Before an organisation reaches the benefits, they must meet the requirements for data analytics and CRM utilisation, or it creates challenges that mitigate or prevent the benefits from realising. These requirements can be summarised to data, organisational culture, leadership, strategic use, skills of the individuals, and technologies. In addition to data existing, it needs to be good quality so it can be used to bring value. Bad quality data can also be analysed, but it slows the analytics process, as the data must be cleaned and defined, bringing unnecessary costs for the organisation (Redman, 2016). Even after corrections, it is not guaranteed to bring benefits, as the results can be erroneous.

But data is not the only requirement, although it is of paramount importance. Organisations need skilled employees and suitable tools to analyse the data. They need business understanding of how to transform insights into business value, and a data-driven culture driving them forward. Leadership implementing common procedures regarding analytics and communicating strategy to employees is also important for analytics to gain foothold in the organisation. (Davenport and Harris, 2007; Koohang and Nord, 2021) Challenges and aspects mitigating benefits of data analytics are displayed on Table 2 with examples of difficulties organisations could face.

Table 2. *Challenges in data analytics.*

Aspect	Example
Data	Bad quality (erroneous) data. Difficulties to access data.
Organisational culture	Organisation is not data-driven. Analytics are not utilised systematically.
Leadership	Leadership cannot communicate the results. Leadership does not act based on analytical results.
Strategic use	Analytics do not have a clear focus. Organisation does not have understanding to transform analytics into business value.
Skills	Incompetent employees. No resources to educate employees.
Technology	Improper tools for analytics. Technologies do not work well together.

As Table 2 demonstrates, data analytics has requirements from multiple different dimensions, and they should cooperate well and support each other, so the organisation could compete with analytics and gain benefits (Gillon *et al.*, 2014; Grover *et al.*, 2018). If the dimensions do not cooperate, the organisations can gain benefits from data analytics, but the benefits might be mitigated, as the organisations does not have necessary capabilities or understanding to utilise the results, derive insights from them, or challenges communicating and sharing them. It is important to figure out the state of organisation's capabilities so the weaker capabilities could be improved to utilise the results of analytics more effectively, allowing more benefits to be realised.

Table 3 collects the topics of this thesis and their attributes and items, and links them into theories and literature presented earlier in this thesis.

Table 3. *Topics of the thesis along with related theories and literature.*

Topic	Attributes and items	Theories and literature
Types and functions of used CRM systems	Analytical, collaborative, operational, social, and strategic CRMs.	Xu and Walton, 2005; Payne, 2006, Chapter 1; Cuthbertson and Messenger, 2008; Greenberg, 2010; Kumar and Reinartz, 2012; Khodakarami and Chan, 2014; Buttle and Maklan, 2019 pp. 3–24
Types of analytics, and analytical maturity	Descriptive, diagnostic, predictive, and prescriptive analytics.	Davenport and Harris, 2007, pp. 58–64; Banerjee, Bandyopadhyay and Acharya, 2013; Ransbotham, Kiron and Prentice, 2015; Gartner, 2018
Collected customer data	Customer data, customer feedback, demographic, geographic, market, psychographic, relationship, social, transaction data.	Mosley and Brackett, 2010, p. 176; Kumar and Reinartz, 2012; Falck and Koenen, 2020
Data analytics - Data	Quality, availability, reliability, relevancy, quality's impact to analytics.	Davenport, Harris and Morison, 2010; Gillon *et al.*, 2014; Cai and Zhu, 2015; Ji-fan Ren *et al.*, 2017; Gartner, 2018; Grover *et al.*, 2018; Hagiu and Wright, 2020
Data analytics – Organisational culture	Data-driven organisation, information sharing and use, impacts of analytics, common processes.	Davenport, Harris and Morison, 2010; Gillon *et al.*, 2014; Gartner, 2018; Grover *et al.*, 2018
Data analytics – Leadership	Leadership is encouraging, data exploration is encouraged, data-driven decision-making, leadership is competent in analytics.	Davenport, Harris and Morison, 2010; Gillon *et al.*, 2014; Chen and Nath, 2018; Gartner, 2018; Grover *et al.*, 2018; Koohang and Nord, 2021
Data analytics – Strategic use	Analytics are strategically and systematically used and monitored, analytics have a focus, organisation has good resources and knowledge to translate analytics into value	Davenport and Harris, 2007, pp. 45–64; Davenport, Harris and Morison, 2010; Gillon *et al.*, 2014; Grover *et al.*, 2018; Koohang and Nord, 2021
Data analytics – Skills of the individual	Employees are educated, they have business understanding, they are trained.	Davenport, Harris and Morison, 2010; Gillon *et al.*, 2014; Grover *et al.*, 2018; Koohang and Nord, 2021
Data analytics – Technologies and tools	The tools are provided, are easy to use, suitable for the analytics, and the tools work well together.	Gillon *et al.*, 2014; Chen and Nath, 2018; Gartner, 2018; Grover *et al.*, 2018
CRM - Benefits	Better customer knowledge, customer retention, gained profits, improved customer satisfaction, improved decision-making, improved information sharing, increased efficiency, increased productivity, more won sales or deals, and saved resources (e.g. time, money).	Galbreath and Rogers, 1999; Reichheld, Schefter and Rigby, 2002; Xu and Walton, 2005; Payne, 2006, chap. 3; Chang, Park and Chaiy, 2010; Reimann, Schilke and Thomas, 2010; Mithas, Ramasubbu and Sambamurthy, 2011; Kumar and Reinartz, 2012; Banyte and Dovaliene, 2014; Chorianopoulos, 2016; Anshari *et al.*, 2019; Buttle and Maklan, 2019
Data analytics – Benefits	Better customer understanding, better customer segmentation, improved customer satisfaction, improved decision-making, improved marketing capabilities, improved prediction capability, increased efficiency, increased productivity, increased profits, more accurate pricing of services or products, and saved resources (e.g. time, money).	Brynjolfsson, Hitt and Kim, 2011; Davenport, 2013; Chen and Nath, 2018; Chiang *et al.*, 2018; Grover *et al.*, 2018; Müller, Fay and Brocke, 2018; Barnes *et al.*, 2020; Koohang and Nord, 2021
Mitigating factors for data analytics	Data, organisational culture, leadership, strategic use of analytics, skills of the employees, and technology.	Redman, 1998; LaValle *et al.*, 2011; McAfee and Brynjolfsson, 2012; Gillon *et al.*, 2014; McKinsey & Company, 2016; Chiang *et al.*, 2018; Grover *et al.*, 2018; Kitchens *et al.*, 2018; DiFranza, 2019; Patel, 2019; University of York, 2019

5. SURVEY

To answer how different organisations utilise data analytics with customer data from CRM, a survey was created to inspect findings from literature research, and to answer to the sub-questions of the thesis based on information gained from business environment. The survey was formed with the help of Table 3 from the previous chapter, the questions constructed from the topics, and attributes and items from Table 3. The questions can be found from Appendix A: Survey questions.

The survey was created using Microsoft Forms and, as the thesis is written in English, it was created in English as well. Creating a survey in multiple languages was seen as a risk for confusion among the answers, and as the audience of the survey could include persons from Nordic countries, an English version was seen as an optimal solution. A preliminary version of the survey was created and distributed internally to gain feedback of the questions and of the subject. Based on the feedback, the survey was clarified, and some questions were modified.

The final version of the survey was distributed to ten persons in eight existing customer organisations of Knowit with the help of the customer's account manager. This was seen as a reliable channel to get the survey to the customers using existing relationships with them. The goal was to distribute the survey within the customers with the help of these contacts. The survey was also shared in LinkedIn to get more comprehensive and wider set of answers and via email to 242 different persons from 32 different organisations. Overall, the survey reached 252 persons, from 40 different organisations.

5.1 Data collection

The questions of the survey inspect the maturity of organisations' analytics; applications and services used as analytical platforms and CRM systems; what types of data they collect into CRM; what the respondent's opinion of different aspects of data analytics in their organisation is; what benefits organisations gain of data analytics; and aspects the respondents perceive mitigating the benefits. The survey contains 63 questions, of which 34 are opinion related questions on Likert scale, regarding the challenges of different aspects of data analytics, and 16 questions are otherwise answering the sub-questions (such as what data they collect of customers and complementing other answers). The rest are inspecting demographic information of the respondents and information of the business environment (such as used CRM systems and analytics tools).

The survey is divided into four different sections that are demographics, customer relationship management and data analytics, challenges of data analytics from multiple viewpoints, and benefits of data analytics and CRM. Demographics questions inquire basic information about the respondents and of the business environment, such as in what roles do the respondents work and in how large organisations, what CRM systems and analytical tools do the respondents use, and for what purposes are the systems used. This last point indicates possibly how mature the organisations are analytically and whether they utilise analytics strategically or operationally. These aspects help to understand typical challenges of the business environment based on their analytical maturity. The demographics section does not answer any sub-research question, but it offers valuable insights to the answers. For example, organisation's large size might cause problems with the data sharing as data sources become siloed or person's role might indicate their skills with a data analytics tool, or the respondents long experience with analytics and CRM might reflect positively on their abilities with different tools and their skills.

Respondents' data types and data sources are examined in the customer relationship management and data analytics section, by offering them a multichoice question, where they can mark data they collect of their customers. The respondents also have a possibility to specify their answer by writing and describing additional information. The survey inquires also whether respondents have external data sources, such as open data portals, that they use to complement their own data, and whether they have sufficient data of their customers to form a comprehensive view of them. Different dimensions of data quality are inspected more specifically in different section.

The challenges of data analytics are inspected via the aspects from Table 2, and they are measured on a Likert scale, based on the respondent's experiences and opinions of the different claims. The scale is on five points: “Strongly disagree”, “Disagree”, “Neutral”, “Agree”, and “Strongly “agree”. The claims represent possible challenges a person could face, when analysing data from a CRM system, ranging from data quality to organisational culture. The claims are e.g. “You have necessary tools to perform analytics” and “The tools are difficult to use”. Most of the claims are formatted as positive claims, but there are some that are formatted negatively, to make the respondent pay attention to what they are answering to. This part of the survey offers valuable information for the thesis, as it inspects in which aspects are perceived difficult and thus scored low, indicating that the organisations could need help with the aspect.

Lastly in the survey, the benefits of CRM and data analytics are examined based on the perceived value and benefits to the respondent. Measuring direct benefits of data analytics is difficult due to the short timeframe and the nature of the thesis, but the perceived benefits offer useful information for the purposes of the thesis. Respondents are asked if they have gained noticeable benefits while using a CRM system and whether they have gained additional benefits due to data analytics, and if they feel that the benefits are mitigated by some particular aspect(s).

With the help of the survey, a comprehensive view is created of how different organisations utilise data analytics with customer data from CRM systems, by inspecting what data organisations have of their customers, what challenges are faced in data analytics, and what benefits are gained of analysing customer data.

The survey was sent in late November to ten persons in eight different organisations to further distribute the survey within their organisations. This method was very unsuccessful as the survey gained only eight answers, indicating that the survey was not distributed in the customer organisations. To get additional answers and a larger sample for the thesis, the survey was further distributed in social networks (LinkedIn) and via email. For this second email collection, 242 additional emails were collected from 32 different organisations, and the survey was sent to them in January.

Overall, the survey reached 252 persons from 40 organisations, and it gained 21 answers. Of these 21, one was ignored and dropped, as the answer contained no information. The other answers were deemed to be qualified for the research, as they contained rational answers, and the respondents had given thoughts for the questions and answers based on their response times. The response rate was 7,9 % (20 / 252), which is rather poor, but the time constraints of the writer did not allow for a third answer collection period. Table 4 presents demographics of the twenty respondents. All of the respondents work in Finland.

Table 4. *Sample demographics.*

Variable	Category	Frequency (n=20)
Roles in organisations	Employee / Staff	9 (45 %)
	Team Leader / Manager	6 (30 %)
	Unit Leader / Senior Manager	3 (15 %)
	Department Head / Director / Vice President	2 (10 %)
	C-level / Executive	0 (0 %)
Departments	IT	8 (40 %)
	Marketing	3 (15 %)
	Sales	3 (15 %)
	Administration	1 (5 %)
	HR	1 (5 %)
	Other	4 (20 %)
Size of organisation	Large Business (more than 250 employees)	14 (70 %)
	Small Business (10 - 49 employees)	4 (20 %)
	Medium Business (50 - 249 employees)	2 (10 %)
Experience with data analytics with CRM (in years)	1-2	6 (33,3 %)
	3-5	7 (38,9 %)
	6-10	3 (16.7 %)
	over 10	2 (11,1 %)
Do you analyse data…	within CRM and with external application(s).	11 (57,9 %)
	with external application(s).	7 (36,8 %)
	within CRM.	1 (5,2 %)
Do you bring the refined data back into CRM?	Yes	10 (55,6 %)
	No	8 (44,4 %)

The survey gained answers from almost every role in organisation, most of whom were normal employees, so the sample represents well an average organisation. The answers give opinions throughout an organisational structure, including those who use data analytics for operational and strategic purposes. Most of the respondents represent a large business, that has over 250 employees, and they are working in IT department, and few are from business processes, working in marketing or sales. All of the respondents analyse their customer data from CRM, so no answers were eliminated for not qualifying for the subject of the thesis. Most use some external application, such as Power BI or Tableau, to analyse the data and they bring the data back into the CRM, to display additional information and analyses of the customers.

Of the respondents, 18 answered that analysing data from CRM has brought them additional benefits, one did not answer the question, and one answered that they have not gained additional benefits, but later they defined that, analytics have brought them benefits, such as better customer understanding and customer segmentation.

5.2 Survey results

In addition to the survey answering the research questions, it also proved an excellent chance to inspect what tools are being used and for what purposes in the business environment. Over half (11 respondents) reported that they use Salesforce as their CRM system, a clear majority compared to others. Other choices received few answers; Microsoft Dynamics 365, SAP CRM, and custom systems were used by three respondents; HubSpot by one respondent; and one reported using legacy systems. Most of the respondents were happy with one system, but four used two or more systems for their customer relationship management. The purposes of CRM utilisation differ little between the respondents and offer no surprises: 16 (80 %) use CRM for strategic purposes, 14 (70 %) for analytical purposes, 14 (70 %) for operational purposes, 11 (55 %) for collaborative purposes, and 2 (10 %) for social purposes. The two respondents using CRM for social purposes work in HR and marketing, which explains the low value as others do not need to communicate with customers via CRM and social media. Mostly the CRM is used to create long-term value with the customers and used to help developing the relationships. Operational CRM offers the respondents help in automating their customer-facing processes and offers support for daily tasks.

Table 5 displays the types of customer data organisations collect of their customers. The collected data responds well with the purposes of the CRM systems. Few uses CRM for social purposes, so social media data is not much collected. Many collect only basic information of the customers, mainly their contact information and location data. Surprisingly few collect transaction data and market intelligence, which contain valuable information and could be used to predict for example upcoming payments or orders from a customer.

Table 5. *Types of collected customer data.*

Data type	Frequency (n=20)	Example
Customer data	19 (95 %)	Contact information, recent events
Geographic data	18 (90 %)	Address, country
Customer feedback	14 (70 %)	Contacts to support, feedbacks
Market intelligence	12 (60 %)	Key personnel, industry
Transaction data	12 (60 %)	Invoicing, orders, payments
Demographic data	9 (45 %)	Age, employment status
Relationship data	5 (25 %)	Connected users, duration
Social media data	3 (15 %)	Accounts, posts
Psychographic data	1 (5 %)	Behaviour, interests
Other	3 (15 %)	Competitor data, weather data, building data, building automation data, energy data

Ten respondents (50 %) tell that they complement their data by combining it with external data sources. The most common ones are weather data, contacts and sales leads, and market intelligence data, such as company size, industries, signals, and key figures. 13 respondents (65 %) are satisfied with the data they have of their customers, saying that they have enough data to form a comprehensive view of the customer, while the remaining seven respondents (35 %) say that they do not have a comprehensive view of the customer. According to their answers they are missing demographical information, data of customer interactions, and some are missing financial data of the customers. Two recognise bad data quality or missing data as the limiting factor of having a comprehensive view of their customers. Even though some recognise their lack of data, and some do not, the respondents reported gaining many benefits by utilising CRM. 17 (89 %) have better customer knowledge, 11 (58 %) have improved decision-making and improved information sharing, 10 (53 %) have improve customer satisfaction, and 8 (42 %) have retained customers, saved resources, and won sales or deals.

If this data were to be analysed, could the organisations gain additional benefits? This was also inspected in the survey. Analytical tools used by the respondents are presented in Table 6.

Table 6. *Analytical tools used by the respondents.*

Analytical application	**Frequency (n=20)**
Excel	12 (60 %)
CRM native reporting tools	10 (50 %)
Power BI	10 (50 %)
Tableau	8 (40 %)
Qlik (Sense)	4 (20 %)
Google (Looker)	2 (10 %)
Google Datastudio	2 (10 %)
Python (or similar)	2 (10 %)
Other	3 (15 %)

As Table 6 presents, Microsoft products have a strong present in the organisations. 12 respondents (60 %) tell that they use Excel and 10 (50 %) tell they use Power BI to analyse and visualise their customer data. A major competitor to Power BI, Tableau, is also represented well, as 8 respondents (40 %) define it as their analytical tool. CRM native reporting tools are also broadly used, as 10 respondents (50 %) utilise them. This is not an unexpected result, as many use Salesforce as their CRM and Salesforce has acquired Tableau and integrated it as a part of their CRM experience and offering eays integration between the tools (Tableau, 2019). Very few of the respondents (2, 10 %)

use programming languages to analyse their data, which indicates that most of the respondents do not refine the data, or they do not have to transform it much. This can also be due to the respondents working with transformed data, focusing on creating business value of it, not preparing it for others for analyses, or the data being well documented in correct form for analytics in the CRM systems. Also, many analytical tools allow some data transformations, so it can be easier for workers to do so in their preferred tool, rather than programming.

When inspecting the different types of analytics the respondents utilise to inspect their analytical maturity, as proposed by Banerjee, Bandyopadhyay and Acharya (2013), many seem to be highly mature as they use predictive analytics, not only to describe and visualise recent events but also predict future events based on the historical data. Table 7 presents the compilation of the analytical types used by the respondents, sorted by ascending analytical maturity.

Table 7. *Types of analytics.*

Type of analytics	**Frequency (n=20)**
Descriptive	18 (90 %)
Diagnostic	12 (60 %)
Predictive	15 (75 %)
Prescriptive	5 (25 %)
Other	3 (15 %)

Rather interestingly, not all use descriptive analytics, which is a basic form of analytics, where events are described based on data (e.g. a line chart of monthly sales), or diagnostic analytics, that allow drilling into the data and inspecting it more closely. These could be due to the respondents not utilising these types of analytics in their work, or the respondents not understanding the types due to bad descriptions in the survey. Otherwise, the results indicate that many at least utilise more mature analytical methods, as 15 respondents (75 %) use predictive analytics. Highly mature methods, prescriptive analytics, where optimal solutions for events are analysed by simulating different scenarios, are less used, 5 respondents (25 %) report using those methods. Other methods respondents defined are prediction of future events, self-learning algorithms (e.g. NLP and dynamic pricing), and clustering. The high frequency of predictive analytics can be explained with the tools used. Every tool displayed in Table 6 allows users to forecast data, and in most of the tool's forecasting is easy and requires no coding, which could be a limiting factor.

High analytical maturity can be seen well in the responses to the question whether the respondents have gained additional benefits from CRM data due to data analytics. One person did not answer the question, but every other respondent reported gaining additional benefits. These benefits are displayed in Table 8.

Table 8. *Benefits of data analytics.*

Benefit	**Frequency (n=19)**
Better customer understanding	18 (94,7 %)
Better customer segmentation	15 (78,9 %)
Improved decision-making	11 (57,9 %)
Improved prediction capability	10 (52,6 %)
Saved resources (e.g. time, money)	10 (52,6 %)
Improved marketing capabilities	8 (42,1 %)
Increased efficiency	8 (42,1 %)
Improved customer satisfaction	7 (36,8 %)
Increased productivity	7 (36,8 %)
Increased profits	7 (36,8 %)
More accurate pricing of services or products	6 (31,6 %)
Other	2 (10,5 %)

Common benefits, that over 50 % of the respondents have reported, are better customer understanding and customer segmentation, improved decision-making and prediction capabilities, and saved resources, such as time or money. Some of the respondents can attribute increased profits, productivity, and efficiency to data analytics. Other benefits told by the respondents include having better visibility of the data and the KPI's, and one told that analytics help them planning and implementing strategy.

When asked, which aspects of data analytics (data, organisational culture, leadership, strategic use, analyst's skills, and technology) the respondents felt like mitigated the benefits gained from data analytics, most responded that the strategic use was the greatest difficulty. Results are collected to Table 9.

Table 9. *Aspects mitigating benefits from data analytics.*

Aspect	**Frequency (n=19)**
Strategic use of analytics	10 (52,6 %)
Data	9 (47,4 %)
Organisational culture	7 (36,8 %)
Leadership	7 (36,8 %)
Your skills	6 (31,6 %)
Technology	4 (21,1 %)
Other	2 (10,5 %)

Most of the respondents are content with the technologies they are using and their skills in data analytics, as only six respondents (31,6 %) stated their skills and four respondents (21,1 %) stated technology as limiting factor to the benefits of data analytics. A bit under half (nine respondents, 47,4 %) defined data as one of their mitigating factors.

Otherwise, it seems that the greatest challenges are in making the working environment suitable for data-driven actions, as organisational culture and leadership are fairly often mentioned as the mitigating aspects (seven respondents, 36,8 %), and as the greatest challenge is strategic use of analytics, which is mentioned by ten respondents (52,6 %). Other aspects that are mentioned to mitigate the benefits are old technology and lack of time and resources.

5.3 Analysis

This thesis aims to answer how to utilise data analytics with CRM customer data, and important part of it, is to understand what additional benefits data analytics bring and what aspects mitigate these benefits. To answer these questions data analytics was divided into different aspects, which are data, organisational culture, leadership, strategic use of analytics, and skills and technologies of employees. These aspects have been linked to data analytics and benefits (e.g. Davenport, Harris and Morison, 2010; McAfee and Brynjolfsson, 2012; Gillon *et al.*, 2014; Kitchens *et al.*, 2018; Koohang and Nord, 2021), so they formed a basis for inspecting data analytics of the respondents. These aspects were inspected by creating different claims about them, and the respondents rated them on a point Likert scale, answers being: “Strongly disagree”, “Disagree”, “Neutral”, “Agree”, and “Strongly agree”. The claims can be seen from appendix A: “Survey questions”. Summarisation of the answers to the survey claims measured on a Likert scale can be found in appendix B: “Likert scale results”.

For the purposes of statistical analysis, these answers were turned into numerical values, with the following logic: “Strongly disagree” = 1, “Disagree” = 2, “Neutral” = 3, “Agree” = 4, and “Strongly agree” = 5. Some claims, which were negatively toned, were changed along with their answers to make all the answers be similar (e.g. “The tools are difficult to use” → “The tools are easy to use”).

For overall view of the analytical capabilities, an average was calculated for each of the aspects, along with the average of all the aspects, and the averages were plotted on a box plot. This plot is displayed in Figure 6.

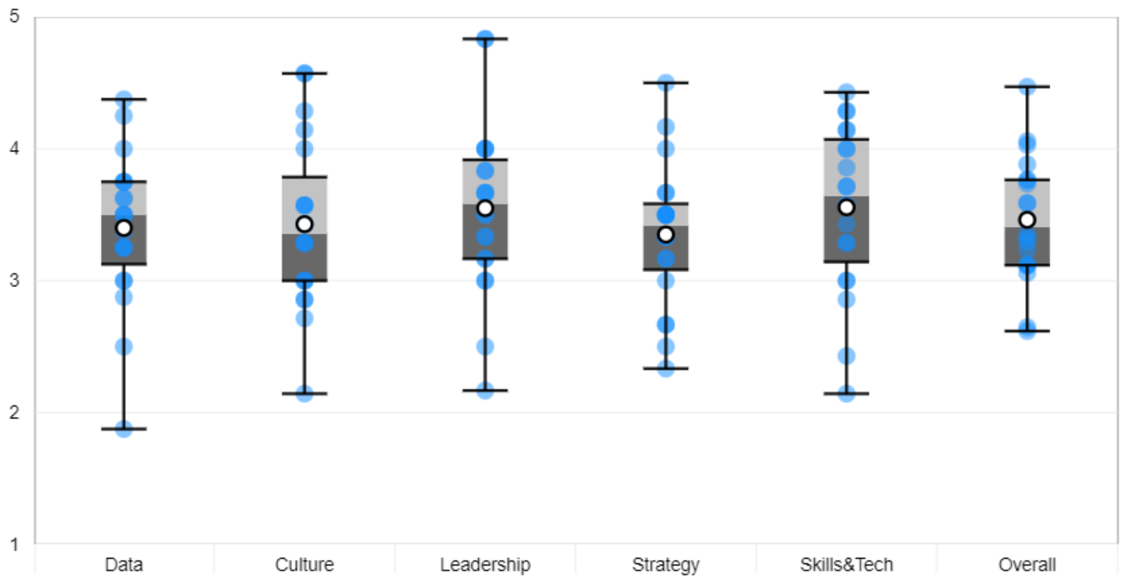

Figure 6. *Box plot of the average analytical aspects.*

The blue dots in Figure 6 represent the answers of the respondents and the white dots represent the calculated average for the aspect. The analytical capabilities of the respondents are on a good level, as the average for each aspect is greater than 3, which is the halfway point for the scale and considered as an adequate level of analytical capabilities. The overall average of the aspects is also on a good level, as the value is 3,46 and only two respondents (10 %) being below 3. These results correspond well with the results from Table 9, most of the respondents reported strategic use of analytics as being the primary challenge of gaining benefits of data analytics, and in Figure 6 the aspect (strategy in the figure) scores the lowest. Other values compare similarly: data is the second most challenging; culture is the third most challenging; leadership is the fourth most challenging; and skills of the respondents is the least challenging aspect.

For the statistical analysis of these aspects affecting the benefits gained from data analytics, the answers to the Likert scale questions were summed together per respondents, so every respondent got a summed value of each of the analytical aspects, so the variables could be represented (Emerson, 2017). These summed values can be found from Appendix C: “Summed Likert values”. Minimum value for an overall score for a respondent is 34, and maximum score is 170.

Mann-Whitney U test was used to inspect the aspects and their equality to the other aspects, to see if they are likely to derive from the same population (Boston University School of Public Health, 2017). This is done to test that the aspects are independent of each other and can be further analysed. Mann-Whitney U test is used because the sample size is small, and no assumption are made of the distribution of the data. Table 10 displays the results of Mann-Whitney U test, where $n_1=n_2 = 20$ and the test was two-tailed. H_0 is that the populations are equal, and H_1 is that the populations are not equal.

Table 10. *Mann-Whitney U test, cells display p-value and U.*

Aspect	Data	Culture	Leadership	Strategic use	Skills & Tech
Data Median = 28	p = 0,9891 U = 200	0,0462 126	0,0009 77	0,0001 59	0,1789 150
Culture Median = 24		0,9891 200	0,0474 126,5	0,0051 96,5	0,3849 167,5
Leadership Median = 22			0,9891 200	0,2949 161	0,0089 103
Strategic use Median = 21				0,9891 200	0,0007 75
Skills & Tech Median = 26					0,9891 200

Of the different combinations of the aspects, distributions did not differ significantly ($P > 0.05$) in “Data” – “Skills & Tech”, “Culture” – “Skills & Tech”, and “Leadership” – “Strategic use”, and these support H_0. If these combinations are used in later analyses, the results might be erroneous. Other combinations support H_1 and are not dependent of each other.

To inspect the effect of data analytical capabilities to the benefits gained from data analytics, the summarised Likert values were compared to coded values of the individual benefits in a binary fashion. If the respondent had gained a benefit (e.g. improved decision-making), the coded value is 1, and if not, then the value is 0. Summarised values were compared to the gained benefits with logistic regression, which models the relationship between multiple variables, and is suited to predict a binary outcome, such in this case (Seufert, 2014). Logistic regression is used to obtain odds ratio, and the result is the impact of each variable on the odds ratio of the observed result. It models a chance of an outcome based on individual characteristics (Sperandei, 2014).

Logistic regression indicates the goodness of the fit in Pseudo R-squared value, that is formatted on a range from 0 to 1. It presents how correlated the values are, 0 being no correlation and 1 being strong correlation, similar as R-squared value (Seufert, 2014). Pseudo R-squared is calculated using McFadden’s Pseudo R-squared, and values of 0,2 to 0,4 represent an excellent fit (McFadden, 1977). P-values that are smaller than 0,05 are considered statistically significant. Table 11 displays logistic regression made by comparing the respondents overall scores to the benefits, with statistically significant results bolded.

Table 11. *Results of logistic regression, overall score to benefits.*

Benefit	Coefficient	Pseudo R-squared	P-value
Customer understanding	intercept: 0,0225 overall score: -0,0008	0,00002464	0,9857
Customer segmentation	0,0433 -0,0281	0,03507	0,3744
Customer satisfaction	-0,0114 0,0047	0,001065	0,8681
Decision-making	**-0,0808** **0,0732**	**0,1880**	**0,02293**
Marketing capabilities	**-0,0844** **0,0696**	**0,1753**	**0,02983**
Prediction capability	-0,0626 0,0549	0,1215	0,06650
Efficiency	-0,0535 0,0431	0,08040	0,1412
Productivity	0,0190 -0,022	0,02285	0,4417
Profits	**-0,1100** **0,0890**	**0,2458**	**0,01164**
Pricing	0,0003 -0,0076	0,002731	0,7962
Saved resources	**-0,0925** **0,0812**	**0,2185**	**0,01384**

Coefficients of the logistic regression compares the odds ratio of a variable to the intercept, or the reference category, in which the overall score is set to 102 (total sum of coded Likert scale values, where all of the answers were "Neutral" or 3). Logistic regression shows a positive and statistically significant relationship between the overall score of the respondents' analytical capabilities and the following benefits of the data analytics: **improved decision-making, improved marketing capabilities, improved prediction capability, increased profits, and saved resources**. Of these, increased profits and saved resources show an excellent fit, as their Pseudo R-squared is above 0,2. To get the results, or the odds against the reference, exponential function must be used (e^x, where x = coefficient). Table 12 presents benefits, that are statistically significant, the odds ratio, and the p-value for the overall score.

Table 12. *Transformed results of logistic regression, overall score to benefits.*

Benefit	Odds ratio	P-value of overall score
Decision-making	1,0759	0,053
Marketing capabilities	1,0721	0,062
Profits	1,0931	0,042
Saved resources	1,0846	0,042

Increase of 1 point in the overall score multiplies the odds of gaining benefit by the odds ratio. When inspecting individual p-values from the models, the relationship between overall score and profits and saved resources remains significant, and decision-making and marketing capabilities being close to be significant with $P < 0,05$ restriction.

The odds ratios are low, but positive, so a small correlation can be seen between the overall score and the benefits, indicating that the higher data analytical capabilities an organisation has, the more likely they are to gain benefits from data analytics. Interestingly data analytics leading into increased customer understanding is not supported, even though 94,7 % of the respondents reported gaining the benefits. This could be due to low sample size and low variation in the sample, as nearly everybody reported it as a benefit, so the model was disturbed as there were so many positive results.

When forming the logistic regression with every aspect of data analytics to every benefit, no statistically significant models were found. Appendix D: “Data analytical aspects to benefits” displays the resulting models. When comparing individual aspects, or combinations of data analytical aspects, to benefits, some statistically significant models can be found, and these are displayed on Table 13. Many of these models show an excellent fit, as their Pseudo R-squared is higher than 0,2. Combinations of the aspects that were deemed too dependent of each other as a results of Mann-Whitney U test were ignored. For these, the intercept, or the reference group, was set for the lowest total possible of the combinations’ values, and the value is displayed in the table next to the intercept.

Table 13. *Logistic regression of analytical aspects to benefits.*

Benefit	Variable	Coefficient	Odds ratio	P-value
Customer segmentation Model's p-value: 0,04857 Pseudo R-squared: 0,2689	Intercept (14) Data Leadership	0,6954 -0,4842 0,2499	 0,61618995 1,28389702	0,139 0,093 0,188
Decision-making Model's p-value: 0,04195 Pseudo R-squared: 0,2304	Intercept (14) Data Leadership	-0,6284 0,0538 0,3621	 1,05527353 1,43634257	0,055 0,458 0,074
Decision-making Model's p-value: 0,01676 Pseudo R-squared: 0,2079	 Intercept (6) Leadership	 -1,2761 0,03723	 1,03793172	 0,071 0,063
Marketing capabilities Model's p-value: 0,001796 Pseudo R-squared: 0,4697	Intercept (13) Culture Leadership	-0,9514 0,828 -0,3867	 2,28873669 0,67929485	0,043 0,038 0,169
Marketing capabilities Model's p-value: 0,001664 Pseudo R-squared: 0,3673	 Intercept (7) Culture	 -1,7219 0,4787	 1,61397487	 0,023 0,028
Profits Model's p-value: 0,02070 Pseudo R-squared: 0,2995	Intercept (14) Data Strategic use	-0,8814 0,1111 0,4211	 1,11750665 1,52363663	0,039 0,528 0,189
Profits Model's p-value: 0,008080 Pseudo R-squared: 0,2709	 Intercept (6) Strategic use	 -2,0048 0,5522	 1,73707037	 0,049 0,057
Saved resources Model's p-value: 0,04016 Pseudo R-squared: 0,2319	Intercept (15) Data Culture	-0,5508 0,1788 0,1438	 1,19578156 1,15465315	0,063 0,255 0,322
Saved resources models p-value: 0,02115 Pseudo R-squared: 0,1917	 Intercept (8) Data	 -0,835 0,2467	 1,27979512	 0,112 0,102

The models are all statistically significant (P < 0,05) but in the models many of the variables are not supported, leading to conclusion that there is no significant relationship between the variables and the benefit. One relationship is supported: organisational culture's relation to improved marketing capabilities, where an increase in culture score multiplies the odds of gaining improved marketing capability by 60 %. It should be kept in mind, that the results could change if there would be more variance in the answers and a larger sample size. Of the individual aspects of data analytics, data can be found as a variable in many of the model, verifying that it is an important individual aspect of data analytics in gaining benefits from data analytics. It was not significantly supported as an explanatory variable, but this can be due to low sample size or errors in analytics.

6. DISCUSSION

The aim of this thesis was to inspect how organisations utilise data analytics in the context of CRM customer data, and this was done by forming a survey to inspect how data is analysed in different organisations that analyse data from their CRM systems. This chapter discusses the finding of the survey and compares the results to the theories from literature and ponders the impact of the results.

The main goal of the thesis is to inspect how to utilise data analytics in the context of CRM customer data. The process in short is that customer data is stored in different CRM systems, depending on the purpose of the CRM. CRM can be a strategic CRM, supporting strategic planning and long-term value creation of the organisation; operational CRM, automating and supporting operational functions of the organisation, such as sales or marketing; analytical CRM, that processes, analyses, and reports the data to offer refined information; and collaborative CRM, helping cross-functional functions to share information and interact with different stakeholders (Xu and Walton, 2005; Payne, 2006, chap. 1; Greenberg, 2010; Buttle and Maklan, 2019, pp. 3 – 24). These were the main types of CRM found in the survey, as 16 respondents (80 %) use for strategic purposes, 14 (70 %) for analytical and operational purposes, and 11 (55 %) for collaborative purposes. CRM systems help organisations to create value for them and their customers, and main benefits of CRM, reported by over half of the respondents are better customer knowledge, improved decision-making, improved information sharing, and improved customer satisfaction. These results correspond well with theories and findings from literature as many report CRM creates more intimate relationships with customer, as organisations have more information of them, and CRM enabling information management of customer data, offering good quality data available for many (Galbreath and Rogers, 1999; Chen and Chen, 2004; Xu and Walton, 2005; Mithas, Ramasubbu and Sambamurthy, 2011). Not many respondents (6, 31,5 %) attributed profits with CRM, but this could be due to bad wording and not explaining the benefit well enough. Every respondent but one defined gaining benefits due to CRM, and the one exception might not possibly work with CRM systems directly, thus attributing no benefits to CRM.

Customer data in CRM systems is mostly customer data or automatically collected transaction data, corresponding with the literature (Xu and Walton, 2005; Greenberg, 2010; Reimer and Becker, 2015). Based on the survey, organisations collect mostly customer information, customers’ geographical data, customer feedback, market intelligence of other organisations, and transactions of events with the customer. Psychographic data, which is used to inspect customer's behaviour, interests, and opinions, is rarely used, even though it would allow organisations to segment the customers based on their interests and help organisations to improve their customer segmentation. The rare occurrence can be due to the sample, as three respondents said that they work in marketing, and the data type could face the most utilisation in that function. Half of respondents also complement their own data with externally collected data, mostly related to additional information of the respondent's business environment, or competitor and customer information such as key personnel, contacts, and company sizes and industries. Of the respondents, 13 (65 %) define, that they have enough data to form a comprehensive view of the customer, where they can access the combined customer data across the organisation and its different functions. Seven respondents (35 %) say they do not have a comprehensive view, citing missing data and data quality being the issues.

All of the respondents say that they analyse the data. One respondent analyses the data directly in the CRM, and the others either with external applications, or within CRM and external applications. The data is analysed mostly by descriptive methods, where historical and current data is used to describe events, such as showing monthly sales on a line chart, and predictive methods, where historical data is used to predict future events (Banerjee, Bandyopadhyay and Acharya, 2013). Based on the analytical methods, organisations seem mature in analytics, as they use sophisticated methods and use analytics for improving their customer knowledge (Banerjee, Bandyopadhyay and Acharya, 2013; Ransbotham, Kiron and Prentice, 2015).

The analytical maturity of the respondents was inspected with dividing data analytics into five different aspects, that were found to be requirements for data analytics from the literature. These aspects are: data, organisational culture, leadership, strategic use of analytics, and skills and technologies, following theories and frameworks from (Davenport, Harris and Morison, 2010; Gillon *et al.*, 2014; Grover *et al.*, 2018; DiFranza, 2019; Koohang and Nord, 2021). These aspects were inspected with values gained from the respondents' answers to questions on a Likert scale, which were coded into numerical values. Overall, the analytical maturity was on a good level among the participants, the average being 3,46 on a scale from 1 to 5. Of the aspects, strategic use of data analytics is the lowest value with an average of 3,35. This indicates that the respondents have difficulties to strategically use the results of data analytics, many citing that they have too few resources to analyse the data. Other possible problems might be that data analytics are used to support current needs and then forgotten, and not utilised strategically to support the long-run. Or the focus of the analytics could be too broad and not used to address a local or fundamental issue.

Analytically mature organisations can utilise data analytics more effectively to bring gain more benefits (Davenport and Harris, 2007; Ransbotham, Kiron and Prentice, 2015; Gartner, 2018). Of the 20 respondents, 18 said that data analytics have brought them additional benefits, one responded no, and one gave no answer. Similarly to theories from literature (e.g. Brynjolfsson, Hitt and Kim, 2011; Davenport, 2013; Grover *et al.*, 2018; Müller, Fay and Brocke, 2018; Barnes *et al.*, 2020; Falck and Koenen, 2020; Koohang and Nord, 2021) reported benefits of data analytics include better customer understanding, better customer segmentation, improved decision-making, improved prediction capability, saved resources, improved marketing capabilities, increased profits, and increased customer satisfactions. When analysing and modelling the overall score of the analytical aspects with logistic regression, statistically significant results ($P < 0.05$) were found with decision-making, marketing capabilities, profits, and saved resources. When analysing combinations or individual aspects against the benefits, no benefits were validated, due to the variables not being statistically significant. Overall, the results sound reasonable, with data analytics leading to benefits and higher analytical maturity improving the chances to gain benefits, corresponding with the literature (Ransbotham and Kiron, 2017; Chen and Nath, 2018). Unfortunately, no comprehensive model could be validated to explain the dependency of a benefit with the analytical aspects.

When asked to tell what aspects of data analytics the respondents have felt to mitigate the benefits gained from data analytics, the responses corresponded well with the averages of the analytical aspects, gained from analysing the Likert scale values. Between all of the respondents, the average score for strategic use of data analytics was the lowest, and most of the respondents (10, 52,6%) answered that strategic use of analytics has mitigated their benefits. Based on the survey, organisations allocate too few resources to support the tasks of data analytics, be it time, tools, or employees. Management of people and their skills is an important factor in data analytics (Davenport and Harris, 2007, pp. 144–148; Davenport, Harris and Morison, 2010, pp. 19–21; Gillon *et al.*, 2014; Koohang and Nord, 2021) and the managers are responsible for the allocation of available resources or getting more of them. To utilise data analytics strategically and improve the strategic use of analytics, more care should be focused on the resource management, and the targets of data analytics should be kept realistic and feasible, in the terms of available resources (Davenport, Harris and Morison, 2010, pp. 73–90; Mithas, Ramasubbu and Sambamurthy, 2011; Grover *et al.*, 2018; Koohang and Nord, 2021). Other perceived challenges in the strategic use of analytics could due to the results being intangible or hard to perceive, as the benefits focus on a long-time scale. The results might also indicate that even though organisations measure and monitor the use of analytics, they are not utilised well, and the monitoring has no impact. Monitoring is reported as another data point among others, with no strategic use in mind.

Another highly reported (9 respondents, 47,4 %) aspect mitigating benefits was data. Data is the cornerstone of data analytics, it is of paramount importance to data analytics, as you cannot be analytical without data (Davenport, Harris and Morison 2010, p. 22). The respondent's capabilities with data were analysed by inspecting their data quality based on data quality dimensions availability, usability, reliability, and relevance (Cai and Zhu, 2015). Data quality was felt to affect data analytics negatively and some problems were reported in the data being outdated, ambiguous, and unclear. Data being duplicated and scattered in multiple places was also reported as challenges. Some mentioned data management being the problem with data quality, indicating that master data management and data governance need more attention in these organisations. Proper data management allows organisations to create working practises for data storing and to catch erroneous data (Ransbotham and Kiron, 2017), so data would be better available in a sensible location, without the need to search for it from multiple places and creating unnecessary work. No results were validated that data quality mitigated benefits, but this conclusion is supported in other findings (Redman, 1998, 2016; Nagle, Redman and Sammon, 2017) and, as many respondents perceived data being a problem regarding analytics, special attention should be paid for data quality.

Other aspects are not that often reported as mitigating the benefits. Organisational culture and leadership were reported by seven respondents (36,8 %) to mitigate the benefits. Leadership is on a good level in the organisations, leaders and managers are reported to competent in analytics and supporting and encouraging data-driven culture and competence development. Biggest challenge in leadership was reported to be that the leaders act based on intuition and experience, rather than knowledge gained from data. Still, over half of the respondents reported their organisation to be data-driven. The biggest challenges in organisational culture were organisations not having common terms, definitions, or processes for analytics. As 70 % of respondents are from large businesses that have over 250 employees, the challenges are not unexpected. This could create problems and waste valuable resources when working with others, as different employees might not be familiar with the analytical processes done and these processes have to be explained to them to create an understanding of the analytics and possibly of their results. Otherwise, organisational culture is on a good level with the respondents, as analytics and their results are shared, utilised purposefully and regularly, and the results have an impact.

The respondents perceive their skills and technologies used to mitigate possible benefits gained from data analytics the least. They define that they are very capable of data analytics and say that they have necessary skills and knowledge to analyse the data and transform it into business value. The tools are suitable for their purposes, and they are perceived as easy to use. Employees are educated well if they need education in some aspect. Only problem with the tools were reported to be compatibility between different tools, and outdated technologies.

The overall view of utilising data analytics with customer data from CRM from Figure 5, seems to display the results well. Organisations collect customer data into their CRM, analyse it, gain benefits through it, and some analytical aspects mitigate these benefits. Even though they collect the data into CRM, where it should be structured well, data quality is one problem. The data is entered into the CRM mostly by humans, so human errors, such as entering wrong or incomplete, happen. This leads to unnecessary work to check and correct the data (Redman, 2016) or into erroneous results in analytics. Master data management is needed to correct and keep the data up-to-date (Ransbotham and Kiron, 2017). A greater aspect mitigating the benefits from analytics is the strategic use based on the respondents, due to scarce resources, and challenges in defining the goals of analytics and monitoring the success of these goals. The analytics of this data are used to produce information, such as customer understanding, customer segmentation, and predictions of events, to support decision-making. The analytics are mainly concerned with inspecting the present and predicting the future, as the main types of analytics used were descriptive and predictive.

The aspects of data analytics used in this thesis seem to be a good base for a comprehensive model of data analytics, as no respondent reported any other aspect mitigating their benefits and literature supports these aspects (Davenport and Harris, 2007; Gillon *et al.*, 2014; Grover *et al.*, 2018; Koohang and Nord, 2021). Two respondents complemented their answers and wrote of other aspects, but the answers (old technology and lack of resources) could be categorised into the aspects (technology and strategic use). Unfortunately, the model could not be validated to inspect whether an organisation could gain benefits based on their scoring on the aspects, possibly due to low sample size and low deviations in the answers.

Based on the results, organisations should pay more attention to the compatibility of the tools, and the business-IT alignment. The organisations have necessary culture, skills and tools to gain benefits of the analytics, but they need to improve the quality of the data and the strategic use of analytics to improve the benefits further, based on the results of the analysis. Many of the respondents use CRM for strategic purposes and the benefits they reported gaining of CRM utilisation are focused on improving their customer knowledge and information sharing. Less than half of the twenty respondents reported gaining improvements in saved resources, efficiency, and productivity, important aspects in creating internal value (Payne, 2006, Chapter 3), indicating that they fail to utilise it properly. Reasons why CRM fails to deliver value is the lack of commitment and support from the top management, due to them not fully understanding how to utilise it strategically (Reichheld, Schefter and Rigby, 2002; Croteau and Li, 2003; Edinger, 2018). This lack of strategic utilisation can be seen in the answers, where most of the respondents define strategic use, as the main aspect mitigating the benefits from data analytics, and from the types of analytics used. Most if the respondents focus on inspecting the present and predicting the future, but diagnostic and prescriptive analytics, which focus on analysing how to change the business, are not common among the answers. This indicates that most of the respondents do not have clear goals for analytics and plans on improving them, and the answers support this, as the respondents seem to have problems with systematically measuring and monitoring their analytics and not having enough resources or proper focus for analytics. These are an important part of data analytics and its value creation (Davenport, Harris and Morison, 2010, pp. 73–90; Grover *et al.*, 2018; Koohang and Nord, 2021). It is harder for organisations to compete with analytics and create value of them, if they do not focus on data analytics strategically, and improving the processes comprehensively (Kitchens *et al.*, 2018).

Despite of the lowered level of data and strategic capabilities, that it just lowers the benefits gained, as they are only two aspects of five. Overall, organisations still gain benefits of data analytics, as they have some capabilities supporting the value creation. While inspecting these results, it is important to remember the low sample of this study, as the survey gained only twenty answers and might not represent a larger population. The impact of this is discussed in the next chapter.

7. CONCLUSION

The purpose of this thesis was to answer how different organisations utilise data analytics with customer data from their CRM, and it was done successfully by answering sub-research questions. The sub-research questions inspected what data organisations collect of their customers into their CRM, what challenges organisations face when analysing the data, and what benefits are gained from the analytics and what prevents them from realising. These were answered by inspecting different studies and theories of the subjects, formulating a model of the process, and testing it in a real business environment. A survey was created to test the model, and the result were analysed to validate the results. The survey was sent to 252 persons in 40 organisations, and it gained 20 answers suitable for analysis. The sample is low, which affects the results.

Theoretical contribution of the thesis is that it offers models to inspect how different analytical aspects affect different benefits gained from data analytics and explains the state of data analytics in different Finnish organisations, providing a reference point to compare analytical maturities to. The thesis validated that some of the aspects formulating data analytics are not distributed equally, so if an organisation is doing well in one of the aspects, it is not the same for another aspect. Distributions were found to be similar between “data and skills & technologies”, “organisational culture and skills & technologies”, and “leadership and strategic use of analytics”, indicating some similarities in the distributions of the aspects. No comprehensive model was found to be statistically significant between the analytical aspects and a benefit, but it offers others a starting point to improve the models between analytical aspects and the benefits.

The practical contribution of this thesis is that it brings insight on how Finnish organisations analyse their data from a CRM system, what benefits it brings, and challenges they face while doing so. Benefits and challenges are introduced from current literature, and they are validated empirically. Results were found that most organisations collect basic customer data to their CRM (customer information, geographic data, customer feedback, market intelligence, and transaction data) and many complement this data by combining external data, such as competitor and demographical data, to it. When analysing the data, validated perceived benefits it brought were improved decision-making, improved marketing capabilities, increased profits, and saved resources. Aspects mitigating these benefits were reported to be strategic use of the data analytics, the data being low quality, organisational culture not supporting organisation wide analytics, and leadership not acting data-driven. The result offers valuable information for those who analyse their

CRM customer data, as it describes the common issues with subject, and provide information of the subject. Useful for those who are beginning their analytical journey, or to those who are analysing their data, but do not gain benefits from it. Especially management of organisation could get help to plan the strategic use of analytics well, an aspect that was found to mitigate the benefits the most. Of course, also the client organisation benefits of this thesis as well, as they provide services regarding analytics to their customers, and they gain knowledge of the challenges their customers are facing, helping them to offer more relevant services and good quality customer service.

Overall, the thesis was successful, though it has some limitations. The researcher had a time constraint, that had an impact on collecting the data and sample size. The first surveys were sent to too few recipients and too much faith was put to the recipients forwarding the survey within their organisations. Holiday season disrupted and delayed the second data collection phase, so no time was remaining for a third collection phase. In the end, the sample size was low, only 20 answers, leading to low statistical power. Due to the low sample size, the results might be skewed and do not represent a large population, such as large organisations in Finland. For comparison when inspecting organisations in Finland that have over 50 employees, a proper sample size would be 94 with confidence level of 95 % and margin of error of 10 %, to properly represent the total population of 3715 organisations (Tilastokeskus, 2022). When allowing a margin of error of 20 %, that represents how much the answers could differ from the whole population's answers, a proper sample size would be 24. So there is room to be improved, as the low sample size reduces the chances of detecting true effects and impacts, and it also reduces the likelihood, that the observed results are correct (Button *et al.*, 2013). This effect could be seen in this study, as almost every respondent defined better customer understanding as a gained benefit from data analytics, but the analysis found no statistically relevant relationship between the overall score of data analytics and customer understanding. This was possibly due to the high number of positive results against negative results.

Other improvements are that the analytical aspects and their impact on benefits could have been inspected more thoroughly by creating more questions, but this could have impacted the sample size negatively as not many might have the interest to answer a long survey. The analysis of the survey results could had been planned with more care straight from the beginning so only relevant questions would have been surveyed. Also, the analysis of the results and their interpretation are affected by the researcher and their experiences, though the data was inspected and analysed without biases.

The subject of this thesis allows for multiple possible studies in the future. As the results indicated that there are problems regarding the strategic use of analytics with CRM, that could be interesting to study further. It would be interesting to see if there any similarities among organisations that use similar technologies, or more practical research could be to inspect how to implement a CRM system that utilises data analytics with strategic measures in mind, that focus on specific goals. Improvements to this study would be focusing on to more specific areas, for example focusing on individual technologies used, specific roles in the organisations, or specific types of organisations. Individual aspects of analytics would be interesting to study to inspect their impacts on data analytics and their results, possibly explaining how they mitigate the benefits gained from data analytics. A wider audience and bigger sample size could help to formulate a model how analytical aspects affect the benefits gained from data analytics. This would be greatly helpful for organisation, as it would help them understand how to improve themselves and how to create more value with the help of data analytics. Fortunately, they can start to understand how to do so, with this thesis.

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APPENDIX A: SURVEY QUESTIONS

Regarding challenge	Question?	Answer choices
	What is your role in your organisation?	Employee / Staff, Team Leader / Manager, Unit Leader / Senior Manager, Department Head / Director / Vice President, C-level / Executive
	Which department do you belong to?	Administration, Customer Service, Financial, HR, IT, Marketing, Sales, Other
	What is the size of the organisation, that you work in?	Micro Business (less than 10 employees), Small Business (10 - 49 employees), Medium Business (50 - 249 employees), Large Business (more than 250 employees)
	What is your country of employment?	User input
	Do you utilise data analytics with CRM?	Yes, No
	For how long you have analysed data from CRM?	User input
	Which CRM systems do you use?	HubSpot, Microsoft Dynamics 365, Oracle CRM, Pegasystems, Pipedrive, Salesforce, SAP CRM, Upsales, Zendesk, Other
	Which analytical tools do you use?	CRM native reporting tools, Excel, Google (Looker), Oracle Analytics, Power BI, Qlik (Sense), Sisense, Tableau, ThoughtSpot, Yellowfin
	For what purposes do you utilise CRM?	Analytical, Collaborative, Operational, Social, Strategic
	What types of analytics do you utilise?	Descriptive, Diagnostic, Predictive, Prescriptive
	If you use some other types of analytics, please describe the method and scenario.	User input
	What types of customer data do you collect into CRM?	Customer data, Customer feedback, Demographic, Geographic, Market, Psychographic, Relationship, Social, Transaction data, Other
	Do you buy or use data from external sources to complement your own?	Yes, No
	Please share shortly, what kind of externally collected data do you combine to your own?	User input
	Do you feel you have enough data of your customers to form a comprehensive view of them?	Yes, No
	What data or information are you missing from the comprehensive view? I.e. what data would you need, that you do not have?	User input

Challenges, Data	Your data is of good quality.	Likert Scale (1 - 5)
	Your data is available for your needs.	Likert Scale (1 - 5)
	Your data is unambiguous and clear.	Likert Scale (1 - 5)
	Your data is accurate.	Likert Scale (1 - 5)
	Your data is not reliable.*	Likert Scale (1 - 5)
	Your data is up-to-date.	Likert Scale (1 - 5)
	Your data is relevant for your needs.	Likert Scale (1 - 5)
	Your data quality has affected data analytics negatively.*	Likert Scale (1 - 5)
	If you have some specific challenges regarding data not mentioned above, please share them.	User input
Challenges, Organisational culture	Your organisation is data-driven.	Likert Scale (1 - 5)
	Analytics and their results are available only for your department.*	Likert Scale (1 - 5)
	Many departments utilise same results from analytics.	Likert Scale (1 - 5)
	Analyses have an impact and are meaningful.	Likert Scale (1 - 5)
	Analyses are utilised purposefully and regularly.	Likert Scale (1 - 5)
	You have common terms and definitions for analytics.	Likert Scale (1 - 5)
	Your department has a common process for analysing data.	Likert Scale (1 - 5)
	If you have some specific challenges regarding organisational culture not mentioned above, please share them.	User input
Challenges, Leadership	Your leadership encourages and supports data-driven culture.	Likert Scale (1 - 5)
	Competence development is not encouraged.*	Likert Scale (1 - 5)
	Experimentation with data is encouraged.	Likert Scale (1 - 5)
	Your leadership acts on intuition and experience, rather than knowledge gained from data.*	Likert Scale (1 - 5)
	Your leadership is competent in analytics.	Likert Scale (1 - 5)
	Your leadership can discuss about analytical processes clearly.	Likert Scale (1 - 5)
	If you have some specific challenges regarding leadership not mentioned above, please share them.	User input

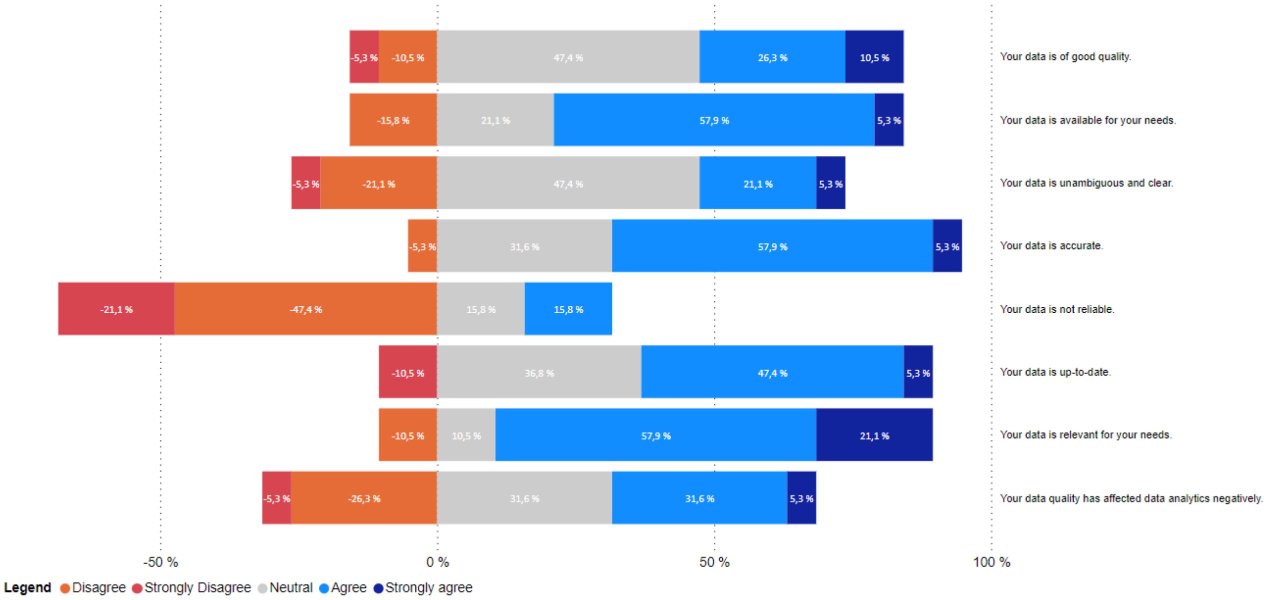
Challenges, Strategic use	You have a plan how to analyse your data (e.g. a roadmap or next steps).	Likert Scale (1 - 5)
	Your organisation systematically measures and monitors how you utilise analytics.	Likert Scale (1 - 5)
	Measuring and monitoring of analytics have an impact.	Likert Scale (1 - 5)
	You do not have a clear focus or goals for data analytics.*	Likert Scale (1 - 5)
	You have enough resources to analyse data.	Likert Scale (1 - 5)
	You have knowledge and understand how to translate analytics into value.	Likert Scale (1 - 5)
	If you have some specific challenges regarding strategic use not mentioned above, please share them.	User input
Challenges, Skills & Tech.	You have necessary skills and understanding to perform data analytics.	Likert Scale (1 - 5)
	You have received education or training how to analyse data to your needs.	Likert Scale (1 - 5)
	You can communicate your analyses and results clearly.	Likert Scale (1 - 5)
	You have necessary tools to perform analytics.	Likert Scale (1 - 5)
	The tools are difficult to use.*	Likert Scale (1 - 5)
	The tools perform well.	Likert Scale (1 - 5)
	Different tools perform and work well together.	Likert Scale (1 - 5)
	If you have some specific challenges regarding your resources not mentioned above, please share them.	User input
	Have you gained any of the following benefits due to CRM?	Better customer knowledge, Customer retention, Gained profits, Improved customer satisfaction, Improved decision-making, Improved information sharing, Increased efficiency, Increased productivity, More won sales or deals, Saved resources (e.g. time, money), Other
	Do you analyse data...	Within CRM, with external application(s), within CRM and external application(s)
	Do you bring the refined data back into CRM?	Yes, No
	Do you feel data analytics have led to improved or additional benefits (such as saved resources or more information for decision-making)?	Yes, No
	Have you gained any of the following benefits due to data analytics?	Better customer understanding, Better customer segmentation, Improved customer satisfaction, Improved decision-making, Improved marketing capabilities, Improved prediction capability, Increased efficiency, Increased productivity, Increased profits, More

	accurate pricing of services or products, Saved resources (e.g. time, money), Other
Any other benefits, that you would like to mention or highlight?	User input
Do you feel that some of these following aspects mitigate benefits gained from analysing CRM data?	Data, Organisational culture, Leadership, Strategic use of analytics, Your skills, Technology, Other
Any other aspects mitigating possible benefits to your mind?	User input

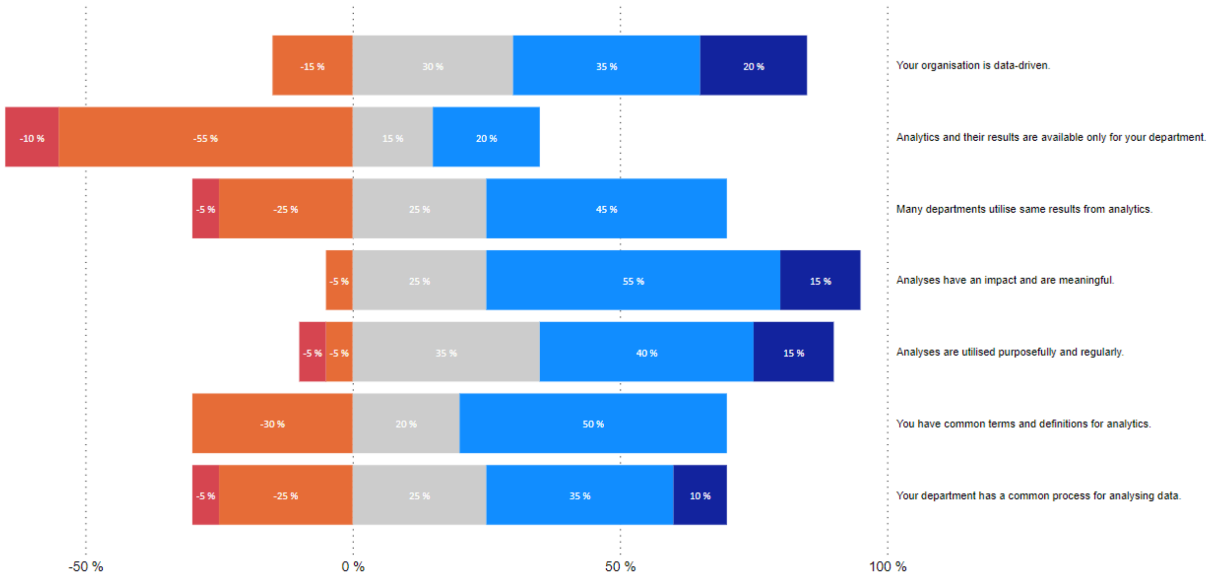
* Changed for statistical analysis, and turned from negative meaning to positive.

APPEND B: LIKERT SCALE RESULTS

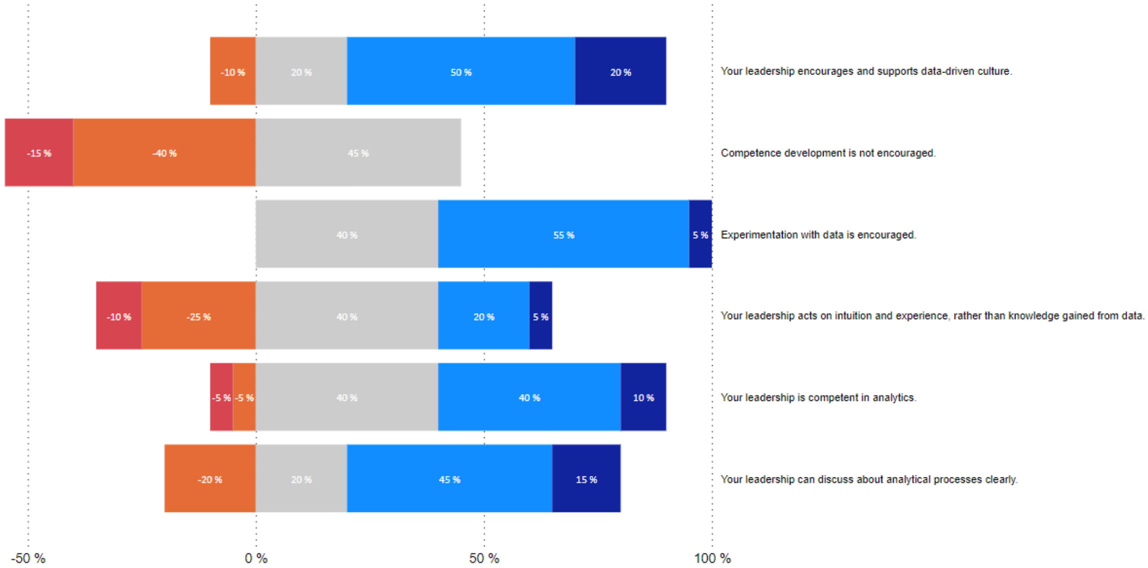
Likert scale results of Data, n = 19.



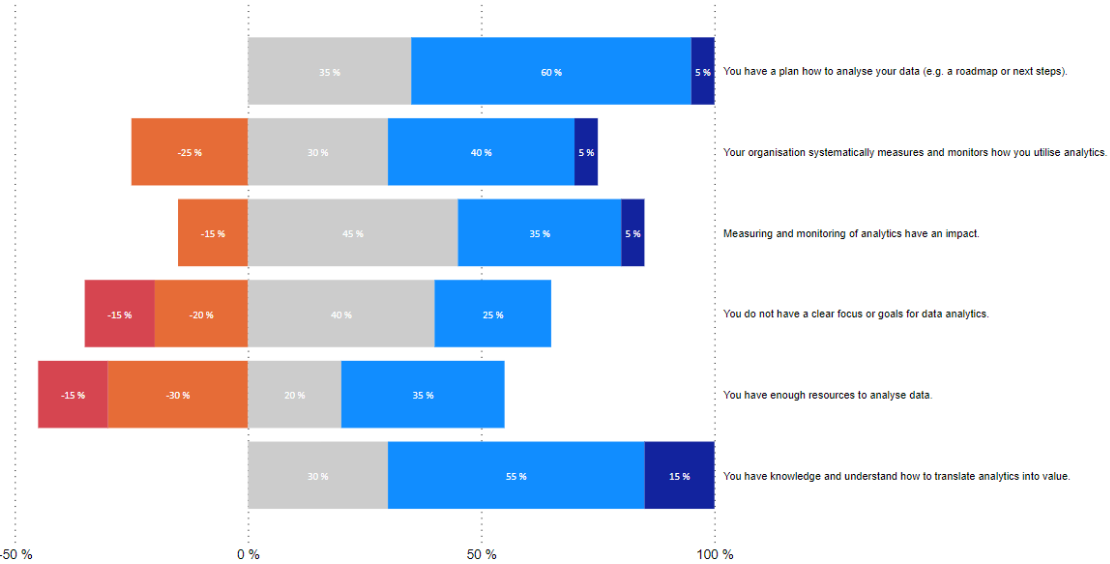
Likert scale results of Culture, n = 20.



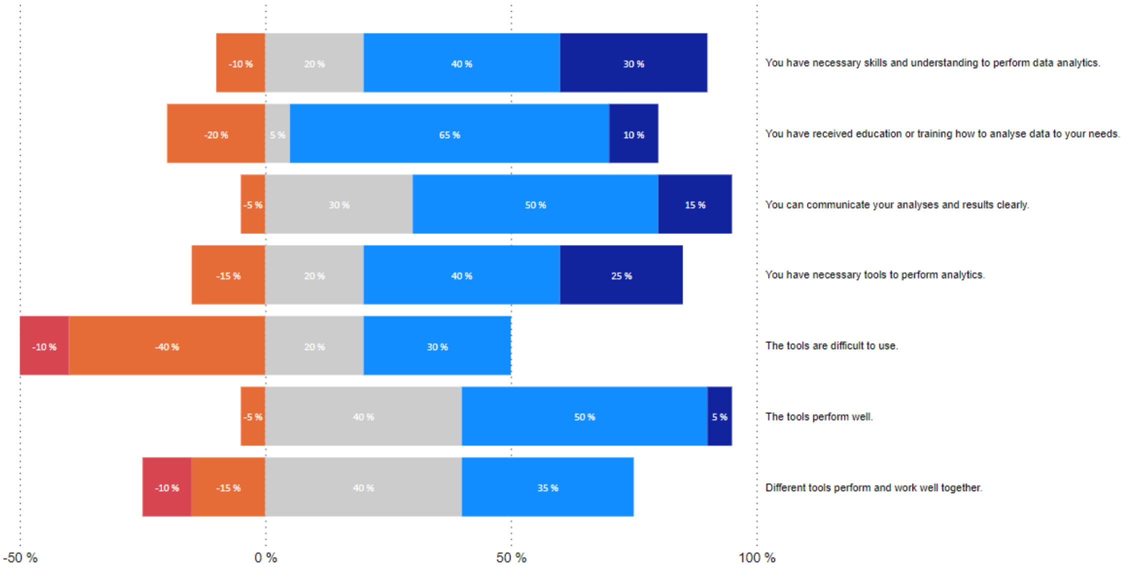
Likert scale results of Leadership, n = 20.



Likert scale results of Strategic use, n = 20.



Likert scale results of Skills & Tech, n = 20.



APPENDIX C: SUMMED LIKERT VALUES

ID	DATA SCORE	CULTURE SCORE	LEADERSHIP SCORE	STRATEGY SCORE	SKILLS & TECH SCORE	OVERALL SCORE
1	28	20	13	15	30	106
2	28	25	29	21	25	128
3	26	25	20	16	23	110
4	23	20	22	20	29	114
5	0*	21	21	20	28	90
6	28	23	21	21	29	122
7	20	23	19	19	25	106
8	29	21	18	19	17	104
9	30	23	18	21	21	113
10	26	15	15	18	15	89
11	29	29	24	22	24	128
13	35	30	29	27	31	152
14	34	28	24	24	28	138
15	27	32	23	20	30	132
16	24	21	22	16	23	106
17	30	32	23	25	27	137
18	15	19	22	14	20	90
19	30	24	20	22	26	122
20	32	24	24	21	26	127
21	26	25	19	21	21	112
MIN Score	**8**	**7**	**6**	**6**	**7**	**34**
MAX Score	**40**	**35**	**30**	**30**	**35**	**170**

* Did not provide answers to the questions.

APPENDIX D: DATA ANALYTICAL ASPECTS TO BENEFITS

Model's P-value: 0,2801 Pseudo R-squared: 0,2791.

Customer segmentation	Coefficient	P-value
Intercept	9,8273	0,131
Data	-0,4493	0,169
Culture	0,0547	0,832
Leadership	0,2480	0,385
Strategic use	-0,0207	0,962
Skills & Tech	-0,0798	0,642

Model's P-value: 0,2130 Pseudo R-squared: 0,2581.

Decision-making	Coefficient	P-value
Intercept	-10,8627	0,040
Data	0,0559	0,496
Culture	-0,0843	0,680
Leadership	0,3234	0,180
Strategic use	0,1293	0,604
Skills & Tech	0,0936	0,563

Model's P-value: 0,01160 Pseudo R-squared: 0,5470.

Marketing capabilities	Coefficient	P-value
Intercept	-12,5341	0,102
Data	0,2463	0,436
Culture	1,1560	0,086
Leadership	-0,2732	0,310
Strategic use	-0,5918	0,356
Skills & Tech	-0,2021	0,336

Model’s P-value: 0,1490   Pseudo R-squared: 0,2934.

Prediction capability	Coefficient	P-value
Intercept	-7,2165	0,149
Data	-0,0020	0,985
Culture	0,1706	0,421
Leadership	0,2896	0,287
Strategic use	0,2696	0,340
Skills & Tech	-0,3419	0,137

Model’s P-value: 0,3904   Pseudo R-squared: 0,1937.

Efficiency	Coefficient	P-value
Intercept	-5,5659	0,218
Data	0,2926	0,203
Culture	0,1845	0,354
Leadership	0,0994	0,571
Strategic use	-0,3146	0,332
Skills & Tech	-0,1287	0,419

Model’s P-value: 0,5896   Pseudo R-squared: 0,1438.

Productivity	Coefficient	P-value
Intercept	2,3702	0,579
Data	-0,1318	0,208
Culture	0,1830	0,334
Leadership	-0,2672	0,202
Strategic use	0,0962	0,694
Skills & Tech	-0,0123	0,928

Model’s P-value: 0,1573 Pseudo R-squared: 0,3082.

Profits	Coefficient	P-value
Intercept	-12,2409	0,050
Data	0,1019	0,582
Culture	0,0225	0,913
Leadership	0,0874	0,685
Strategic use	0,3787	0,342
Skills & Tech	-0,0568	0,764

Model’s P-value: 0,6578 Pseudo R-squared: 0,1340.

Pricing	Coefficient	P-value
Intercept	-1,4099	0,715
Data	-0,1405	0,172
Culture	0,0796	0,693
Leadership	0,0808	0,689
Strategic use	0,2734	0,339
Skills & Tech	-0,2055	0,319

Model’s P-value: 0,2406 Pseudo R-squared: 0,2431.

Saved resources	Coefficient	P-value
Intercept	-9,5061	0,068
Data	0,1497	0,359
Culture	0,0813	0,668
Leadership	0,0096	0,958
Strategic use	0,1254	0,662
Skills & Tech	0,0376	0,788