CAPABILITY MATURITY MODEL FOR DATA-DRIVEN MARKETING

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ABSTRACT

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Abstract

Data-driven decision-making is gaining buzz and popularity across organizational functions and industries. Consequently, data analysis and marketing analytics enable companies of various size and business volume to leverage sustainable performance outcomes and continuous growth through data-driven marketing. Still, marketing professionals lack the tools, skillsets and procedures in turning this data into insights, and, furthermore, insights into action. Furthermore, research has yet not addressed these issues of data-driven marketing practice. Hence, this thesis aims to tackle a gap in current research and practice, and to gain further knowledge into the fragmented research on data-driven marketing.

The goal of this study is to discover and understand the current level of data-driven decision-making as well as marketing analytics usage in marketing departments. Additionally, this thesis seeks to discover possible barriers that hinder such process development and usage of analytics for marketers. In doing so, this thesis aims to identify and create a model that describes the degree to which marketing analytical insights and data-driven methods are used in an organization and what may block the progression in this model for marketers.

This thesis takes a qualitative approach to the research dilemma. The data and methodology used in this research include ten marketing professionals' interviews, as well as a thorough literature review to describe the theoretical framework and to position for this thesis. The data-driven marketing maturity and capability of each case organization was evaluated through qualitative analysis by reflecting the interviewees' answers on the different levels of the Maturity Model. Through this, a Data-driven Marketing Capability Maturity Model was conceptualized. The thesis further extends the existing research on Capability Maturity Models by introducing barriers to data-driven marketing. These barriers were classified into three different categories: organizational structure barriers, organizational culture barriers and top management barriers. The barriers were placed onto the Data-driven Marketing Capability Maturity Model, to identify the major obstacles to moving forward in each level.

Keywords
Digital marketing, marketing analytics, data-driven marketing, marketing measurement, data-driven decision-making, Capability Maturity Model

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Tiivistelmä

Datalähtöinen päätöksenteko ja -prosessit ovat saaneet osakseen huomiota ja kiinnostusta läpi organisaatioiden toimintojen ja ylitse useiden toimialojen. Datan ja markkinointianalytiikan hyödyntäminen antaa yrityksille mahdollisuuden luoda jatkuvaa kasvua, yrityksen koosta tai liikevaihdosta riippumatta. Tästä huolimatta markkinoinnin ammattilaisilta puuttuu työkaluja ja taitoja muuttaa nämä tiedot oivalluksiksi, sekä edelleen jalkauttaa nämä oivallukset toimintaan. Lisäksi, nykyisessä datalähtöisten markkinointiprosessien tutkimuksessa on kuilu datan ymmärtämisen ja sen hyödyntämisen välillä.

Tämän maisterintutkielman tavoitteena on ymmärtää datapohjaisen päätöksenteon nykyinen taso sekä hahmottaa markkinoinnin analytiikan käyttöä organisaatioissa. Tässä tutkielmassa tunnistetaan lisäksi mahdollisia esteitä, jotka estävät datalähtöisten prosessien kehitystä sekä analytiikan käyttöä markkinoinnin ammattilaisille. Tämän tutkielman tavoitteena on konseptoida kypsyysmalli, joka kuvastaa missä määrin markkinoinnin analyyttisiä oivalluksia ja dataohjautuvia menetelmiä käytetään organisaatiossa ja mikä voi estää tässä mallissa etenemisen markkinoijille.

Tämä maisterintutkielma lähestyy tutkimusongelmaa laadullisin menetelmin. Tutkimuksessa haastateltiin kymmentä markkinoinnin ammattilaisten sekä suoritettiin perusteellinen kirjallisuuskatsaus teoreettisen kehyksen hahmottamiseksi. Kunkin haastateltavan markkinoijan organisaation tietopohjainen markkinointikypsyys ja -kyvykkyys arvioitiin kvalitatiivisella analyysillä heijastamalla haastateltavien vastauksia kypsyysmallin eri tasoihin. Dataohjautuvien markkinointivalmiuksien kypsyysmalli luotiin haastatteluihin ja aiempaan kypsyysmallien tutkimukseen perustuen. Tutkimus laajentaa olemassa olevaa kypsyysmallien tutkimusta tuomalla esteet tietopohjaisen markkinoinnin hyödyntämiseen osaksi mallia. Nämä esteet luokiteltiin kolmeen eri luokkaan: organisaation rakenteelliset esteet, organisaation kulttuurilliset esteet ja ylimmän johdon aiheuttamat esteet.

Asiasanat
Digitaalinen markkinointi, markkinoinnin analytiikka, dataohjattu markkinointi, markkinoinnin mittaaminen, datalähtöinen päätöksenteko, kypsyysmalli

Säilytyspaikka
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1 INTRODUCTION

1.1 The growing need for data-driven marketing capabilities

The large variety of data available to organizational use can both overwhelm and present opportunities for marketing professionals of today. The ever-growing online sphere presents marketers with new ways to measure, optimize and automate marketing processes, creating pressure for making marketing analytics central to marketing decision-making (Day & Moorman 2016, 12). Despite marketing data interfaces and services being entrenched, analytics and insight from data is not yet not utilized as broadly to affect decision-making outcomes, as may be anticipated. Simultaneously, marketers are facing an increasing demand from top management to quantify their input and the marketing activities' contribution to the organization's profitability (Järvinen 2016). The appropriation levels of data by organizations is high, however, the strategic utilization of them remains shockingly low (Chaffey & Patron 2012).

The utilization of online marketing analytics to improve online and offline marketing efforts goes back to the end of the 20th century when the main marketing analytics frameworks and foundations for data collection were created. However, ongoing research proposes that numerous organizations are neglecting to use best analytical practices and are consequently not getting the full potential back from data and analytics, as to what would be possible (Chaffey & Patron 2012). This study surveys the opportunities organizations must apply marketing analytics easily to improve marketing processes and data-driven decision-making. In this thesis, a data-driven marketing Capability Maturity Model is characterized as a system to define the level to which marketing analytics are utilized in the organization e.g. how developed the data-driven marketing capability maturity of a company is and how to develop these capabilities further. The research depicts methods that can be utilized to set up data-driven marketing practices into place, including an elaboration on which barriers hinder them as of now in developing these capabilities further.

The quantifiability of consumer behavior and the rise of big data have contributed to the superiority of digital media when contrasted to any other media since the beginning of 1990s, when web analytics first began to be developed (Chaffey & Patron 2012). Personal computers came to the mass market by IBM in 1981, and this provided marketers with means for data storage and, for example, survey research through interviews (Wedel & Kannan 2016). Numerous marketing professionals understood that the ability to gauge associations of websites' users through logs already adds an obscure degree of knowledge into the viability of digital marketing efficiency which the marketing field previously lacked completely. The potential that marketing analytics holds in terms of improving organizational performance is widely recognized (Branda et al. 2018). To this day numerous tools for marketing analytics have been created and many of them hold a lengthy history while still being major players in the market today, for example, Salesforces' CRM system in 1999 and marketing analytics systems such as Google Analytics in 2005 (Chaffey & Patron 2012; Wedel & Kannan 2016). The variety of analytical tools and services have kept on improving and evolving till this day (Singal et al. 2014).

1.2 Problem setting and research questions

The shortage of current analytics tools, despite the variety, is that none of them offer straightforward answers to more common questions, such as, why a visitor did not convert or why a certain social media post performed better compared to another piece of content (Jansen 2009). Furthermore, a frequent misconception is common where marketing analytics are merely seen as databases and technology (Hauser 2007; Fayyad 2007). As a result of this, marketers often leave the understanding of meanings and outcomes in the analytical process to e.g. the information technology department (Hauser 2007; Nicholls 2006). In extreme cases marketers do not address these problems at all and, instead, assume that the technology behind marketing analytics will provide them with ready-made answers (Hauser 2007). However, marketing analytics are unable to offer such usable steps for optimization or shed light for the data-driven decision-making processes of companies (Hauser 2007; Jansen, 2009). Hence, marketers are often overwhelmed by the amount of data available with no clear guidelines to move forward (Branda et al. 2018). Since data by itself is unable to guide decision-making processes and, instead, needs to be translated into doable actions in order to be useful, many companies have started to invest in, for example, integrated cross-channel software to make sense of the vast amount of data they collect and to acquire competitive advantage (Branda et al. 2018). Nevertheless, data analysis skills are crucial for the success of such investments. According to Jansen (2009) data analysis consists of making sense of big data and finding out the insights and reasons behind the numbers and, furthermore, translating these into actions. While marketing analytics and big data are here to stay and serve as the foundation for analysis and data-driven marketing, most companies consider the data analysis process an especially challenging task that many have yet to tackle (Jobs et al. 2016; Verhoef et al. 2016; Wedel & Kannan 2016). Previous studies have shown that with data analysis and complex marketing analytics utilization in place, companies of different size and business volume are able to leverage sustainable performance outcomes and continuous growth through data-driven marketing (Branda et al. 2018; Germann et al. 2013; Järvinen & Karjaluoto 2015).

Previous studies (Chaffey & Patron 2012; Hauser 2007; Jobs et al. 2015; Järvinen & Karjaluoto 2015; Liu et al. 2016; Martens et al. 2016; Netzer et al. 2012; Viktor et al. 2012; Verhoef et al. 2016; Wedel & Kannan 2016; Wilson 2010) have focused on numerous micro-level themes surrounding, or partially overlapping, data-driven marketing and marketing analytics practices. Earlier research related to these themes has evolved around e.g. marketing metrics (Järvinen &

Karjaluoto 2015; Martens et al. 2016; Netzer et al. 2012), data mining (Kumar et al. 2016; Viktor et al. 2012; Wilson 2010), big data analytics (Esposti 2014; Jobs et al. 2015; Verhoef et al. 2016), customer behavior (Hauser 2007; Wedel & Kannan 2016), social media analytics (Liu et al. 2016), modeling (Germann et al. 2013; Jobs et al. 2016) and value-added marketing (Chaffey & Patron 2012). Studies have highlighted both the fundamental shortage of marketing data professionals, and the lack of knowledge as to what extent companies are currently using data-driven decisions in marketing (Erevelles et al. 2016, 902) and describe a need for knowledge on effective marketing analytics capabilities (Day & Moorman 2016, 12). These studies discuss marketing analytics themes and highlight the benefits of analytics in marketing as a mean to quantify and understand customer behavior to assist the organizations' decision-making processes. Similarly, to the shortage of analytics tools in practice, research fails to address an important factor in this process of marketing analytics utilization: how are capabilities towards optimized data-driven marketing developed? Day and Moorman (2016, 8) issue a need for gaining practical knowledge by studying both the factors that influence marketing metric adoption, as well as the process that goes into metric adoption further. Thus, both practice and scholarly research call for further knowledge and research into the gap between data and its usage for the practice of data-driven marketing and barriers thereof, which is what this thesis aims to tackle.

The purpose of this thesis is to discover and understand the current level of data-driven decision-making as well as marketing analytics usage in organizations. Additionally, this thesis seeks to discover possible barriers that hinder such process development and usage of analytics for marketing professionals. In doing so, this thesis aims to identify and create a model that describes the degree to which analytical insights and data-driven methods are used in an organization and what may block the progression in this model for marketing professionals. This research relies on previous research as well as ten professional interviews. The thesis was conducted in the Finland and included interviewees from various industries, for example, technology, manufacturing, service and retail. Additionally, the researcher purposefully included informants from varying organizational lifecycles and sizes. As stated previously, this thesis aims to tackle a gap in current research and marketing practice, and to gain further knowledge into the fragmented research on data-driven marketing. In short, this research strives to widen the knowledge of data-driven marketing capabilities and barriers. Thus, the research questions can be specified as follows:

RQ1: How are marketing professionals utilizing marketing analytics in decision-making processes through data-driven marketing methods?

RQ2: What barriers hinder the usage and development of marketing analytics and its analysis for data-driven marketing methods?

The first research question is focused on discovering and elaborating the current state to which marketing professionals use analytics and, moreover, perform data-driven marketing practices. The second question aims to find obstacles and barriers that hinder the development of marketing measurement and data-driven marketing capabilities. These two research questions were set to complement each other and to give a thorough understanding of the current situation of data-driven marketing and marketing measurement in Finnish companies.

1.3 Methodology, data and study structure

This thesis takes a qualitative approach to the research dilemma. The data and methodology used in this research include ten marketing professionals' interviews as well as a thorough literature review to describe the theoretical framework and positioning for this thesis. The interview data was gathered and analyzed in a four-month time period. The methodologies and data analysis aim to answer the research questions presented in this chapter. In order to gather insight to the first research question, the data-driven marketing maturity and capability of each case company was evaluated through qualitative analysis by reflecting the interviewees' answers on the different levels of the Maturity model. Through this, a Data-driven Marketing Capabilities Maturity Model was conceptualized for further analysis. More insight was be formed with questions regarding the current barriers that hinder the marketing professionals from achieving a higher level of data utilization.

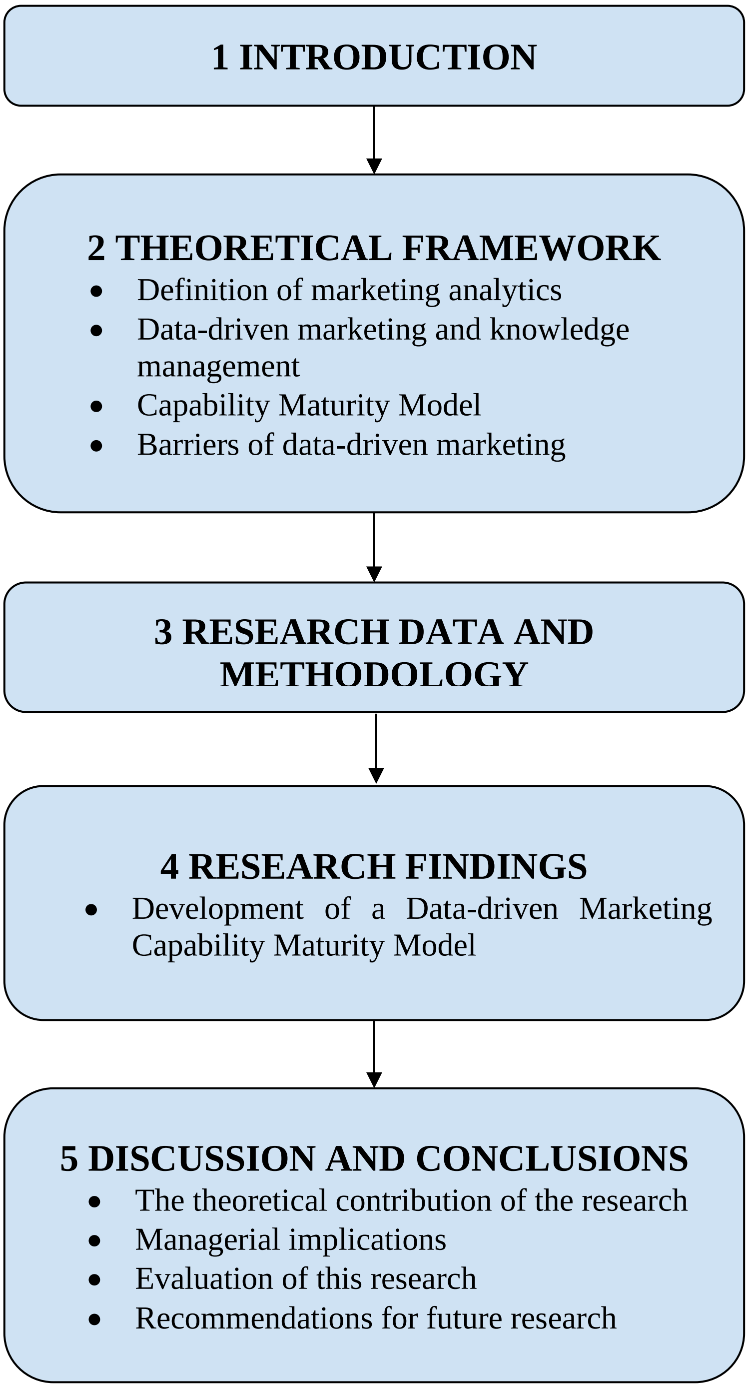

FIGURE 1 The structure of this thesis

This master's thesis is structured in a total of five sections (see Figure 1). In a chronological order, the sections are as follows: the second chapter provides a literature review to provide a thorough conceptualization of key terminology and background research in this thesis. The chapter starts with an introduction to the history of data-driven marketing and lays out explanations for the growth of a data-rich society. The theoretical framework of the Capability Maturity Model is explained and the utilization of this model in the context of this thesis is justified. Data selection and methodology are elaborated further in chapter three. The fourth chapter presents the results, findings and modeling of this thesis. Based on previous research, as well as professional interviews, a Marketing Analytics Maturity Model is formulated. Finally, in chapter five of this thesis, the limitations of this study as well as recommendations for future research are presented. Moreover, the final chapter presents the theoretical contribution, managerial implications and suggestions for future research.

1.4 Assumptions and definitions of the study

Marketing can be approached from varying perspectives, e.g., as a strategic function or as an organizational-wide culture (Day & Moorman 2016). Since this thesis dives into the concept of marketing capabilities, intertwining and overlapping themes that affect such capabilities need to be considered.

A literature review by Day and Moorman (2016), ranging from the 90’s to 2015, concluded the four elements of marketing organizations: (1) capabilities, meaning the collection of organizational information and skills that execute marketing activities and organizational changes, in response to its marketplace environment, (2) culture, meaning a set of beliefs and actions inside the organization, (3) configuration, meaning the measurement systems, metrics used and the organizational structure, and, (4) the human capital, meaning leaders and employees that build, incorporate and assess the organizational performance and strategy (Day & Moorman 2016, 6–11; see Figure 2). As this thesis sets out to grow a better understanding of the utilization of data-driven marketing through profound analysis and insights, and what barriers this holds for professionals in various industries, understanding key concepts relating to the three other elements of an organization's’ marketing is needed. For this thesis, these elements are barriers of adoption (culture), marketing analytics (configuration) and knowledge management (human capital) (see Figure 2).

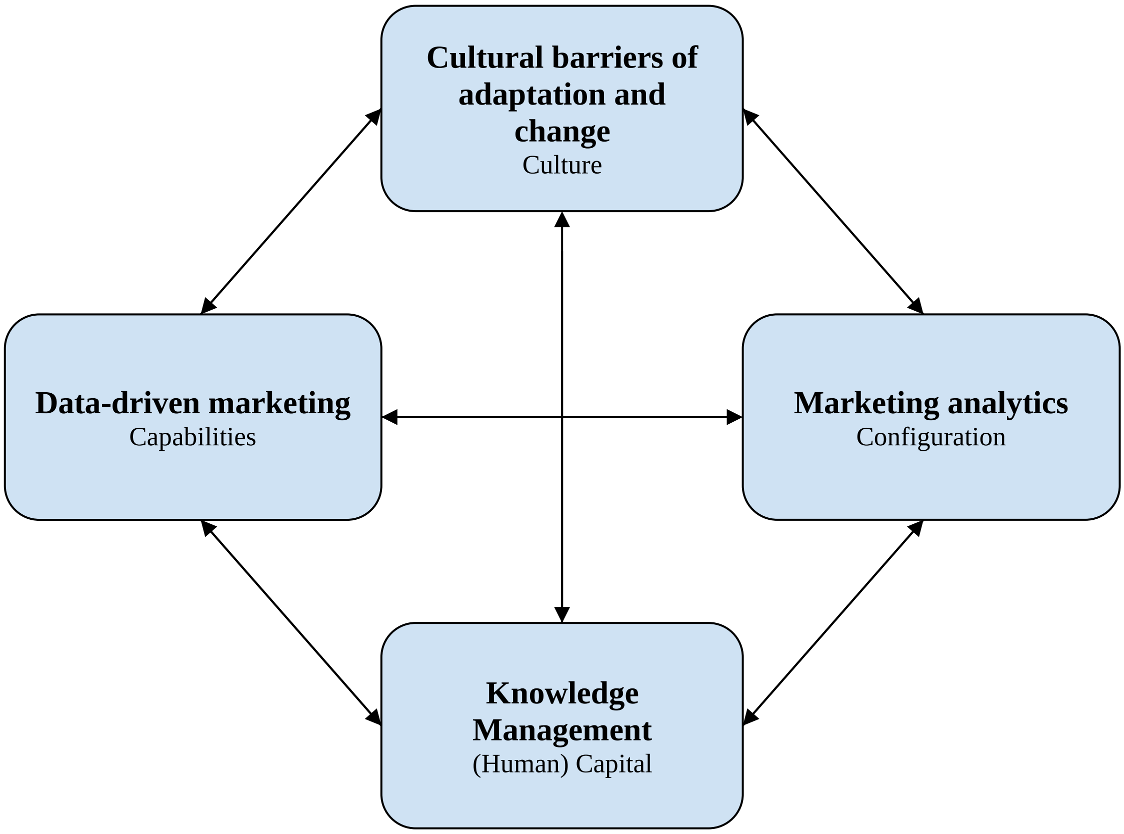

FIGURE 2 Four elements of an organization: as barriers for data-driven marketing (adapted from Day & Moorman 2016, 8)

Understanding all these elements is necessary due to their interconnected nature and their effect on one another. The meaning of these concepts and terminology is described in brief in Table 1. The concepts and terminology presented in Table 1 will be described in further detail in chapter two of this thesis, which aims to lay out the theoretical framework and key concepts for this research. In addition to these four elements, this thesis relies on the Capability Maturity Model (CMM), developed by Watts Humphrey (1988), which describes the process capability maturity in a five-level process evolution model. The CMM aids in process development modelling and has been widely used in, e.g., software and business processes development. (Humphrey 1988; Mughrabi & Jaeger 2017).

TABLE 1 Main concepts and definitions of the study

Concept	**Definition**
Marketing analytics	Marketing analytics applies data and analytical methods that enable marketing performance and consumer behavior measurement and quantifiability, which aims to optimize marketing efforts in a data-driven manner (Branda et al. 2018; Iacobucci et al. 2019; Kumar et al. 2016; Wedel & Kannan 2016).

Data-driven marketing	Data-driven marketing drives informed decision-making processes, a deeper understanding and innovative insights from various pieces of data (Camilleri and Miah 2017; Erevelles et al. 2016).
Knowledge management	Knowledge management (KM) consists of the process of discovering, creating, sharing, utilizing and managing information in an organization that aims to improve organizational performance (Girard & Girard 2015; O'Dell & Grayson 1998).
Barriers for change	"Organization culture can be a strong enabler or an insurmountable obstacle to implementing change in organizations. Most organization change efforts require some degree of culture shift. Yet changing an organization's culture continues to be a highly challenging and often elusive endeavor" (Levin & Gottlieb 2009, 31).

2 THEORETICAL FRAMEWORK

2.1 The impact of big data and new technologies for the marketers of today

The ways in which new technologies, big data and a hyperconnected environment have changed the business world is multidimensional. It is apparent that both the amount of data available and the ways of utilization in the current is exponential compared to even a decade ago, which is a complete change to the possibilities of the past century (Cukier & Mayer-Schoenberger 2013). A common belief amongst technologists is that the digital revolution witnessed during the 1980's marks the beginning of big data culture (Cukier & Mayer-Schoenberger 2013). Simultaneously, the technologies available for processing these growing amounts of data has increased equally as fast (Wolf 2014). This increase in technological developments has been more recent than the growth of data (Wolf 2014), which makes it a current and upcoming possibility to address in both practice and research. In the very beginning of big data and marketing analytics, some authors viewed the rise of a data-oriented marketing process negatively, predicting "analysis paralysis" and "analogous effects" from excessive information gathering (Peter & Waterman 1982). According to Germann et al. (2013), in many cases the top management enhanced such negative views on data gathering and analysis, i.e., data-driven marketing. However, both research and practice have showcased a correlation between data-driven marketing practices and increased organizational performance (Chaffey & Patron 2012; Germann et al. 2013; Day & Moorman 2016; Wedel & Kannan 2016).

Previous studies looking precisely at marketing data have characterized it by its largeness in size as well as its predominantly high dimensionality (Ho et al. 2010). Furthermore, significant shifts in the analysis of marketing data have shaped the formation of data-driven marketing. Davenport (2014) describes six significant changes in the industry of marketing analysis as: (1) from panel to big data, (2) from aggregate to granular, (3) from PowerPoint templates to interactive dashboards, (4) from manual practices to the utilization of machine learning, (5) from weekly or monthly reporting to real-time insights and (6) from mere insight to concrete actions. Such shifts for marketing data analysis have brought possibilities for real-time responses and serving as add-on knowledge for intuitive and simultaneously informed decision-making in, e.g., customer relationship management (McAfee & Brynjolfsson 2012; Van Auken 2015). Moreover, industries and ecosystems at large have been going through a paradigm shift from the digital transformation towards data-driven businesses and ecosystems (Ylijoki 2019). Germann et al. (2013) explained that the utilization of marketing analytics enables the company to create and provide their customers with services and products that answer to their customers' needs, which, then again, lifts organizational performance and fosters competitive advantage.

However, marketing data and analytics cannot provide valuable insight and actions to organizations on their own. Wolf (2014) argues, that both people and tools are required to generate any kind of value, regardless of the industry. Cukier and Mayer-Schoenberger (2013) describe data as a tool and resource of knowledge, which purpose is to inform rather than to explain. According to Barton and Court (2012), to benefit from big data, an organization needs to develop in three areas: (1) Having multiple and meaningful data sources, (2) build prediction and optimization models, and, (3) transform organizational capabilities. Chaffey and Patron (2012) add that more marketers need data analysis skills, and to see the reasons why some changes in the data are happening, instead of just realizing the difference. At the same time, it is precisely the knowledge of why something is occurring that enables the marketers to take action to change it (Chaffey & Patron 2012). Another factor that expands the need for data analysis skills in organizations is the discontinuity of the environment around them, i.e., the ever-changing market demands, and increasing competition (Gonzalez & Melo 2017). Therefore, in addition to acquiring systems, tools and metrics to answer such needs of information, organizations need to focus on developing the human capital (Day & Moorman 2016; Gonzalez & Melo 2017). Additionally, organizational culture should aim towards fostering learning, sharing and sustaining knowledge (Gonzalez & Melo 2017).

Driving from these concepts, the theoretical framework studied in this thesis depends on a couple of essential ideas: marketing analytics, data-driven marketing, knowledge management and the Capability Maturity Model. Each of these will be explained more in-depth. Furthermore, this thesis includes dimensions with the perspective of organizational culture barriers that have an effect on marketing analytics and data-driven marketing implementation and utilization.

2.2 Marketing analytics definition and framework

The vast and frequent availability of data and analytics for marketers to use has prompted various implications of data-driven methods in organizations. Similarly, past studies have described data and analytics with varying terms, based on, for example, the source of the data (e.g. social media analytics or web analytics), the characteristics of the data (e.g. big data) or the utilizing function of such data (e.g. business analytics). Based on such conceptualization, the term utilized in this thesis, *Marketing analytics* (MA), is chosen due to its proven effect on and connection, to the efficiency of data-driven marketing functions (Wedel & Kannan 2016). Since data-driven decision-making, specifically in marketing, is a key aspect in this research, it is vital to utilize terminology that is both suited for the context and as accurately chosen as possible, based on previous, fragmented research in this subject.

Evidently, there is no clear answer to establishing the meaning of marketing analytics. The American Marketing Association (2017) describes *marketing* as "the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large". Everelles et al. (2016) describe the term *analytics* as tools to discover and extract hidden patterns in data. Moreover, the concept of marketing analytics has been said to consist of both metrics and analytical methods (Wedel & Kannan 2016). To exhaustingly describe the coined term "marketing analytics", a broader understanding of overlapping and synonymous terms was collected (see Table 2). Marketing analytics has a close relation and partly derives from terms such as web analytics, big data, business analytics and social media analytics. Thus, to understand the whole concept of marketing analytics, a complete understanding of such relating terms is required to form a critical opinion of the meaning of the term.

TABLE 2 Definitions of Analytics

Term	**Definition**
Big data	"Big data analytics is the use of advanced analytic techniques against very large, diverse data sets that include structured, semi-structured and unstructured data, from different sources, and in different sizes from terabytes to zettabytes" (IBM 2018). "Big data is often characterized by the four "Vs": volume (from terabytes to petabytes), velocity (from one-time snapshots to high-frequency and streaming data), variety (numeric, network, text, images, and video), and veracity (reliability and validity) ... Sometimes a fifth "V" is added: value" (Wedel & Kannan 2016, 102).
Social media analytics	"[Social media analytics] primary goal is to develop and evaluate scientific methods as well as technical frameworks and software tools for tracking, modeling, analyzing, and mining large-scale social media data for various purposes" (Stieglitz et al. 2014, 90). "Social Media Analytics makes use of advanced techniques to analyze patterns in semi-structured and unstructured social media data to enable informed and insightful decision-making" (Bekmamedova & Shanks 2014, 3728).

Business analytics	"Business analytics refers to the extensive use of data, statistical and quantitative analysis, explanatory and predictive models to drive fact-based management decisions and actions" (Davenport and Harris 2007, 7).
Web analytics	"Web Analytics is the measurement, collection, analysis and reporting of internet data for the purposes of understanding and optimizing web usage" (Chaffey & Patron 2012, 34). "... [the use of web analytics] offers companies a metrics system to measure digital marketing performance" (Järvinen and Karjaluoto 2015, 117).
Marketing analytics	"Marketing analytics involves collection, management, and analysis—descriptive, diagnostic, predictive, and prescriptive— of data to obtain insights into marketing performance, maximize the effectiveness of instruments of marketing control, and optimize firms' return on investment (ROI). It is interdisciplinary, being at the nexus of marketing and other areas of business, mathematics, statistics, economics, econometrics, psychology, psychometrics, and, more recently, computer science" (Wedel & Kannan 2016, 98). "Marketing Analytics is the study of data and modeling tools used to address marketing resources and customer related business decisions" (Iacobucci et al. 2019, 156).

As stated previously, this thesis utilizes the term marketing analytics, due to its broad look on analytics, and their utilization in the field of marketing (Germann et al. 2013; Wedel & Kannan 2016). In past research, marketing analytics has been profoundly linked to decision-making (Germann et al. 2014). In this thesis, marketing analytics is seen to consist of big data analytics, web analytics and social media analytics (see Figure 3). As can be formulated from the descriptions in Table 2, these analytics have a very closely linked meaning, but a different function. In this thesis, they are all seen to be a part of MA (see Figure 3), since marketing analytics utilizes customer and market data of all sorts (Germann et al. 2013), and the process of utilizing marketing analytics is interdisciplinary by nature (Wedel & Kannan 2016). Also, the description of marketing itself is broad and overlaps multiple organizational functions (American Marketing Association 2017).

FIGURE 3 Marketing analytics definition in this thesis

The utilization marketing analytics require analytical skills, methods and tools, as well as the data itself (see Figure 3; Wedel & Kannan 2016; Iacobucci et al. 2019; Germann et al. 2013). Thus, the framework for the term marketing analytics can be seen in Figure 3. Moody and Walsh (1999) conceptualized the seven laws of information way before the time of big data, which go as follows: (1) Information is (infinitely) shareable, (2) the value of information increases with use, (3) information is perishable, (4) the value of information increases with accuracy, (5) the value of information increases when combined with other information, (6) more is not necessarily better and, (7) information is not depletable. Despite having been conceptualized prior to such concepts as big data and marketing analytics, the laws of information still apply today and give important principles to the utilization of analytics (Ylijoki 2019). The concept of big data promises that, through analysis and categorization, organizations are able to gain valuable knowledge and develop effective decision-making processes (Ferraris et al. 2019). However, this promise can only be realized through the utilization of various analytical skillsets, tools and methods.

2.3 Knowledge management and organizational culture

2.3.1 Knowledge management and organizational culture that foster data-driven marketing

Research describes knowledge management in various ways depending on the industry and context of the practice. In the past three decades knowledge management has evolved from incomplete concept into a necessity for all kinds of organizations (Girard & Girard 2015). Girard and Girard (2015, 14) collected and researched over a hundred descriptions for knowledge management and created the following definition: “Knowledge Management is the process of creating, sharing, using and managing the knowledge and information of an organization". Furthermore, other studies describe Knowledge Management as a systematic concept that includes knowledge from various functions, e.g., market, customer, finance, process or product information, and manage and leverage these as the organizations' knowledge resource (Cope et al. 2006; Dunn & Neumeister 2002). Ferraris et al. (2019) imply that knowledge management possesses a mediator effect in relation to the outcomes of big data analytics capabilities. Thus, knowledge management is a key component in data-driven marketing development. Petrides and Nodine (2003) further highlight knowledge management's role in aiding decision-making by improving the utilization and sharing of information and data. Christensen (2003) approaches the term from a managerial and human resource angle and points out that knowledge management should note the people and processes that influence the information, and simultaneously, take into account the organizational structures and mechanisms that are required for handling the knowledge.

Kumar and Kumar (2015) emphasize that since knowledge management mainly involves people, the fact that knowledge management affects people's behaviors and work patterns should always be taken into account. Hence, knowledge management includes both humans and technology, i.e., the technology and science of analytics should be combined with managerial intuition to gain the most out of both and establish data-driven practices in organizations (Davenport 2014). In addition to being affected by human resources, knowledge management requires learning-oriented culture and knowledge sharing supporting structures (Gonzalez & Melo 2017). Furthermore, Germann et al. (2013) emphasize a combined role for top management in nurturing employee's analytical skills, meaningful data, enough technology and culture in deploying marketing analytics. The researchers further highlight the culture's role and linkage to knowledge and insight sharing and deployment (Germann et al. 2013), in addition to knowledge management. Consequently, all of the previous aspects are crucial in successful data-driven marketing.

To increase the human capital, i.e., knowledge management practices, investments into relational and organizational capital are needed (Gonzalez & Melo 2017). This means establishing a sharing culture as well as a culture of taking risks and encouraging creative processes (Gonzalez & Melo 2017). Hence, human capital is highly linked to culture as well as showcased in Figure 2 in the framework of this thesis. A pioneer in the field of organizational culture, Schein (2016, 6) defined organizational culture as "the accumulated shared learning of that group as it solves its problems of external adaptation and internal integration. This accumulated learning is a pattern or system of beliefs, values, and behavioral norms that come to be taken for granted as basic assumptions and eventually drop out of awareness" (Schein 2016). Collaborative processes that foster integration between individuals and departments that break silos through knowledge sharing, are essential to knowledge management as well as data-driven marketing capabilities (Gonzalez & Melo 2017).

2.3.2 Importance of human capital and culture in the data-driven marketing process

As established previously, this thesis relies on specific key ideas, i.e., the four elements of an organization (Day & Moorman 2016). In order to be data-driven, concise and meaningful, data, as well as systems, have to be in place, i.e., marketing analytics. While marketing analytics is the configuration in this framework, knowledge management presents the human capital needed for data-driven marketing processes (see Figure 2). If an organization strives to gain tangible value from big data and marketing analytics, the importance of data-driven decision-making must be integrated into the marketing department of the organization (Wedel & Kannan 2016, 116). Thus, this chapter aims to describe how data-driven marketing links to knowledge management; the human capital in the framework of this thesis (see Figure 2). Studies have shown that the ability for organizations to answer to external changes rapidly in today's competitive and continually changing industry environments drives competitive advantage (Erevelles et al. 2016, 897; Lin & Wu 2014, 407). Other studies have shown how data-driven decision-making can aid in organizations in, e.g., analyzing consumer behavior (Malhotra et al. 1999; Wedel & Kannan 2016) budget allocation (Lubell 2018; Wedel & Kannan 2016) and customer segmentation (Fotaki et al. 2014; Miguéis et al. 2012). McAfee and Brynjolfsson (2012) discovered a correlation between data-driven organizations and improved objective measurement of various functions. Given these numerous benefits, it's unfortunate that the amount of data available exceeds the company's ability to utilize this data, and some organizations lack entirely the knowledge of driving insight and informed decisions from data into the field of marketing (Erevelles et al. 2016, 897). Furthermore, Germann et al. (2013) point out that most organizations and managers are still not convinced about the benefits of marketing analytics. Moreover, studies present very few systematic cases in which knowledge management and data-driven practices provide a competitive edge, and instead focus on a few "success stories" (Germann et al. 2013).

Hauser (2007) pointed out the importance of a deep understanding of data, statistics and databases for marketers using marketing analytics. This is because whereas data can help to discover insights, it is the marketers' job to transform these insights into actions that drive market advantage (Erevelles et al. 2016). The idea of utilizing various models and systematic statistics has been around for a while, even from a marketing perspective (Wedel & Kannan 2016; Kumar et al. 2016). Still, marketing analytics and data-driven marketing need more research and real-life cases to establish their significance in the business economy. Both corporate marketers and researchers in the marketing field have expressed the need to drive marketing decisions from data. Data utilization could help to shift the perception of marketing from merely being a necessary and costly function towards a quantifiable value generating part of an organization (Kumar et al. 2016). Erevelles et al. (2016) discuss the potential that the utilization of big data holds in aiding strategic decision-making across all organizational functions by discovering insights from, e.g., consumer data. According to Day and Moorman

(2016) the cooperation of multiple functions is often necessary for any type of marketing capabilities to develop, knowledge management capabilities included. Also, most companies strive to implement data-driven decision-making across multiple functions in their organization (Wedel & Kannan 2016). Wedel and Kannan (2016) highlight that analytics can be utilized in a data-driven way in all functional areas of an organization, e.g., management, finance, human resources, marketing and sales. Both data-driven decision-making and knowledge management theories have a long history in the business and operational side of a company (Wang et al. 2017). Though, the same issue regarding turning business analytics into organizational value still exists today (Suryanarayanan & Saji 2018; Wang et al. 2017). Thus, knowledge management skills and practices are needed to turn this data into the insight's managers desire. Additionally, human capital is required for the problem definition phase of the data-driven marketing process. According to Davenport (2014) data-driven decision-making process can be divided into six steps: (1) Recognize the problem or question, (2) review previous findings, (3) model the solution and select the variables, (4) analysis of the data and (5) presenting the findings. Davenport (2014) further highlights the preeminent importance of the first two steps for knowledge management, as those are the ones that require experience and intuition the most.

Consequently, management needs to take culture into account when developing marketing analytics and data-driven marketing capabilities. Culture provides the logic behind the actions and the ways of communication inside an organization (Deshpandé & Webster 1989). In addition, culture affects management by providing shared values, behavioral norms and beliefs to the managers making decisions in an organization that have a concrete effect on data-driven marketing processes (Deshpandé et al. 1993; Germann et al. 2013; Schein 2016, 6). Though organizational cultures are challenging to create, changing them is even harder (Schein 2016). Hence, once a culture that supports marketing analytics has been established, an organization gains sustainable value that is difficult to lose.

2.4 Capability Maturity Model

According to Day and Moorman (2016), capabilities in addition to culture, configuration and human capital are four of the most essential parts to marketing excellence. Furthermore, Kerrigan (2013) states that processes evaluated by the Capability Maturity Model cannot be considered in disconnection from two other key elements: people and technology. In this thesis, these aspects have been further defined as Knowledge Management and marketing analytics. Taken together, this triad can be utilized as a reason for assessing organizational capability (Kerrigan 2013). Thus, these aspects are intertwined to each other and should be looked at together. Looking at the process itself, this chapter will describe the evaluation of capabilities utilized in this thesis.

In this thesis, a maturity model is utilized to assess the data-driven marketing capability of each organization and, thus, analyzed in a coherent, systematic and structured manner. The existing theoretical frameworks that are used to describe data-driven marketing abilities of a company are fragmented and, due to their short history, don't have a large set of research to validate them. Because of these shortfalls, a more widely used and credible model was utilized in this thesis to serve as the foundation for this research, the Capability Maturity Model (CMM), which was created by the Software Engineering Institute in Carnegie Mellon University (Kerrigan 2013). The Software Engineering Institute based this idea on the work of Watts Humphrey (1988), who created the foundation for this model by developing the original process maturity framework in the late 1980's while working at IBM (Chen & Wang 2018). The CMM was established for software development from a government contractors' perspective, enabling the ability to objectively assess their processes in performing a contracted software project (Kerrigan 2013). However, nowadays, diverse organizations perceive the CMM as a straightforward course to ceaselessly create competitive advantage and to accomplish strategic schemes in the implemented entity (Mughrabi & Jaeger 2017). Thus, the model has since aided various other fields in process development modelling, e.g., Business Analytics research (Fan et al. 2015; Sekiguchi & Tsuda 2014). Qin et al. (2017) utilized the CMM to address data from the research management capabilities and optimization perspective. The model has even been utilized in the field of education, e.g., by Chen et al. (2012) in the creation of the Teaching Capability Maturity Model (T-CMM). In the same field, Mughrabi and Jaeger (2017) developed a Project-Based Learning Capability Maturity Model (PBLCMM) that enables the systematic assessment and optimization of the learning process of students. The People Capability Maturity Model (P-CMM) was studied by, e.g., Curtis et al. (2007) and Chen and Wang (2018). Some previous studies have briefly touched upon utilizing the model in the scope of marketing, e.g., digital marketing governance (Chaffey 2010), social media Capability Maturity Model (SMCMM) in the business to business environment (Wang et al. 2017) and marketing software development (Grossmann 2018; Chaffey & Patron 2012). Grossman (2018) developed the Analytic Processes Maturity Model (APMM) to research how advanced organizations' analytics modeling practices are developed. Carroll (2017) developed the Inner Source Capability Maturity Model (IS-CMM) to address and close the Inner Source strategic value gap though value co-creation activities. According to a study by de Bruin et al. (2005) over a decade ago, hundreds of varying maturity models had been developed. In practice, no matter the size of the organization, CMM practices can benefit organizations' continuous improvement (Humphrey 1996). Yet, current research lacks a more coherent implementation of this model from a data-driven marketing management perspective.

The Capability Maturity Model highlights processes in a controllable, measurable and improvable light (Humphrey 1988, 74). This is in-line with the principles of data-driven marketing and knowledge management, as described in the previous chapter. The CMM aims to increase performance through structured and gradual developments (Mughrabi & Jaeger 2017). The model consists of five levels of maturity that visualize and guide the process evolution in growing order: initial, repeatable, defined, managed and optimized (see Figure 4; Chen and Wang 2018).

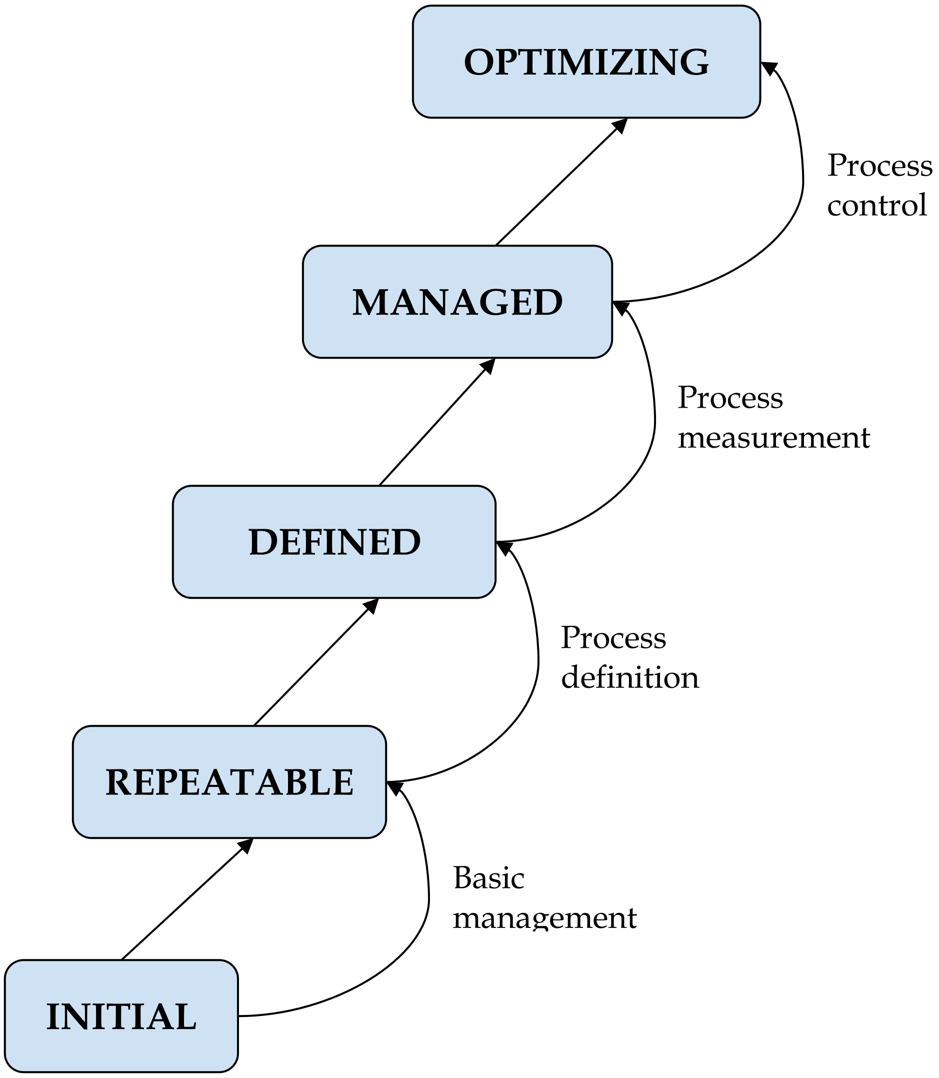

FIGURE 4 The five levels of process maturity (Humphrey 1988, 74)

The first level, *initial,* is the prior statistical control of the process. On this level progress or improvement is nearly impossible, as it is chaotic and lacks orderly procedures for project control, documentation, definition and repeatability (Humphrey 1988, 74). The reasoning behind many companies working in disorganized process environments that lack control, is due to their inexperience in the possibilities of developing more process maturity, and lack of knowledge in the consequences of uncontrolled processes (Humphrey 1988, 75). During developing past this level in the process, the organization gains an understanding of the current state of the process in question. Project management and management oversight are central when maturing past the initial level. Quality of the process, as well as controlling possible changes in the process, must be looked at in detail (Humphrey 1988, 75). Chen and Wang (2018) describe this level as an inconsistent process in the P-CMM. Many developments of the CMM cut the initial level out and merely present four levels, e.g., the SMCMM (Wang et al. 2017), as it is often seen as merely the starting point and not a step in itself. Kerrigan (2013) states that on this level the organization lacks all formal digital investigations capability.

At the second level, *repeatable*, a basic set of project management has been established. Successful processes can be repeated, and commitment is controlled (Humphrey 1988, 75). In the repeatable level, prior experiences can be turned into further success in current and future processes. Due to this, the process achieves stability and repeatability by initiating rigorous project management of various process functions, e.g., commitments, costs and changes (Humphrey 1988, 74). Documentation and definition of projects and processes have been put into place. Moving beyond the mere repeatability, a vision for the desired process must be drafted (Humphrey 1988, 74). Additionally, a key action is to name a member or a group of staff responsible for the development of the process. The SMCMM describes this level as the technological level where basic functionalities and platforms are in use but not managed coherently (Wang et al. 2017). Carroll (2017) highlights technological gaps as well as narrowness of the process as typical for the second level of the Inner Source Capability Maturity Model (IS-CMM).

The *defined* level is the third one in the CMM, where the organization has a defined process that makes a consistent integration of the process, as well as provides a basic understanding of the desired process development (Humphrey 1988, 74). Even with such leaps of improvement, this level is still mainly qualitative with minimal data or insight on the effectiveness of the process in question (Humphrey 1988, 76). When evolving beyond level three, effective and meaningful measurement of the process and its various functions must be put into place. Also, the development requires the establishment of a process resource to gather and maintain information as well as educate other project members on its use and benefits (Humphrey 1988, 77). However, analytical insights might be missed or misjudged because of the absence of inclusion of analytics professionals in the arranging and vital heading of investigations (Kerrigan 2013). Thus, tracking historical experiences in similar projects and making knowledgeable and strategic assessment from them is vital when moving forward.

In the fourth step, *managed*, major leaps in the process, as well as organizational function quality, have typically been made (Humphrey 1988, 77). The organization is monitoring and controlling its processes by collecting and analyzing data continuously. The decision of which data to analyze must be evaluated with precision and reflected to the goals of each measurement (Humphrey 1988, 77). Kerrigan (2013) describes the features of this level as established measurable quality goals and objectively managing performance. The data and analysis must be meaningful and defined. For the IS-CMM, this level of progression is strategically enacted, and plans are continuously executed and monitored within the process (Carroll 2017). Advancing from the fourth level to the final one is done by putting automatic data collection and analysis into place, that are utilized for optimization by preventing problems and improving efficiency (Humphrey 1988, 79).

The final level of the CMM is the *optimizing* level. In this level the data is utilized to constantly improve the process itself and projects in the process, which results in major productivity and quality improvements for the organizational function (Humphrey, 1988, 79). This is done by monitoring feedback from past processes and projects and by introducing completely new and innovative ways to higher organizational performance. Faults in projects and processes can be identified and fixed or eliminated based on the data analysis (Humphrey 1988, 79). Concise terminology is utilized that facilitates the shareability of knowledge beyond organizational silos. Chen and Wang (2018) describe this level as Change Management that aims to continuously improve practices. Carroll (2017) defines this level as continuously measured and evolving, with new processes being adapted and technology being evaluated. All in all, on the optimizing stage, the professional has the means to understand the project's performance and can find possible areas of improvement efficiently.

The objective of the Capability Maturity Model is to reach a measurable and controlled process, which establishes the foundation for continuous improvement and optimization of the process (Humphrey 1988). It serves as an assessment tool that helps in the identification of the maturity status of a specific organizational function. In addition to this the CMM develops a management system that produces the foundation for the implementation of the orderly actions required to improve the process. Through the assessment of the maturity level, the organization is able to focus its efforts and resources on the key development areas to move to the next level. In summary, CMM provides orderly support to complex processes and their management (Humphrey 1996, 80). Therefore, it serves as a solid foundation for the development of a data-driven marketing Capability Maturity Model.

2.5 Barriers of data-driven marketing

Most Capability Maturity Models do not take into account the barriers and hindering factors nor highlight them, hence, the five-level model aims to evaluate progress not obstacles. However, in order to reach the goals of this research and to answer both research questions profoundly, barriers of data-driven marketing will be inspected and taken into account in this research. According to a market report published by Forbes (2015), 64 percent of marketing professionals strongly agree that “data-driven marketing is crucial to success within a hypercompetitive global economy”. Still, many companies have not yet been able to implement such processes when designing and implementing their marketing strategy. Various factors may affect an organization’s capabilities in adapting data-driven processes. One of the main aims of this research is to shed light on the reasons behind this lack of adaptation, which is a contradiction to the amount of buzz and excitement around data and marketing analytics today.

According to Chaffey and Patron (2012), challenges with people, structures and processes have surpassed challenges that link to data integration and technology, as barriers that prevent companies from improving conversions. Various other research endorses such thinking of problems lying elsewhere than in the lack of possibilities in integrating the technology (Branda et al. 2018; Davenport & Harris 2007; Germann et al. 2013; Gonzalez & Melo 2017; Wedel & Kannan 2016). To understand such barriers in people, processes and structures, this research looks at the overlying factor, *organizational culture*. organizational culture is a concept cultivated in the 1990's, which argues that shared organizational beliefs and values affect, for example, routines, reactions to issues, constructions in an organization, the meaning of work and employees' thoughts in various ways (Levin & Gottlieb 2009; Schein 1992). Thus, organizational culture is additionally closely linked to top management characteristics and organizational structure (Banerjee & Srivastava 2017; Groysberg et al. 2018).

The shared values, an integral part of organizational culture, provide a common basis and direction for the whole organization (Banerjee & Srivastava 2017). Wedel and Kannan (2016) emphasize, that the main stepping stone for the utilization of marketing data and analytical methods for organizations lies, firstly, in the fact whether the organizational culture and structure enable data-driven decision-making and, secondly, whether the organization invests in the education and training of analytics professionals. In the understanding of Germann et al. (2013) establishing marketing analytics positive culture is needed for successful deployment since it ensures the effective sharing of insights gained from marketing analytics within an organization. Branda et al. (2018) discovered various organizational and psychological factors that affect the marketing analytics orientation readiness of an organization, such as attitudes towards change and inadequate top management leadership. Furthermore, since culture explains the logic of how and why "things happen", studies have suggested that both a marketing analytics supportive culture as well as top management utilizing analytics strategically are crucial for the implementation (Deshpandé & Webster 1989; Germann et al. 2013). Analytics supportive organizational culture is concentrated on gaining knowledge, continuous information sharing, and cultivating a setting where people are urged to try different things with new arrangements from an experimentation viewpoint in order to be able to foster data-driven marketing development (Gonzalez & Melo 2017; Mezias et al. 2001). Furthermore, as stated previously, it is crucial for an organization's top management to get involved and foster such creative, experimental and open viewpoints (Mezias et al. 2001).

Organizational culture is inextricably linked to leadership (Groysberg et al. 2018). Therefore, various research discussing culture barriers cite *top management* as a possible issue for marketing analytics integration. Davenport and Harris (2007) argue that top management support is necessary for the implementation of an Analytics strategy. Other studies support the importance of supportive top management for a successful marketing analytics integration into organizational functions (Branda et al. 2018; Kiron et al. 2011). Kumar et al. (2016) highlight that human capabilities, tools and configurations are not sufficient as a base for data-driven decision-making, and state that in order to "increase the inclination for managerial adoption, it is important to get the users to "see" the benefits of data-driven marketing". Additionally, it is often the founders and influential managers that set cultures moving and engrave thoughts and values that endure for a considerable length of time (Groysberg et al. 2018; see Figure 2). Furthermore, implementing data-driven marketing to an organization predominantly requires some form of change (Levin & Gottlieb 2009). Thus, an organization's history may present a barrier to organizational change (Rosenberg & Mosca 2011). Furthermore, the capability to shift an organizational culture through change is, in addition to top management, a key factor of barriers in data-driven marketing implementation. Past studies have showcased the impact of culture on both organizational change and insufficiency in top management (Branda et al. 2018), thus all three of these factors have to be taken into account when progressing data-driven marketing in an organization. Previous research has come to the unanimous conclusion that resistance to organizational change is significantly high (Rosenberg & Mosca 2011). Mezias et al. (2001) argue that communities' past thinking is integrated into, not only rules, routines and programs, but even human capital. Consequently, the mentioned cultural barriers of data-driven marketing highly link to knowledge management and human capital as well. Thus, this research inspects top management as one of the main barriers for data-driven processes, e.g., lack of top management participation and support (see Figure 5).

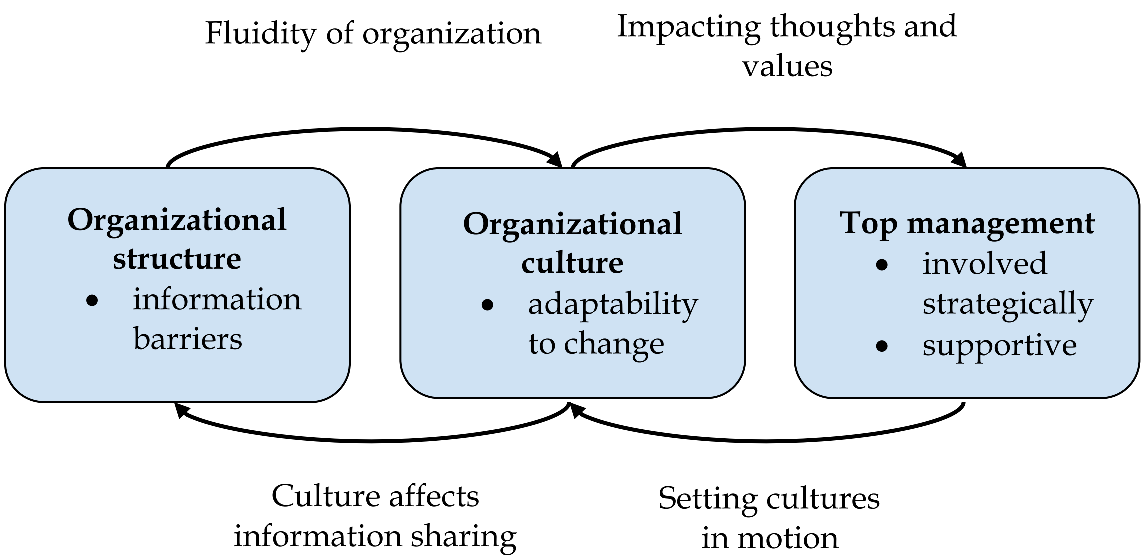

FIGURE 5 The framework of 'Barriers of data-driven marketing' based on past research (Day & Moorman 2016)

Organizational change, learning and adaptivity need fluid *organizational structure* (Banerjee & Srivastava 2017). Thus, another important factor relating to barriers regarding culture is the structure of an organization. 61 percent of marketing professionals name silos and data barriers across internal departments as the main issue for furthering data-driven marketing initiatives, as this requires the free flow of information (Forbes 2015). Chaffey and Patron (2012) list company culture, conflict of interest between departments, and a siloed organization as barrier contributors for the integration of web analytics. According to Banerjee and Srivastava (2017) culture is transcendent in forming the structure of an organization. Furthermore, structure alongside culture is unpredictably related to the manner in which advancement and innovation are managed or executed in any association (Banerjee & Srivastava 2017). Thus, organizational culture, organizational structure and top management characteristics and the factors within them that may present barriers to data-driven marketing deployment are visualized in Figure 5. This master’s thesis aims to give more depth and insight into these barriers through expert interviews and the analysis that follows.

3 RESEARCH DATA AND METHODOLOGY

3.1 A philosophical approach to the research paradigm

Research paradigms are a basic set of beliefs which are based on the suppositions of three research philosophies; *ontology*, meaning the reality itself, *epistemology*, the relationship of this reality with the researcher, and *methodology,* the method(s) the researcher uses in order to uncover this reality (Carson et al. 2001, 16; Cuba and Lincoln 1994, 107). Saunders et al. (2009) have argued, that in research philosophy each researcher pursues significant perspectives on how they see the world. Moreover, these perspectives and presumptions will extraordinarily influence the problem stating, execution, data collection and analysis of the research (Carson et al. 2001, 20). Therefore, taking the philosophical approach of this research into account is critical, since it enables a deep understanding of varying types of methodologies as well as assists the researcher in the data collection process through a more profound outlook on context and perspectives.

The marketing research field has previously offered two distinct philosophical systems for marketing research: positivism and interpretivism (Wang 2019, 349). Positivism aims for an objective and relatively structured way of research, while contrastingly, interpretivism may vary from semi-structured to unstructured data collection methods that are based on the belief that relative truths arise from interaction (Carson et al. 2001, 67; Wang 2019). As marketing is often seen as both a positivistic and scientific discipline as well as an interpretivist art form, a blended approach of positivism and interpretivism is suggested for marketing research (Bowser et al. 2000). Furthermore, interpretive studies aim for in-depth understanding; on *why* and *how* certain things occur, whereas more quantitative methods answer *what* and *how many* related questions (Carson et al. 2001). This thesis aims to answer both types of questions, which is why using both of these aspects is justified.

Critical realism is in between these confrontational approaches that hold opposite views on reality and the ways to discover it (Easton 2002; Wang 2019). In the field of marketing research, where the paradigm has widely been positivist, critical realism succeeds to acknowledge the complex, socially developed world that cannot be otherwise ideally measured and describing its various phenomena, in a way that enables scientific analysis (Easton 2002, 120; Ryan et al. 2012, 308). For these reasons, this thesis adapts a critical realist view, in order to successfully convey the current state and barriers of data-driven marketing and usage of marketing analytics, based on individualistic perspectives of the marketing experts interviewed in this research. Critical realism is increasingly favored in for example management research and represents an alternative for artificially flattening ontologies, by accepting an emerging, bedded view of reality and society (Armstrong 2019; McGhee & Grant 2017; Wang 2019).

3.2 Qualitative research and methodology

3.2.1 Qualitative research

Qualitative research aims to describe real-life phenomena and its concepts in the most accurate way possible through decoding, translating and other means of portraying meanings (Hirsjärvi et al. 2009, 157). Such interpretive techniques of phenomena and meanings are harder or, in some cases, impossible to execute with quantitative methods (Petrescu & Lauer 2017, 2249). A qualitative research interview was a likely method for the scope of this master's thesis since the study has a focus on the possibilities and barriers of marketing analytics and data-driven decision-making that marketing professionals perceive. More precisely, this thesis focuses on the usage of data-driven marketing in varying companies marketing departments in the Finnish region. As this specific topic has not been previously widely studied, the adjustable and exploring nature of a qualitative approach provides a suitable setting for this thesis (Carson et al. 2001). To answer the research question, a set of marketing expert interviews were conducted. The data collection for this thesis consisted of ten individual interviews.

The field of marketing is constantly evolving due to technological changes (Kolb 2008). Thus, information production and research inside the field of marketing research is expanding at a huge rate while simultaneously staying divided and interdisciplinary (Kolb 2008). This makes it difficult to stay aware of the newest cutting-edge research. Furthermore, it is becoming increasingly difficult to evaluate all possible evidence in a specific research field. To tackle these issues, a successful literature review gives a firm basis for knowledge production and facilitates hypothesis development (Webster & Watson 2002). Hence, the literature review in this master's thesis provided an incremental basis for this qualitative research, in addition to the interviews.

3.2.2 Interview-based research

In the past decade, interviews have become the most utilized method for data collection in top marketing journals (Petrescu & Lauer 2017). This is mostly owing to the implications of interview research; as a research method its best suited for situations where the study is concentrating on the discovery of, e.g., experiences, interpretations, attitudes, values and feeling that cannot be portrayed in a more systematic way, which is a common problem for marketing research (Carson et al. 2001, 75; Hirsjärvi et al. 2009, 205). Thus, interviews were selected as a data collection method for the scope of this thesis due to its high dependency on the subject's context.

Data collection through interviews can be divided into three primary categories; structured interviews, semi-structured interviews and in-depth interviews that are differentiated by the amount of control in the interview process (Corbin & Morse 2003). In this thesis, a semi-structured interview was used due to the method's flexible nature that allows the interviewees to, e.g., share their opinion but simultaneously giving the interview some level of structure in leading the interview forward. Semi-structured interviews derive flexibility from aspects such as the possibility of varying interview questions from one to another (Saunders et al. 2012). Thus, the reasoning behind the chosen interview category was the need for preserving the possibility to alternate the order or even wording of the interview questions if necessary. Additionally, semi-structured interviews allow for more in-depth data collection by focusing mostly on how and what questions (Koskinen et al. 2005, 109). Compared to both in-depth and structured interviews, a semi-structured interview generally gives more constructed and systematic material to work with but at the same time gives more freedom to the interviewer as well as hosting an informal atmosphere that nurtures sharing (Hirsjärvi et al. 2009).

3.2.3 Choosing the interviewees

The selection of the interviewees was one of the first steps taken in the process of this thesis. Previous studies have highlighted the importance of selecting cases that provide the most in-depth information for the research (Merriam 2002; Patton 1990). This means selecting a sample of study participants that are able to give most insights to the research questions (Merriam 2002; Patton 1990, 169). Thus, the interviewee and case selection should not be done by chance (Easton 2010, 123–124). During this study the researcher took multiple steps to ensure the strategic, yet subjective selection of interview participants. One of the steps taken to maximize the credibility of this qualitative research was utilizing *theoretical sampling*, which is defined as the purposive selection of interviewees based on their relevance, and the potential they offer for establishing new concepts considering their characteristics and dimensions (Colin et al. 2001; Corbin & Strauss 2008). Thus, relevance overruled the exhausting representation factor in this study.

To ensure both a valid theoretical sampling basis as well as a broad representation, specific criteria were set so that the selected interviewees had to meet to qualifications of this study (see Table 3). This criterion was based on similar previous studies made regarding the concepts of marketing analytics analysis and data-driven marketing. Firstly, all the interviewed experts had to present companies that operate in the Finnish region. The restriction to companies operating in Finland was also an essential criterion for the feasibility of the study, as the study was conducted in Finland. The second criteria established was that the interviewees had to have a level of authority in the company so that they were able to execute marketing actions based on their possible data analysis and insights. The last three criteria sought to ensure that the interviewed experts would represent a wide variety of company sizes, company lifecycles and industries, giving the answers diversity and depth. Furthermore, despite the small number of interviews, these criteria allow wide applicability of the research results.

TABLE 3 Interviewee selection criteria

Criteria	**Description**
Finnish company	A Finnish based or autonomously working company in the Finnish region.
Ability to make actionable marketing decisions; management or similar	The interviewees have to have the ability to act on the possible insights found, therefore, holding a managerial or otherwise independent job position.
Varying company sizes	The interviewees chosen should present varying company sizes, to enable a broader perspective on the research questions.
Varying company lifecycle	The interviewees chosen should present varying company lifecycles, to ensure a broader perspective on the research questions.
Varying industries	The interviewees chosen should present varying industries, to provide and inter-industrial perspective on the research questions.

For the purpose of this study, interviewees were contacted through networks and social media, such as LinkedIn where various posts were made to discover possible interested participants for this research. Some of the interviewees were found through networking events. This ensured the selection of a large variety of participants from varying backgrounds, and reduced biases due to acquiring mostly previously unfamiliar participants.

3.3 Research process

3.3.1 Data collection and the interview process

The interviewing phase of this thesis started in October 2019 and was finalized in February 2020, lasting for a total of over four months. The ten interviewed marketing professionals for this thesis were all from different organizations. While all of the organizations are located in the Finnish region, some of the companies even had business abroad, or were the Finnish branch of an international organization. The company sizes varied considerably, both in terms of turnover as well as number of employees. The smallest startups interviewed consisted of less than ten employees, while the larger organizations employed over 2 000 individuals. The turnovers of the organizations interviewed ranged from 20 000 euros to over 900 million euros. Some of the organizations had a longer history, stretching even further than the beginning of the digital era, whereas several of the organizations had fewer years of operation behind them. The industries in which these organizations operated involved both business-to-business and business-to-consumer industries, as well as a mixture of the two. The professionals interviewed worked in organizations focused on, for example, technology services, retail, industrial wholesale, marketing services, IT-consulting, furniture and industrial chemicals.

The titles of the interviewees included, e.g., Chief Executive Officer, Co-founder, Marketing Manager, Marketing Specialist, Head of Global Marketing, Customer Experience Manager and Marketing Director. The common thread for all these professionals was the ability to take action based on the possible data insights discovered, as stated in Table 3. Such possibility of actionable insights was central for this research since professionals with no input on the measures taken based on the insights would not be able to provide enough relevant data for this master's thesis. Furthermore, while the titles consisted of a wide range of positions, all the professionals interviewed focused on some or all functions of marketing in their organizations.

TABLE 4 Interview information

Interviewee	**Duration**	**Date**	**Situation of interview**
Company A	31:22	18.10.2019	face-to-face
Company B	27:10	19.11.2019	face-to-face
Company C	19:46	22.11.2019	via phone
Company D	35:08	11.12.2019	face-to-face
Company E	32:01	18.12.2019	face-to-face
Company F	44:21	20.12.2019	face-to-face
Company G	25:30	23.12.2019	via Skype
Company H	20:51	27.12.2019	face-to-face
Company I	17:42	13.01.2020	via phone
Company J	35:18	05.02.2020	face-to-face

A brief preparation email was sent to all the interviewees one day before the interview to perform the interviews as efficiently as possible (see Appendix 2). The purpose of the study was once more laid out in the email, to complement prior discussions with the interviewees, as well as clarifying the meaning of certain terminology in this thesis beforehand. No further preparation was needed for the interview. Nonetheless, the email was sent to make sure the interviewees' thoughts were aligned with the question's terminology, to inform them about the possibility of recording the interview, and to serve as a general reminder about the reasons and benefits of the research. Thus, all the interviews were recorded in this process, with the explicit consent of the interviewees, which led to a total of over five hours of recorded interview material (see Table 4). Remote interviews were recorded using the loudspeaker and a separate recorder.

The interviews were preferably, and if possible, performed face-to-face, as this form of interaction forms a solid basis to fully understand the meanings and thought processes of other individuals (Krauss 2005). However, mostly due to time limits, some interviewees opted for a phone or Skype interview (see Table 4). The one-on-one interviews were guided by the prior set interview questions (see Appendix 1), in a flexible manner in the frames of a semi-structured interview. This ensured the researcher with the option to lead the meetings and increase required data but simultaneously provided a setting for added questions when seen vital. The semi-structured interviews assisted the researcher in gaining a deeper knowledge and keeping the exchange going forward. Thus, the interviews progressed in a conversational way, and some questions were left out in the process, due to being answered prior in the conversation. The interviews started off with more general questions as a warmup and aimed to gather general information about the interviewee as well as the organization in question (see Appendix 1). The interview then moved onto discovering the current state of marketing within the organization in question and progressing towards finding the practices and processes that the organization is currently using in a data-driven marketing manner (see Appendix 1). After establishing the current state of data-driven marketing in the organization, the third section of the interviews consisted of discovering the perceived barriers of data-driven marketing. In addition to bringing light to possible barriers, this section listed some contradicting questions to bring more depth to the data, e.g., question 17: "When measuring and optimizing marketing performance, what do you find easy to quantify and understand?".

The pilot interview had an exploratory nature, and its underlying endeavor was to check whether the views of the subject being examined are sufficiently caught by the proposed interview structure and questions. After conducting the pilot interview, a few changes were made to the interview structure and formulation of the questions. Firstly, question number 7: "What are the most important activities of Your digital marketing efforts?" and number 9: "What tools do you currently use to measure marketing efforts?" were originally set the other way around. The change was made to increase the logical flow of the interview. Secondly, question number 7: "What are the most important activities of Your digital marketing efforts?" was originally formulated as "What digital marketing activities does Your company perform?". The reasoning for this alternation was the broadness of the original question, which made it a difficult one to answer on the spot. Instead, focusing on listing a few of the most important activities was more straightforward to articulate for the interviewees, while still providing valuable data for the purpose of the research.

After each interview, a preliminary analysis was conducted based on the top of mind thoughts of the researcher. Following this, the material was fully transcribed, with minor exceptions in the case of repetition. The transcribed material added up to a total of approximately 68 pages to be analyzed.

3.3.2 Data analysis

The data analysis process in qualitative research aims to gain social knowledge of others through, e.g., interactions with others to access people's minds (Krauss 2005). Thus, the completion of the interviews was followed by the data analysis phase, in which the previously transcribed material was analyzed through thematic analysis. This form of analysis is utilized in qualitative research and highlights discovering patterns or themes of significance inside information with a flexible approach to qualitative data analysis (Braun & Clarke 2006; Guest et al. 2012). The thematic analysis moves past looking for unequivocal words or expressions and concentrates on recognizing, portraying and expressing thoughts within the data such as codes and themes (Guest et al. 2012).

Since thematic analysis includes more interpretation from the researcher's part in terms of development and choices of codes and themes, reliability becomes a greater concern in comparison to for example content analysis (Guest et al. 2012). Such issues are often addressed by utilizing standardized themes and codes established by previous research. However, no prior coding themes were discovered due to the absence of empirical literature relating to data-driven marketing utilization, which poses additional challenges for the scientific grounding of the research. Thus, a general inductive approach was employed in discovering the frequently appearing themes by allowing theory to appear from the data (Strauss & Corbin 1998; Thomas 2006). The main role of the inductive methodology is to enable discoveries to rise from the successive, predominant, or noteworthy thematic characteristic in crude data, without the limitations forced by organized approaches (Thomas 2006). An example of coding and thematization is presented in Table 5.

TABLE 5 An example of interview data thematization and coding

Interview quote	**Themes**	**Codes**
"Things get a lot easier when you don't need a person in between, and advanced artificial intelligence does it all. When there is a person in between, one must always prioritize what to focus on. The ability of a business or even a marketing to leverage it all in decision-making is necessarily limited. When everything cannot be done, it is not worthwhile to measure everything."	Barriers of limited resources Human knowledge Meaningfulness of data	Human capabilities Limited resources Objective setting

According to Braun and Clarke (2006), inductive thematic analysis is constructed of six steps; (1) familiarization with data, (2) generation of initial codes, (3) searching for themes among codes, (4) reviewing themes, (5) defining and naming themes and (6) producing the final report. This research followed these principles when moving through the data analysis phase. Additionally, in this master's thesis the researcher utilized ATLAS.ti for data analysis and management. The ATLAS.ti software program helps in gathering and analyzing qualitative content in an analytical way through coding of the content. Such assisted analysis is CAQDAS which means Computer Assisted Qualitative Data Analysis (Rademaker et al. 2012). Through this process, the researcher aims to capture meanings in the data and display occurrences that simple text-based searching cannot discover. Despite its numerous advantages, CAQDAS does not take out the need nor substitute the role of the researcher in the comprehension and understanding of the information.

Resulting from the analysis and based on previous research as well as the Capability Maturity Model, this research conceptualized a basis for a Data-driven Marketing Capability Maturity Model (DMCMM). The study added to the model by defining barriers for each level of the model. These barriers were categorized based on previous research and defined best on the data analysis (Day & Moorman 2016; see Figure 2; see Figure 5).

4 RESEARCH FINDINGS

4.1 The current state and barriers of data-driven marketing

Through the interview data, the current state and barriers of data-driven marketing in Finnish organizations were identified. The answers of the interviewees were reflected onto the five-level framework of the Capability Maturity Model, and barriers were identified and categorized according to a framework based on past research (Humphrey 1988; see Figure 5). Additionally, several other barriers for data-driven marketing could be identified in light of the interview data. Through these constructs, a Data-driven Marketing Capability Maturity Model was established.

All the interviewees described an important but varying role for marketing in their organization. Due to its varying role, the practices in measuring and evaluating marketing processes presented an equally wide range of answers to the question "How do you measure marketing success?”. Half of the informants highlighted the complexity in the marketing field in general, faced with constant change due to new technological advances and high expectations by the operational and business side of the organization. Such growing expectations and constant disruptive change in the field has additionally been mentioned in previous research (Day & Moorman 2016; Gonzalez & Melo 2017; Ylijoki 2019). Contradicting to the high expectations, many informants described a reluctance to invest in marketing as this function is often unable to present exhausting return on investments and is often overruled by operational or business functions:

> The role of marketing has been a little confusing in the past, perhaps even operational and fulfilling in its role. The modern role of marketing is not yet understood in our organization, nor by many other companies in this field. (Interviewee C)

> Being at such an early stage this company has not yet been able to focus so much on marketing, but of course visibility and marketing is extremely important for the company as well as the company. We will start developing marketing once we get other things up and running. We have focused on project planning and business building in general, and there is a lot to do in these functions, which is why we’ve not really focused on marketing as of now. But I personally believe in it’s potential. (Interviewee A)

> Marketing is tremendously important but is often overlooked. I think it would be terribly difficult to do without marketing. But its role is still quite undefined in such an old-fashioned industry as ours. Without communication, for example, our product range would be difficult to bring to the attention of our customers, which come from a total of five different industries. Marketing is needed to focus all of this. I can say that there are more than enough challenges, but it is extremely interesting. (Interviewee C)

Nevertheless, both the importance of marketing itself, and the role of data are noted by all of the interviewed professionals. Data is seen as a basis for proper establishment for return on investment for marketing functions in an organization, which was previously close to impossible, causing friction between for example marketing and sales teams:

> There is also a lot of resistance to invest in marketing nor are its results often seen or can even be downplayed by for example the salespeople. A common misconception is that marketing in a company like ours does not work or doesn't accomplish any added value. But with these reports and data, I can show factual and concrete numbers and verify the role of marketing and increase assurance internally. (Interviewee C)

Utilizing data in marketing does not only help the company succeed and gain competitive advantage. Data utilization can aid the organization in discovering better ways to communicate with or help their customer:

> I see data from many directions. When doing something, for example, using HubSpot, of course we are able control customer actions based on data. But in the same way, we can learn what our customer is interested in, what they are about and even predict future behaviors. (Interviewee D)

Furthermore, the customer's interest in their own data was a common subject. Some interviewees told that their organizations had already applications and processes in place which enabled customer data to be shared with the consumers themselves. Solutions that showcased past buying behavior and served highly personalized experiences for customers based on their data were seen as beneficial and successful for both the organizations and the customers. Consequently, a few of the informants argue that organizations that are able to harness and exploit data in such a way that it profits both parties will be able to gain competitive advantage and are constantly able to optimize their processes for the best possible outcome.

Thus, the importance of marketing and data-driven processes are recognized. In this master's thesis, these processes and development are identified and laid out in a hierarchical, leveled order. Additionally, the interview data is utilized in discovering barriers that the interviewed marketing professional phase in their data-driven marketing advancements.

4.2 How are marketing professionals utilizing data-driven marketing?

4.2.1 The initial data-driven marketing process

The first, initial level of the Capability Maturity Model is chaotic, unmanaged and consists of acting impulsively while doing a mix match of things (Humphrey

1988). In the interviews, such processes were described as having a high level of unpredictability and simultaneously poorly controlled, if control existed at all. According to Carroll (2017), actions are performed reactively, and close to no follow up is performed. Many informants confirmed such thinking:

> At least I haven't actually seen any data-driven decision-making in a company in any area. Yes, it would help, but it has never been the basis for decisions. (Interviewee A)

> For many of our clients, data-driven decision-making is not developed because it has been seen as an opportunity, but because everyone else does it. So, they merely do it to keep up. This, to me, is sort of a backwards way to look at things. Something new is not developed based on possibilities and lean thinking, but instead things will only move forward when all known means fail, as a last resort. (Interviewee J)

In the interviews, initial data-driven processes were described as having a high level of unpredictability and simultaneously poorly controlled, if the control exists at all. More than one-third of the informants listed the lack of clarity in the goal-setting phase, which causes issues for the complete data-driven marketing process. Thus, vague or non-existent objectives in the marketing department are typical for the initial level. This issue is further built upon with the lack of or inconsistent communication with other functions in the organization. Since no clear basis is put in place, the outcome becomes uncertain. Additionally, one of the interviewees pointed out that even though objectives might be clear to the business or operational side of the organization, they are often not clearly communicated or presented to the marketing department. As a result, actions are often performed reactively, as interviewee B states:

> Everyone would like to get [campaign reporting], but if there are no clear goals then how do you report? Still, typically, each objective is unfortunately viewed through the sales perspective: Did the customers you want to reach become active? How much? Does this generate sales? And this is our measurement at its best, there are a lot of campaigns where nothing is watched. And on top of it all, for the goals of marketing we should measure the impact of the media, which is legendarily difficult. These are a bit of a mumble to a large extent. (Interviewee B)

In addition, other interviewees (C, E, H) described inconsistency in their organization’s measurement procedures, whether it is following up on the performance of campaigns or between different functions in the organization. These statements are in line with the initial level of the P-CMM, developed by Chen and Wang (2018). The top management's ignorance towards the consequences of unmeasured processes was seen as a problem by the same informants. This is part of the reason behind organizations staying in disordered and uncontrolled management conditions (Humphrey 1988, 75). Moreover, the interviewees highlighted that another reason is the lack of credit or trust given to the marketing department by other functions in the organization or the top management. Interviewee E described situations, where despite presenting the sales team with concrete numbers and sales achieved through a marketing campaign, these increased sales were not seen as the resulting outcome established by the marketing team.

Furthermore, various problems may hinder the organization from developing into the action phase of data utilization from just talking about it. Half of the informants expressed a hype around data utilization, but this is merely buzz, due to shortcoming in, e.g., the knowledge of available technologies, usage of them, lack of trust from other departments or the top management. Furthermore, the marketing department may have the needed motivation and mindset towards data utilization. Still, the interviewed marketing professionals felt stuck in merely talking about it, as advancements in data-driven processes are not prioritized in the organization. Some of the participants in this study saw clashing ideologies as a complete hindrance for process development:

> Since we help our client companies marketing departments with their digital marketing, we often tried to include data-driven processes in there to give some credibility and systematics to the services we offer. The marketing professionals in client companies are often very excited about this. But their management still sees this as a less attractive idea, considering that this new process thinking will take up more resources. I think this is the wrong way to think, because the end result is often the opposite: data-driven increases efficiency and gives certainty in decision-making. This is difficult or even impossible to deal with because our clients are these marketing people, not their superiors. (Interviewee J)

All interviewees described some lack of control or systematics in at least part of their data-driven marketing processes. However, despite such perceptions, all of the interviewed professionals implied some formal level of marketing analytics utilization, which is beyond the initial level of the data-driven marketing Capability Maturity Model (Kerrigan 2013). Furthermore, this highlights the reasoning behind numerous advancements to cut the underlying level out of the CMM, and simply present four levels, as it is frequently observed as just the beginning stage and not a stage in itself (Wang et al. 2017). However, even though all of the participants in this study presented some level of data-driven marketing maturity beyond the initial level, it may not be an accurate presentation of the overall state of data-driven marketing processes in Finland. This is due to the fact that the informants wanted to participate based on their interest in data-driven marketing and, therefore, inherently or purportedly would have some data-driven marketing processes in place.

4.2.2 The repeatable data-driven marketing process

The repeatable level of the Capability Maturity Model holds some established procedures, which are repeated if the outcomes are perceived as positive ones for the organization. All of the informants had some level of consistency and repetitiveness in their data-driven processes, which links to the repeatable level in the Capability Maturity Model. Nevertheless, on the repeatable level, data-driven processes are still not managed or followed upon (Carroll 2017). Data-driven thinking and decision-making have still not properly established their role

(Carroll 2017). However, there is a consistent willingness to do data-driven marketing; thus, the process is repeated. Furthermore, the repeatable level is not as chaotic as the initial level, as some patterns can be found. Hence, half of the informants described repetition in marketing processes with perceived positive outcomes, though irregularity prevails:

> If a certain marketing method during a project or campaign works well and we are able to deliver tangible results, the method is presented to the entire company and reutilized. it is usually directly proportional to the result and this allows us to accept suggestions on that topic better, because there is data marketing also to potentially new areas with new nuances. (Interviewee A)

Based on the interviews, it can be concluded that on the repeatable level, a fundamental degree of project management already existed in the companies. This is needed to advance beyond the initial level according to Humphrey's definition (1988), which describes the repeatable processes as successful procedures that the organization is able to rehash and in which the responsibilities can be controlled as a part of other project management processes. In the repeatable level, related involvements can be transformed into further accomplishment in the present and future procedures.

Even though an elemental degree of project management is in place, no systematic reporting or follow up exists (Carroll 2017). Due to this, half of the informants expressed an inconsistency in the processes being repeated. What some people might see as a positive outcome, others within the organization might see as insignificant. One of the informants highlighted that merely gaining a certain amount of leads through a marketing action is not enough. The outcome of marketing actions has to be evaluated through sales to exhaustingly determine whether or not these outcomes can be seen as good or not. Thus, combining mere numbers with human knowledge is crucial in gaining a true perspective of the outcome. Additionally, this all comes back to the importance of clear and concise goals needed in organizations, which serve as the foundation for the whole data-driven process. Consequently, some informants highlighted the need for clear and concise goal setting prior to the marketing process:

> There is no comprehensive data-based reporting. Project-specific business reports are of course distributed to management, but we have not done any data-based reporting on marketing. When concluding a project, however, our reports on marketing efforts are somewhat data driven. Who we have reached, how it has worked, what added value it brought? Though I might say, that only looking at these numbers in hindsight is not very fruitful. The goals should be set up front, to really see whether or not something was successful. You can't really evaluate something if it didn't have an aim or a goal to begin with. (Interviewee A)

Over half of the informants had a specific individual or team in charge of advancing data-driven marketing processes as a whole so that learnings could be made from the positive outcomes and could then be repeated. These results are in line with previous research. According to the creator of the Capability Maturity Model, a key action in the repeatable level is to name a person or a team in charge of the advancement of the procedures (Humphrey 1988). A common characteristic for this level is a basic level of documentation, which should advance the organization towards systematics at an ever-increasing pace (Humphrey 1988).

The interviews showed that data-driven processes are seen to bring meaning and concreteness to the marketing actions of the organization. Half of the interviewees described the role of data as a challenge to preconceived notions and existing processes. At an advanced level, the role of data will bring optimization to the data-driven decision-making processes themselves, in addition to marketing actions. Nonetheless, at the repeatable level elemental data-driven methods, and data generated discussions and questions are sufficient. Furthermore, one-third of the interviewees pointed out that in order for data and insight related tools to be of use, the information must be added onto the human knowledge and even intuition that exists in the organization. This is in line with, e.g., the findings of Wolf (2014). Moreover, the value of combining both data and human capabilities is acknowledged in the principles of Knowledge Management (Kumar and Kumar 2015). Various informants provided examples of the role data in combination with human knowledge:

> In my opinion: data doesn't lie. Data doesn't hold preconceived notions, nor does it have underlying goals; therefore, it is objective at its core. However, data can be misinterpreted or even presented in a misleading way. I think this is important to keep in mind when looking at data while making decisions. Even though data doesn't lie, the human entity that is necessary for a data-driven process to take place, may want to twist things, even subconsciously. You may want to see something that isn't there. But with systematics, an open discussion and multiple data professionals involved such pitfalls can be avoided, though it takes some time and resources for sure. (Interviewee J)

> The number one thing about using data is that it helps us learn. Data is bad on its own because it gives a certain perspective to each issue. But the way data is combined seems to help verify things, or, alternatively, to challenge one's subjective opinions. (Interviewee D)

> Introducing data into companies may already help companies in the process of having their decision makers and creators reflect on their own processes that have not previously been questioned or considered. What data we want to collect, why we want it, where we use it. Because what is the use of data if it has no purpose? This applies to everything in business, not just marketing, but even communication, business, strategy and sales. (Interviewee D)

According to Wang et al. (2017), the repeatable level of the Capability Maturity Model should display a fundamental level of technologies, with platforms and functionalities in place. However, although these elements are used, and some processes are in motion, they are not managed nor coherent (Wang et al. 2017). Some of the informants informed such irregularities. Especially when discussing company-wide challenges, the interviewees working in larger organizations discussed an incoherence between functions in the organization, which affects the actions of the marketing department. Nonetheless, with adjustments and advancements, progress was seen as inevitable. Some informants described this as an outcome of the mindset shift in the organization:

> As of now, the mindset is partly there, and some processes are more developed and systematic than others. But this is something we want to develop, and because of this there are development processes going on in the organization that are advancing our data processes constantly. (Interviewee B)

Moving past this level in the data-driven marketing Capability Maturity Model, a vision of the desired process as a whole must be drafted out (Humphrey 1988). As one of the informants described, a common mindset for developing data-driven decision-making in the organization is the basis for advancing in the organization's data-driven capabilities. Other interviewees had similar thoughts when it came to the beginning stages of the data-driven marketing processes. Additionally, on third of the informants highlighted that just having data on display does not equal the productive utilization of data. This is in line with findings of Mayer-Schonberger (2013), which characterized data as a tool and supplier of knowledge, whose purpose is to inform more than to explain. Furthermore, other studies have added onto the same conclusions, stating that in order to take advantage of marketing analytics, organizations require both analytical methods, knowledge and tools in addition to the data itself (Iacobucci et al. 2019; Germann et al. 2013; Wedel & Kannan 2016).

4.2.3 The defined data-driven marketing process

At the defined level of the Capability Maturity Model, the organization has determined a procedure that makes a reliable coordination of the procedure conceivable, and at the same time a fundamental comprehension of the ideal procedure advancement (Humphrey 1988). Carroll (2017) states that at this stage goals should start to be specified and consistent. Furthermore, objectives need to be clearly communicated throughout the organization (Carroll 2017). 90 percent of the interviewees promoted such thinking in their organizations. The researcher found a common need for clarity and consistency from goals and objectives, not only for the sake of data-driven decision-making, but for all functions within the marketing department. Furthermore, half of the informants highlighted that such clearness in objectives and transparency in requirements from the top management is crucial. Thus, a defined data-driven process begins with an understanding of the meaning of data utilization. Many of the informants highlight such notions:

> You should go back and ask yourself: Why do we want to collect data? What are we using it for? What do we want to learn from it? And then start building those points where the tools and data sources are best, not the other way around. Although a little less data would be collected, the information collected would be sensible and useful. (Interviewee D)

> Goal setting is one of the, if not the most important, phase in all of this. This point really should not be done vaguely in terms of marketing. Marketing measurement in itself is so difficult, so without proper goals it's nearly impossible. (Interviewee I)

Humphrey (1988) stated that regardless of numerous leaps of progress, the defined level is still mostly subjective with minimal insight or data on the viability of the procedure being referred to. A few interviewees described the connection of multiple diverse data as being the main steppingstone in drawing deeper insights from the data available to them. One of the informants highlighted the possibilities of such data connections as giving added credibility to the precise measurement of marketing and its effects to, e.g., sales. Nonetheless, the researcher found such connections to still be very minimal.

> I would argue that our way of connecting various data points is not terribly systematic. Perhaps we need to bring more data side by side and consider what the connection between them is. We have not made that deeper connection. However, we strive to find those key points between different data sources in order to get some concrete basis for decision-making in the future. (Interviewee A)

All of the interviewees described a varying level of systematics in their marketing measurement and evaluation processes. However, as the interviewees explained marketing is a complex function with various goals that have different weights of importance. Thus, some controlled variation might exist regardless of the level of data-driven marketing maturity and capability. One of the informants mentioned, that the measurement and focus on data is not necessary for all individual actions that the marketing department makes. The researcher found that looking at the overall progress in data-driven decision-making might be more advantageous and give a more accurate representation of the current state of the data-driven maturity. Furthermore, when advancing beyond the defined level, the validity of data usage and measurement must be strategic and constantly evaluated. As some informants explained, measuring all marketing actions does not provide enough value for the resources required for measurement:

> We have a huge variation in this. There are marketing measurement efforts that are not fully nor effectively measured, and then there are big campaigns that are viewed from many angles. But I think such variation is understandable, as not every single poster can or should be measured, as it takes up resources, but the outcomes of such measuring are not so revolutionary. (Interviewee B)

According to Kerrigan (2013), the organization may miss or misconceive important analytical insights due to not including or taking into account the opinions of analytics experts in the planning and management of the processes. Some of the informants mentioned the importance of coherent documentation of previous data-driven processes in marketing for more advised decision-making in the future. Furthermore, one-fifth of the interviewees brought up the significance for equal data collection and interpretation, since only consistent data and reporting made the outcomes of campaigns compatible with similar historical reports.

Reporting at the defined stage becomes more valuable, as metrics are more defined and strategic than before (Carroll 2017). According to Humphrey (1988, 77), improvements towards the defined level requires a foundation for a procedure asset to gather and manage data as well as instructing other staff members of its utilization and advantages. Half of the interviewees emphasized the value of common data-driven marketing goals that are reflected throughout the organization, open communication and involvement of multiple departments:

> I will also try to teach the organization to read these reports and to instill this mindset. Digital channels have shown and proven results, and it is important that others recognize this benefit. (Interviewee C)

> We go through [the monthly marketing reporting] with the marketing team and sometimes the management team also discusses it, especially if there are some channel choices. It's important to go through these results in order to learn from them and so that everyone is up to speed with these advancements. (Interviewee E)

At this stage, the initiatives for open sharing of knowledge and data are discussed, and preliminary change management is introduced in the organization (Carroll 2017). Additionally, Carroll (2017) argues that senior management support is already installed on the defined level of the Capability Maturity Model. However, even though open communication and receptiveness of possible changes were mentioned by some interviewees, overall management support was seen as one of the ultimate and latter steps of data-driven marketing processes. Thus, this research argues that commencing of top management support takes place when on the verge of the managed data-driven marketing process, and not prior. Initial data-focused personnel and teams may take action on the defined level, according to a few of the informants and previous research (Carroll 2017). Nonetheless, a managed process requires top management support in order to form.

4.2.4 The managed data-driven marketing process

Managed data-driven processes require systematic follow-up on the decisions made and evaluating them through data (Humphrey 1988). Data is multidimensional and at least manually combined into richer in-depth insights (Carroll 2017). Over half of the informants described such processes as the current state they are in. Few interviewees saw such a state as a goal for future advancements in data-driven decision-making overall, even though systematicity might exist for some individual campaigns compared to others. According to previous studies, this level requires continuous utilization of the processes, though the process itself might yet not be optimized (Humphrey 1988). Furthermore, each set of data should be carefully chosen to adequately reflect the measured function and its objectives (Humphrey 1988). Most interviewees (A, B, C, D, F, H, I, J) stated some form of data selection efforts based on the goals set.

Humphrey (1988) states that organizational function quality advances on the managed data-driven process level. According to 60 percent of the interviewees, this is visible as major advancements in decision-making formed mostly based on data and not intuition. One of the interviewees stated that minimizing merely intuition-based decisions has led to major efficiency advancements in the long run. Other interviewees supported such remarks. Furthermore, this is additionally in line with Kerrigan's (2013) description of the levels' objectivity in performance measurement.

> We measure sales data, customer information, and especially on digital platforms, campaign measurements are investigated. We measure and monitor things we are able to put into use in our decision-making processes, which is most important for us in all of this. (Interviewee B)

According to Carroll (2017), the fourth level, managed data-driven processes, has an enacted strategy and metrics are continuously measured and reported. For meaningful reporting to be a possibility, technologies have to be fully implemented and further upgrades planned and communicated (Carroll 2017). The importance of both technology and the reporting made possible from various tools was highlighted by over half of the informants. Benefits resulting from technology and reporting were perceived as, e.g., growing efficiency, consistency, easy adaptation into the process, and the opportunity to see the most prominent path to take through, for example, A/B-testing. Over half of the informants expressed having multiple reporting processes in place regarding their marketing actions:

> We do analytics and data-driven reporting for ourselves and our customers. Customers have their own report templates that are used to explore findings and results with customers. The good thing about digital marketing is that it is easy and hassle-free to test things, and then follow-up with data and results without any huge loss, if any. (Interviewee D)

On this level, the processes in question should be planned, executed and monitored consistently (Carroll 2017). This research found systematicity as one of the major perceived benefits and advancements of data-driven marketing. All interviewees were able to provide some examples of situations where a well-planned, and afterwards followed upon marketing action has prompted towards more informed processes and repetition in the future:

> Actions are taken based on whether a certain marketing action is working or not. A/B testing is also sometimes done intentionally, or even when a website is redesigned with data and feedback. Of course, we have all that lean startup thinking and a culture of experimentation in the background that goes well with this kind of modern data-driven doing. (Interviewee D)

> We'll keep track of which stuff has been more popular and when a certain topic is not converting properly, we will change the subject of focus in our marketing. We make quite a lot of conscious decisions. We follow usage on LinkedIn, and we try to

> target our content creation efforts. In general, we have to keep track of which channels to use and where to publish to get the best reach. (Interviewee E)

The research found that on the managed level, developments in the data-driven marketing process incites organizational silos to be broken down. This is due to the fact that this level of data-driven processes required open data collection and sharing across functions in the organizations. One of the interviewees noted, that such data sharing often faces obstacles due to data privacy issues and technology teams' worries regarding giving away direct access to fragile databases. Another interviewee noted that such reluctance to share data might also be caused by resentment of the marketing functions sudden success, which can be seen as underestimating, e.g., the sales team's success. Nevertheless, some informants further highlighted the importance of breaking silos to enable free flow of data in the organization:

> We have different levels of knowledge and understanding here. They are then progressively advanced, the silos are broken and there is more cooperation, functions trade team experts with each other. (Interviewee B)

Such sharing of both human knowledge and data are seen as optimal ways to learn and develop processes by the informants in all types of functions. One of the interviewees argued that organizations in which various functions communicate with each other, at least in terms of data flow, will hold a major competitive advantage in the time to come.

However, the interviewees found some variety on the descriptions of this level. The informants from larger organizations describe the involvement from middle management, which evolves further to top management involvement as the processes progress to the managed level. Smaller organizations with less hierarchical tiers in between marketing and top management displayed involvement of the top management already with the characteristics of the managed level of data-driven marketing. Nevertheless, all the informants describe a need for higher management involvement.

4.2.5 The optimized data-driven marketing process

The optimized data-driven marketing process brings advances due to the data process itself being managed and optimized. In addition to holding all of the advancements and progress made up until the previous level, the optimized process focuses on continuously making the process better itself. Feedback loops are put in place in order to update standards regularly. Although all informants had at least some feedback loops in place for reporting their marketing efforts, only one of the informants described processes where the follow-up procedure was linked to the data-driven process itself. Additionally, such loops ensure that the data-driven process stays contemporary with the changing world and advancing technologies affecting it. Interviewees discussed the possibilities of, e.g., marketing automation regarding the changing world and technologies but none of the informants stated having an automated data-driven evaluation system. Furthermore, some of the informants noted that optimization of data-driven processes requires optimization of the data itself:

> I really think even data utilization in marketing has to be accountable. Even data processes can be optimized through for example marketing automation, even some decisions can be automated nowadays. This is definitely not being taken advantage of enough. (Interviewee J)

> Data utilization must not remain in such a simplified form as staring at numbers and, if something grows, marketing has succeeded and can pat itself on the back. For example, our digital marketing expert always emphasizes that the stupidest thing Facebook can do in marketing is simply staring at the number of likes. That alone is not meaningful data. There were X number of likes, but were they relevant? Did we get good leads? We prefer to do less, but more sensibly, and that is what data can promote. (Interviewee D)

Interviewees saw continuous optimization as a cause of the constant presence of change. This is in line with the viewpoint of Chen and Wang (2018), who describe the optimized level as prompting never-ending change management. Additionally, while common terminology across the organization is vital for the optimized level of Capability Maturity Model, a few of the interviewees (B, J) highlighted the importance of a common language and terminology, and expressed that such procedures are aimed for in the future:

> If we want to get better at this, we really need to start talking the same language as the business side for example. This holds importance, since it affects everything, beginning from objective setting. (Interviewee B)

> [Inconsistency in terminology] is something my client companies struggle with a lot. It causes miscommunication and a sort of natural dysfunction, that often stops advancements in data-driven marketing, or at least hinders them. (Interviewee J)

With everything taken into account, in the optimizing stage, the marketing expert has the means to discover faults in procedures, which can be distinguished and fixed or wiped out depending on the data analysis. Furthermore, positive processes are easily pointed out and repeated for added efficiency.

According to Carroll (2017), the final level of the IS-CMM has an advanced focus on learning based on upcoming needs. Additionally, adaptation strategies are revisited frequently (Carroll 2017). Some informants expressed an integrated learning aspect in their processes. One of the informants discussed internal trainings, where staff across all functions were welcome to familiarize themselves with the customer data available to them. Another interviewee gave examples of data education sessions, which the interviewee frequently hosted to the organization’s client companies.

4.2.6 Opportunities for data-driven marketing

Throughout the interviewees, all informants described an enthusiasm towards data-driven marketing. 70 percent of the interviewees saw data as the first advancement that could help marketing to prove its importance to the organizational performance concretely. However, one informant noted that although such themes as digital marketing and data utilization are current right now, these should not be taken as a truism. The informant added, that as soon as digital media proves to be insufficient for their target audience it will not be utilized anymore, as all marketing efforts are and should be done based on the wants and needs of the target audience:

> Who knows, if in a few years some new way to communicate sweeps all our clients off of social media and onto the next? We will never do some marketing action just for the sake of doing it, or because it's current and trendy. All our resources go into serving and communicating with our clients in the best way possible. (Interviewee C)

This thought was also brought up by another interviewee, who stated that even data utilization might be going through major changes before most organizations even get the chance to take advantage of its possibilities. Data privacy and regulation regarding data are continually evolving based on users' needs and wants, thus major advancements like the General Data Protection Regulation of the EU are no exception.

Nevertheless, all informants described data and its usage in marketing as a conversation starter, from various aspects. Firstly, all interviewees noted that data could help to solve the problem of quantifying marketing actions, providing some solutions to this timeworn issue. Furthermore, over one-third of the interviewees saw data as the answer for especially smaller organizations marketing that have very limited resources, as it aids in terms of efficiency. Additionally, the learning aspect of data utilization in marketing was brought up by almost half of the interviewees. Thus, data may be perceived as shallow on its own, but combined with human knowledge and development is seen as an opportunity to establish a new kind of efficiency. Many of the informants presented examples of cases, where data and human intuition combined provided the best possible results:

> Data also always returns to the surface and raises questions about our own assumptions and opinions. Even though we think something is the best, our customers may not think so. We can optimize even as much detail as our terminology. In my opinion, data helps to make decisions, and after a decision was made, data helps to verify whether that decision was right or wrong and on the other hand also helps to learn. I think in the future, those companies that learn and are open to changing the habits they are used to will thrive. (Interviewee D)

> [Through data utilization] we are able to plan how to do and target our marketing. We have very limited resources that can then be focused on where it is most effective through data usage. I see it as extremely important and we are constantly striving to

> develop what we do and prioritize and focus on getting the most out of these limited inputs. (Interviewee E)

In conclusion, the possibilities of data-driven marketing perceived by marketing professionals themselves are numerous. Still, many marketers have as of yet not been able to integrate data into their marketing. The following chapter will discuss the barriers of data-driven marketing found in this research.

4.3 Barriers for data-driven marketing

The perceived barriers for data-driven marketing processes discovered in this research are manifold. Despite the wide range in organizational size and various life cycle stages, many similarities in perceived and experienced barriers came up during the interviews. Based on previous research, the discovered barriers were categorized into three groups: cultural barriers, structural barriers and top management barriers. Moreover, additional limitations will be discussed as further perceived barriers for data-driven decision-making in marketing.

4.3.1 Cultural barriers

Banerjee and Srivastava (2017) described organizational culture as the shared values that establish a common ground and direction for the whole organization. Schein (1992) defined organizational culture as a set of common hierarchical convictions and qualities that influence, for instance, schedules, responses to issues and change, the meaningfulness of jobs, and staffs thought processes in various manners. Reflecting this perspective, the informants described multiple reasons for barriers relating to organizational culture. 70 percent of the informants discussed the importance of a shared mindset as an enabler for data-driven decision-making in marketing. Interviewees explained that without commonly shared ideas and ambition, moving forward with just a few people or teams that try to advance things, will be faced with setbacks and hindrances caused by clashing ideologies. Some informants noted that changes in culture take a long time to shift and change:

> These are evolving things and take their time. One has to learn yet what is optimal for this, for example, to be organized around these things, that it is by no means self-evident. Probably the most important thing here is that the will is there. There is a lot of ambition, including in business and marketing. The best practices within the organization are widely sought for how to do this better. The meaning of data-driven processes is understood and shared with the concept of it. (Interviewee B)

Although one-third of the interviewees described some challenges being caused by difficulties with technologies and integrations, challenges linked to change, whether related to people, structure or processes, were far more common amongst the interviewees. This is in line with previous research (Branda et al.

2018; Chaffey & Patron 2012; Davenport & Harris 2007; Germann et al. 2013; Gonzalez & Melo 2017; Wedel & Kannan 2016) that claims that such obstacles have surpassed the complications faced with, for example, data implementation.

Moreover, closely linked to organizational culture and the identified need for a common mindset, over half of the interviewees brought up the demand for a common language as well as connected virtual environments that enabled data sharing without boundaries. A few of the informants described a potential in digital, multichannel forums in which the organizations employees would be able to connect, and share data and insights to further data-driven decision-making:

> Through this multichannel environment, everything should be linked, united, and above all, systematic and goal-oriented. In our field, this is a really difficult thing, when decision-making is really spontaneous, and you want to do everything intuitively right now. (Interviewee C)

> The greatest wisdom, what we are going toward, is a common way of talking about customers, not only to produce reports, but also in which forums such customer understanding issues will be systematically addressed in the future. Having one common language also helps to create common goals. (Interviewee B)

> Problematic is also the lack of common terminology, despite the fact that we have shared reporting. (Interviewee H)

These were also found to relate to one another: one interviewee discussed client cases where despite the free flow of data, the divergence in terminology caused issues in data compatibility and linkage. Similarly, some informants raised concerns regarding silos, where despite a common language, the disruption in data distribution caused different decision-makers to have different views on the same case or process. Contradicting, one interviewee (A) saw various viewpoints and background information as a richness in some cases, where common knowledge is not possible to achieve due to limited resources. However, this was a singular viewpoint, and the interviewee A themselves described doubts whether this would be functioning in larger organizations, where silos can mean radically different standpoints.

In some cases, despite shared practices and flow of data between organizational functions, the data is not being utilized in a productive way. Even such issues were found to trace back to organizational culture, where data-driven decision-making was not made a shared goal and priority:

> [Utilizing data in other functions beyond marketing] is our weak point. We are constantly trying to provide data and tools for the sales team, but they just don't have enough time or enthusiasm for data utilization. Although it is always available to them, they do little to direct their actions based on it. If the marketing manager sees that hey, now this one customer in France is constantly looking for information about it or it is just like reading this stuff and then he can put the French sales manager to get connected to this customer. The responsibility will ultimately lie with the sales manager whether he takes action from the delivered lead. (Interviewee E)

As Germann et al. (2013) argue, marketing analytics insights are sufficiently shared through a positive analytics culture. The informants disclosed similar ideas. Some interviewees even mentioned actively working towards a data-driven culture across the organization by sharing data proactively outside the marketing department. A strongly analytical and data-driven culture is focused on picking up information and consistent data sharing (Mezias et al. 2001). Furthermore, almost half of the informants wanted to develop a setting where individuals are encouraged to attempt various things with lean ideology from an experimentation perspective so as to have the option to cultivate the showcasing of information-driven improvement, which was also described by Mezias et. al (2001).

Nevertheless, opposition towards analytics usage is an apparent barrier in the data-driven marketing development process, which is caused by conflicts between diverse organizational cultural ideologies. Whether it's the resistance to adapt to changes, conflicting ideologies within the organization or a lack of common ground and path, all informants saw organizational culture as one of the main barriers for advancing data-driven marketing processes, giving verification to the division displayed in Figure 5:

> Resilience to change is the biggest challenge, with a lot of expectations and justification for the efficiency and choice of digital channels being expected from marketing. And even with that data, there may be comments that belittle these results. For example, sales made through one newsletter were underestimated under the guise that they would have "happened anyway without the newsletter". It is somehow perceived as a threat when those sales come from something other than actions of our sales team. Although one should think and rejoice about the success of the whole house and the strength of the business. (Interviewee C)

> What really matters more is the lack of common best practices to do it. And these should be shared by all functions in the company, not just marketing. Perhaps this is also an organizational culture issue as well. (Interviewee B)

Continuous encouragement for individuals in the organization to learn, advance and work across silos was seen to have a positive impact for data-driven process development, by enabling shifts in the organizational culture. Most informants gave examples of situations where education and organization-wide involvement had a constructive outcome on marketing analytics utilization. Wedel and Kannan (2016) highlighted commonly accepted beliefs in the organization as a central driver for data-driven marketing. Consequently, data-driven marketing and insights utilization are often hindered by steep culturally defined hierarchies and a siloed structure in the organization (Wedel & Kannan 2016). Moreover, organizations that do not invest resources into the education of analytics experts face more difficulties in evolving their capabilities (Wedel & Kannan 2016). Thus, barriers can and have been overcome in past cases through education and by working towards breaking down silos from the cultural perspective.

4.3.2 Structural barriers

In order to gain systematics, enable learning and acceptance towards change, the organizational structure needs to be fluid (Banerjee & Srivastava 2017). Over half of the informants named difficulties in data sharing as a recurring issue in the organization. Part of these problems related to the organizational culture to a greater extent, but a few of the interviewees saw these hindrances as causation of structural barriers.

Organizational silos were seen to be originated from structural problems in data-driven marketing development. Half of the interviewed experts saw some of the cultural reluctance of changing the mindset of the personnel as a result of these structural challenges. In addition, silos within the organization were seen to influence the generation of different levels of expertise between functions. This is consistent with past research that lists organizational silos as barriers for development (Chaffey & Patron 2012). Two of the informants proved to be an exception to this rule. These informants expressed not having issues with silage due to the small size of their organizations; thus, organizational structure issues seem to be more severe in larger organizations. Consequently, informants in larger organizations described problems faced because of the siloed functions:

> Unfortunately, we have a lot of different functions in the silos. Changing the overall mindset is the biggest challenge and takes years of work. (Interviewee J)

> We have different levels of knowledge and understanding here. They are then progressively advanced, the silos are broken and there is more cooperation, the trade team experts with each other. (Interviewee B)

Furthermore, a siloed organization that causes the isolation of marketing from other functions within the organization presented issues for the informants in data-driven marketing procedures. This is also related to the cultural causes that influence the value of different organizational functions. Moreover, in the formation of these problems, half of the interviewees emphasized the importance of common goals once again:

> Marketing should not be a function separate from business, but serve those business goals, but now that these major organizational changes have been made, marketing, in my opinion, still has not redeemed what it really does in this business. A supporting function might be the wrong term, marketing is more of a partner. After all, marketing is everything we do to promote the present and future of this company. (Interviewee B)

> In marketing goals should guide how we budget and what we do, but that is not yet the situation for all our business areas. Since these functions are differentiated, they may not talk to each other. (Interviewee I)

In order to prevent the formation of silos and the isolation of marketing, a few interviewees (B, C, F) made continuous efforts to promote knowledge sharing.

Shared reports and open information sharing seek to clarify and establish the role of marketing in the organization.

> By distributing reports to the entire organization, I'm trying to push that it's not just those sales figures and margins, but the whole chain: that's how much sales came from these clicks from this source. I also import these reports on the intranet so that almost anyone in the business is aware and able to take advantage of these results. (Interviewee C)

80 percent of the interviewees described data linkage and integration of data sets into a common database as an issue created by inflexible organizational structure. A few respondents also saw technological constraints relating to this, but most of the problems were linked to challenges within the organizational structure. The difficulty or impediment to data linking was seen as an important factor in the reliability of the data. According to the respondents, one-sided data is not capable of answering questions in a way that would exhaustively describe the whole picture and provide certainty.

> What we lack currently is getting sets of data to talk to each other. This I think will help in optimizing our marketing and the evolving the data analysis process itself further. So, the next step would be to be able to compare the data with each other and thus better develop data-based marketing. (Interviewee C)

> Here's the challenge, both internally and for our customers: a one-sided data source brings a very one-sided view that can differ significantly from a comprehensive view. That is, dismantling existing silos between different functions in organizations is a prerequisite for truly data-driven thinking. (Interviewee D)

A few of the informants saw steep hierarchies and unavailable top management as a barrier for data-driven marketing. According to the interviewees, if the senior management is structurally “too high up”, their involvement in these vital development processes will become difficult to enable, thus hindering the progress altogether.

4.3.3 Managerial barriers

Top management related barriers discovered in this research were manifold. The way the organization is managed naturally influences all aspects of the business; both the culture of the organization and its structure (Banerjee & Srivastava 2017; Groysberg et al. 2018). Furthermore, due to the strong influence of the leaders, their actions shape the culture and the operating methods of the organization in a way that lasts (Groysberg et al. 2018). Almost all of the informants discussed all of these barriers as highly linked and even partly overlapping. Thus, some issues described in this section might have similarities to the organizational culture and organizational structure chapters, and vice versa. Nevertheless, distinguishing all three problems as separate was found useful for the purpose of this research, as unique solutions to each category were found in the interviews. Furthermore, this categorization and their linked nature is supported by previous research

(Banerjee & Srivastava 2017; Branda et al. 2018; Chaffey & Patron 2012; Deshpandé & Webster 1989; Germann et al. 2013; Kiron et al. 2011; Mezias et al. 2001).

Most interviewees were convinced that top management support is crucial for the successful implementation of data-driven processes. Davenport and Harris (2007) sited collateral ideas, arguing that an analytics strategy requires top management support. Other studies also share this view (Branda et al. 2018; Kiron et al. 2011). Furthermore, according to Kumar et al. (2016), data, technologies and analytics experts need managerial staff to see the benefits of data-driven marketing in order to thrive and enhance data-driven processes across the organization. Similarly, almost all of the interviewees highlighted a desire for a common belief in the benefits of marketing analytics utilization. The perspective of the top management was seen to be of considerable importance by over two-thirds of the informants:

> [Managerial involvement] has to be part of the organization at a strategic level and the management must have the know-how and interest in customer opinions and market development, for example. So, willpower should be driven by leadership so that it can efficiently incorporate into the various functions of the organization. No single corporate hedgehog can push this alone. There are a lot of obstacles out there, at basic hierarchical levels, but this is a bit of a new thing. The companies that understand this will succeed in this. (Interviewee D)

Moreover, even the issues relating to the involvement of management and barriers in this regard for data-driven decision-making highlighted the important role of coherent guidelines and objectives. The interviews revealed problems in communicating the objectives and possible contradictions between management and marketing goals. Also, the inability of management to communicate their marketing objectives had, in some cases, led to the total lack of concrete marketing goals.

> Business leaders may know the goals very precisely, they have set them themselves and know exactly where they are going, but they are not necessarily used to sharing that information with marketing. Then marketing gets those vague briefs, and after the performed marketing actions business leaders ask what the results were. Well, you didn't give us goals so how can we tell you the results? (Interviewee B)

According to the interviews, the involvement of top management in the strategic development, shaping and monitoring of marketing is an important part of the success of data-driven processes. 70 percent of the interviewees argued that if management is not present or interested in marketing or data related to this, marketing has neither the power nor the complete insight to drive change in a sustainable and profitable way. A few interviewees described marketing as a sales partner and as a strategic support function for the company, which requires the presence of involved management to succeed.

> In my opinion, the biggest root cause for not utilizing data-driven marketing is the lack of interest or involvement from the management of the company. For example, we have denied some job offers from potential client companies based on the fact that the board, management team or owners are so disconnected or not interested in marketing. In such cases whoever is in control, is not involved or knowledgeable in data-driven marketing efforts. Thus, while marketing is trying to push data-driven processes forward, nothing is implemented on a higher strategic level and things are not moving forward. Because it lacks that big vision and power of change. (Interviewee D)

Previous research has concluded that if an organization aims to become data-driven, marketing analytics, such as the best tools and data, have to be integrated into the use of the marketing department (Wedel & Kannan 2016). However, these tools require human capital, i.e., knowledge management to generate data-driven processes in the organization in a sustainable way (see Figure 2). Half of the informants mentioned knowledge management oriented top management as a part of data-driven decision-making advancements, with some of them highlighting its role in the progression of data-driven marketing. Thus, according to the insights gathered from the interviews, a lack of knowledge management in the organization's top management might cause a barrier for data-driven processes.

4.3.4 Further perceived barriers of data-driven marketing

The challenges and obstacles identified during the interviews were also found outside of the three-part categorization of organizational culture, structural barriers and top management related barriers. Altogether, three barriers to data-orientation could be identified but not categorized in the framework of this study. A total of five individual interviewees raised these challenges. Lack of knowledge in data utilization was on the issues raised by a few of the informants:

> Of course, sales are only interested in euros, so [marketing analytics] are kind of missing a way in which we could exhaustingly display that, hey that was done, its business impact was this. If we were able to do that, it would certainly increase sales teams' interest in the topic, the data, and how to exploit it. (Interviewee E)

> We are now in a situation where data is being collected from many different sources and places, talking about big data is still in and everyone wants to use Google and Facebook tools and other trendy ones. But when it comes to where and how this data is used, not many people have concrete answers. (Interviewee B)

According to Hauser (2007), an in-depth understanding of statistics, data and databases are central for experts utilizing marketing analytics. Yet, even if the marketing experts themselves are comfortable with the usage of marketing analytics, a lack of the ability of other staff in the organization involved in marketing analytics creates a barrier for effective reporting. Marketing analytics and data-driven processes need to be shared with all the affected functions in the organization for successful deployment, thus, requiring a basic understanding of the reports throughout the organization. Furthermore, one informant saw such lack of understanding presenting additional needs for investing in reporting simplicity:

> I also see the challenge in reporting, especially as to how could it be as comprehensible as possible to anyone? How social media posts combine with newsletters or offline sales and questions like these. Everything is related to everything, but how would I present this. I believe that marketing automation will make this easier too. (Interviewee C)

Technological restrictions to data integration were also mentioned by some of the informants. Moreover, another informant brought up the possibilities that artificial intelligence and marketing automation could bring for data-driven marketing. However, the interviewee saw their own shortcomings in the knowledge of these subjects as a barrier for their utilization, for example, lack of the human capital in marketing analytics usage:

> Analyzes, use of artificial intelligence, in-depth data interpretation and integration, lack of knowledge are definite barriers for data utilization in marketing for us. The use of artificial intelligence is increasingly emphasized, but many are not yet in control of it. Artificial intelligence will certainly make it easier to build analytics and data sets. Demands true familiarity with the subject. It requires tremendous understanding when starting from this level. (Interviewee A)

Despite barriers found outside the categorization, they do present evident conclusions that would invalidate the framework for data-driven barriers utilized in this research. A total of 89 distinct cases for barriers affecting data-driven marketing were identified while interviewing the ten informants. Thus, three irregularities to the categorization brought up by a total of five informants is not grave enough to discard the findings presented within this framework.

4.4 Developing a Capability Maturity Model for data-driven marketing

Regardless of the industry or field, analytics and data have become a necessity for organizational performance and efficient growth, in a similar way that social media and digital marketing disrupted the market over a decade ago (Davenport 2013). Marketing Analytics and related terms such as big data have evolved hype around them, with the likes of Google, IBM and Amazon making major leaps in ways to exploit data (Barton & Court 2012). Still, as stated previously in this thesis, organizations on a larger scale do not know how to move forward with the data they already have (Barton & Court 2012). Based on such needs, this thesis aimed to uncover the current ways in which data is utilized in organizations' marketing departments, and form a Data-driven Marketing Capability Maturity Model from these findings. The findings were established on interview data as well as previous research. Thus, this research was based on the theories as well as the framework of the Capability Maturity Model. Furthermore, barriers for the advancement of data-driven processes in marketing were identified to find corresponding solutions to barriers hindering the successful utilization of data in organizations today. To appropriately and easily coordinate the data-driven marketing maturity Capability Maturity Model into the association, it is important to give clear and unmistakable capacity levels of process maturity that characterize the foreseen abilities of the procedure areas (Mughrabi & Jaeger 2017). The Capability Maturity Model's five-level framework is used in this research as a foundation to interpret the stage of which the marketers interviewed are utilizing marketing analytics. Particular findings were presented in-depth in chapters "4.2 How are marketing professionals utilizing data-driven marketing?" and "4.3. Barriers for data-driven marketing". However, for these findings to be applicable and present value, further development is needed. Managers need tools and frameworks in order to uncover the as-is circumstance of an organization, determine and organize improvement measures, and in this manner control the advancement of their usage (Becker et al. 2009). Maturity models present useful apparatuses for tending to these issues (de Bruin et al. 2005).

Becker et al. (2009) argue that the exponentially growing amount of maturity models suggests the existence of illogicality in their development, which is apparent in, e.g., the lack of documentation on the methodologies utilized in maturity model development. Due to both rapid growth in maturity models and rapid changes in external environments, systematics and transparency in their development are becoming increasingly crucial. Becker et al. (2009) determine in their paper "Developing Maturity Models for IT Management– A Procedure Model and its Application" the following eight steps for successful maturity model development: (1) Comparison with existing maturity models, (2) Iterative Procedure, (3) Evaluation, (4) Multi-methodological Procedure, (5) Identification of Problem Relevance, (6) Problem Definition, (7) Targeted Presentation of Results, and (8) Scientific Documentation. This master's thesis followed this eight-step development procedure, conceptualized by Becker et al. (2009), to ensure systematic and valuable conclusions. This study researched the history of Capability Maturity Models and previous Capability Maturity Models similar to the subject in question, to establish the compatibility of the final model in this research to previous ones. Additionally, this process verified that no indistinguishable models for data-driven marketing process maturity had previously been created. Furthermore, the process pursued a step-by-step approach to the creation of the model, i.e., generating conclusions iteratively. Appropriate academic methodology and documentation were utilized in order to sufficiently evaluate the results and ensure scientific reporting. Additionally, this research resorted to both qualitative data created from professional interviews as well as a literature review; thus, employing a multi-methodological process. Moreover, the problem relevance and definition where presented in the introduction and theoretical framework chapters. Finally, results and analysis were presented in a way, where both managerial and theoretical applications would be possible, thus, the research was constructed, and the results targeted for the purpose of its users.

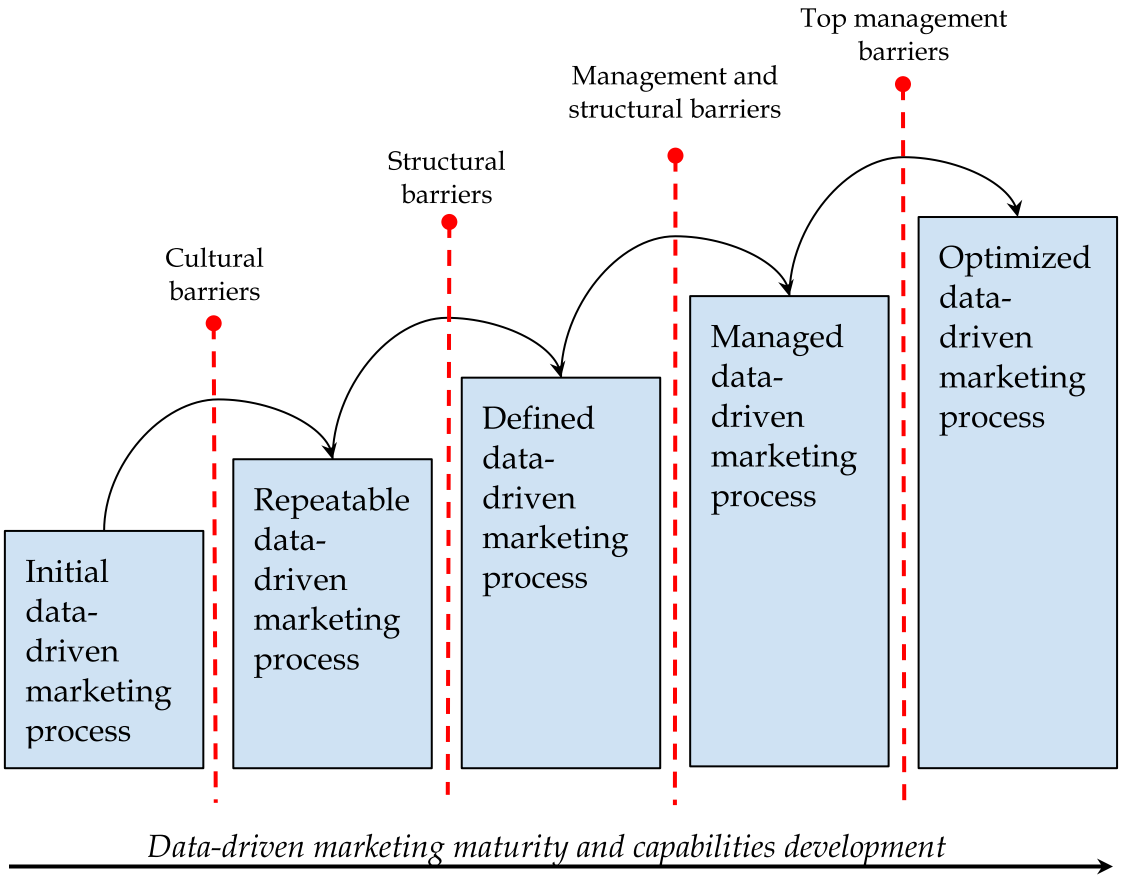

FIGURE 6 Data-driven Marketing Capability Maturity Model

The findings, categorization and results are demonstrated in the Data-driven Marketing Capability Maturity Model (see Figure 6; see Figure 7). The levels were established based on the framework of the Capability Maturity Model as well as ten professional interviews. Furthermore, the perceived barriers, and the advancement from each level to the next, were based on the interviewees' answers on hindrances of data-driven marketing processes. This interview data was combined with information obtained from previous research. The barriers were categorized and linked in between the appropriate data-driven marketing maturity level, based on which part of the process the interviewees felt the specific barrier was preventing. These findings aim to answer a gap in previous research, that has been pointed out by, e.g., Day and Moorman (2016) who called for future research to shed light to the characteristics of effective marketing capabilities. Furthermore, the researchers have argued that the constant "buzz" around big data is pushing the marketers towards active marketing analytics utilization, as this needs to be a central part of the marketing department's decision-making. The findings of this research have been simplified into a visual form, which is presented in Figure 6. In Figure 7, a more exhaustive description of the findings is provided.

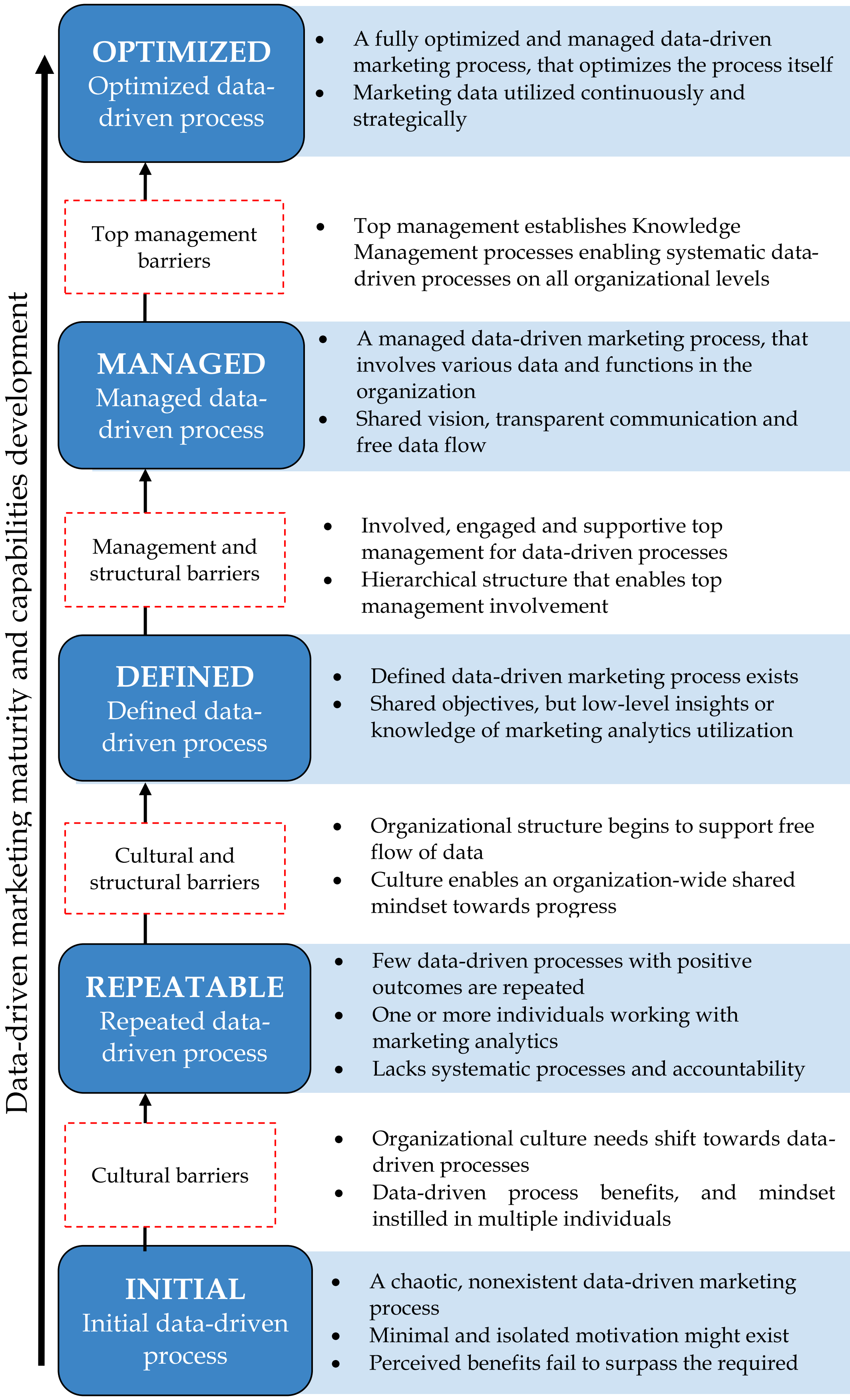

FIGURE 7 Data-driven Marketing Capability Maturity Model in-depth explanation

Though the presentation of the data-driven marketing process (see Figure 6; see Figure 7) is described in this master's thesis in a simplified, hierarchical order, according to the research findings both the development and barriers thereof are intertwined and, in many cases, overlap each other. Thus, this framework should be viewed critically due to its streamlined nature. Nevertheless, a simple presentation of complex entities is common in qualitative research and is presented as one of its strong points for, e.g., business and technology research (Wenzel et al. 2015). This study aims to describe an intricate concept in an understandable way instead of providing conclusions that can be generalized across environments and cultural settings. Moreover, this kind of streamlining is a prerequisite for understanding multilevel and shaped patterns and frameworks to advance thinking and theories in a sufficient yet productive manner.

5 DISCUSSION AND CONCLUSIONS

5.1 The theoretical contribution of the research

This research aimed to shed light on the data-driven marketing capabilities and barriers of today. As discussed in the first and second chapter, comprehensive research on this subject had previously not been done, despite a constant buzz and voiced mindset for the development of data-driven marketing in practice and theory (Chaffey & Patron 2012; Day & Moorman 2016; Erevelles et al. 2016; Jobs et al. 2016; Verhoef et al. 2016; Wedel & Kannan 2016). Moreover, the lack of previous studies in data-driven marketing, despite the expressed need for such research, precipitated this master's thesis. Hence, another purpose of this study was to advance the thinking and theory behind data-driven marketing processes, that could create future advancements on the subject.

The main theoretical contribution of this study is the framework for evaluating the data-driven marketing capability and maturity of an organization, both through the current state and in ways of exploring possible barriers of development. This master's thesis established a foundation for a basic Capability Maturity Model for data-driven marketing that can be used to improve data-driven marketing processes in organizations. The Capability Maturity Model created used and extended the continuous improvement representation that was shown in the CMM (Humphrey 1988; Paulk et al. 1993). This thesis identified characteristics through the interviews for each level of the model: initial, repeatable, defined, managed and optimized. Theory development can be evaluated through to criteria when looking at the extent to which the needed factors are included: comprehensiveness and parsimony (Hueske & Guenther 2018; Whetten 1989). These determine whether all significant elements have been taken into account in the theory, and whether their elements that do not add significant value to the theory are included into it (Hueske & Guenther 2018; Whetten 1989). In this study, an exhausting literature review combined with ten professional interviews aimed to minimize issues with the described criteria. Hence, the conceptualized theory should include all meaningful elements, but not more than those required.

Additionally, in this master's thesis, the focus was on the perceived barriers of data-driven marketing, which provided another previously lacking theoretical contribution. The study categorized these barriers in three categories: organizational culture barriers, organizational structure barriers and top management barriers. The framework of data-driven marketing barriers was formed based on previous research (see Figure 5), aiming to meet the same criteria of exhausting theory-development (Hueske & Guenther 2018; Whetten 1989).

Another factor in theory-development is determining the relation between concepts (Whetten 1989). Such a stage adds the request to the conceptualization by expressly portraying patterns in findings (Whetten 1989). Furthermore, this thesis aimed to introduce causality between the two frameworks by combining them. Hence, analyzing and combining the perceived barriers of data-driven processes in the marketing department, with the findings of the five-level Capability Maturity Model for data-driven marketing was central in this research. Through reflection on past research, this study conceptualized an exhausting foundation for a Capability Maturity Model for data-driven marketing. Even though this study is not able to provide a further examination to the linkage in the created theory, these limits to the methodology in a master's thesis do not to refute the intrinsic causal nature of the hypothesis (Whetten 1989).

5.2 Managerial implications

According to research, a case study research is particularly helpful when researchers want to answer questions of how or why things work in real-life contexts (Yin 1994). Hypothesis created from cases may assist with comprehending the intricate connections that underline marketing analytics and data-driven marketing and clarify why endeavors to improve such processes prevail in certain conditions, however not in others. Hence, this study aims to answer both the how data-driven marketing procedures are currently utilized, as well as the why and how such procedures are hindered. In short, the purpose of the current study was to discover the current state as well as barriers to data-driven marketing processes. The relevancy of this subject could be seen as important due to it being a well-known and general gap in both research and practice. Hence, the managerial implications of this study are manifold.

Findings in this study imply that despite individual motivations towards a more data-driven marketing process, at least a partial organizational culture shift is needed in order to generate advancements in data-driven marketing and decision-making (see Figure 6). Moreover, the perceived benefits of data-driven marketing processes have to surpass the resources required to establish these processes. Thus, multiple staff members in the organization have to see the benefits of marketing analytics and strive towards analytical thinking methods for progress to be made. Moreover, resources put into analytics progression has to be perceived as justified by other functions and personnel in the organization. Otherwise, if this is not the case, developing data-driven marketing will not last long, when the urgency that is seen as more important in the daily life of an organization quickly displaces marketing resources elsewhere. Only if the potential and the effectiveness of the result of the development are identified can data-driven marketing be replicated. Repeated marketing processes are nonetheless merely repeated, and no systematics exists. The benefits of data-driven marketing and decision-making can be recognized within the organization, and resources spent on developing marketing analytics are no longer seen as a negative input-output ratio. Positive outcomes from these processes enable further investments in data-driven marketing. Furthermore, through repetition and with time, the data-driven marketing processes naturally gain systematics and become more defined. However, time and repetition are not sufficient for gaining the required systematics for the defined level of the data-driven marketing processes. According to the findings, the free flow of data enabled by a positive combination of sharing organizational culture as well as a structure that enables such are needed. The findings in this study suggest, that on the defined level of the Data-driven Marketing Capability Maturity Model the organization has established minimal project management for data processes in marketing. The main difference on this level is the shared objectives. Thus, at the defined level of data-driven marketing, both the benefits and the goals of the process are now commonly understood and shared.

As processes and systematics evolve, and in the light of common goals, leading processes are beginning to grow into data-driven marketing processes. According to this study, at the managed level of the management of the organization is opening up to the possibilities of data-driven marketing. Thus, the management is starting to get involved and enabling more resources to be invested in the development. For very large and multi-level companies, this may only mean middle management. Accordingly, for smaller companies with fewer tiers, top management is already involved in the process on the managed level. Nevertheless, when the organization progress towards the optimized level of data-driven marketing maturities and capabilities, top management involvement is required. According to the findings, the optimized level advances to a complete utilization and integration of the data-driven marketing processes. The process is optimized, and its benefits are acknowledged and utilized across the organization.

It was found that in order to build up an advanced marketing strategy in the digital sphere that expands the commitment of marketing analytics to organizations requires cautious thought of the goals of the marketing department. Objectives need to be exhaustingly conceptualized and defined. Furthermore, these objectives have to be clearly communicated to the whole organization in order to clarify the role of marketing amongst other functions. Moreover, this will help the development of a common culture and language, when talking about data-driven marketing, which will advance the breaking of silos in the organization. An involve top management in the data-driven marketing process is crucial and benefits the marketing department to sufficiently report on the results of the data-driven marketing processes. Additionally, the reasonable beginning stage is to audit how the potential incentive from applying marketing analytics adds to businesses competitive advantage, and afterwards contrast this with current capacities and worth created.

The findings of this study point out, combined with findings from previous research, that organizational culture is the main driver for data-driven marketing change in the organization. It was mentioned most often as well as its gravity highlighted the most by the informants in the current research. However, organizations are complex entities, where multiple actions and functions affect each other. Thus, even though organizational culture emerged as the most important and powerful barrier to data-driven marketing, taking into account the roles of both organizational culture as well as the top management is central when identifying barriers for data-driven marketing processes.

5.3 Evaluation of the study

The credibility of the study must be recognized when conducting and evaluating research. This can be especially ambiguous in the case of interview research due to its subjective nature. Both reliability and validity are questionable concepts in this case. In order to assess the current research, its philosophical approach should be taken into consideration. This qualitative research aims to describe a real-life phenomenon, data-driven marketing processes, and its concepts in the most accurate way possible. The depth and intimacy of the interview process enabled a conversational setting which enabled thorough analysis of the results. However, studies have stated that the researcher's perspectives and presumptions affect the problem stating, execution, data collection and analysis of the study (Carson et al. 2001, 20). Furthermore, as this thesis is limited to ten interviews in the Finnish region, it does lose dimension and cannot be applied linearly to a different environment. The current research conducted interpretive techniques, such as thematization, coding and in-depth analysis to provide a solid theoretical basis despite its subjectivity. Nonetheless, this qualitative research attempts to provide a basis for data-driven marketing processes research through a more in-depth look into the topic, instead of presenting generalizable results. Such conclusions might be unattainable to execute with quantitative methods (Petrescu & Lauer 2017). Carson et al. (2001, 68─69) argues that a qualitative research method is applicable in circumstances where the research aims to develop a more in-depth understanding of a subject that has not previously been comprehensively studied. Hence, the philosophical approach of this research justifies the subjectivity of its means.

According to Hirsijärvi et al. (2008) solid research is a procedure that can be reproduced and while doing so, comparative outcomes ought to be gotten. Since the theoretical framework and methodology are laid out in full, the research could, in theory, be repeated. Furthermore, theoretical sampling was utilized in order to gain the most insight to the research question. This can be viewed as an advantage as well as a disadvantage to the credibility of this research. Hence, as the purposefully chosen respondents are able to give more insight to the research questions, the research may lack in representativeness. The current study aimed to minimize this issue by deliberately including a large variety of company sizes and lifecycles. Nevertheless, the issue still exists, partly due to theoretical sampling and partly due to the small sample constraint set by the limitations of a master's thesis. Hence, the small sample of informants presents another restraint

The model developed was based on a literature review and the perspectives of ten interviewees whose answers were affected by the needs and requirements of the organization in questions. Variances in cultural and other environmental factors, as well as the organizational goals, may call for readjustments to this model for it to provide valuable insights in variating settings. Likewise, as Mughrabi and Jaeger (2017) highlight for their PBLCMM, the model needs to be researched further, so that empirical confirmation can be established. This could have been achieved by involving more informants that would lead to more contextual analysis.

The barriers of data-driven marketing described in the current research were viewed based on a specific categorization (see Figure 2; see Figure 5). Hence, the possibility exists that, if this framework would be expanded or replaced, the discovered barriers additional or even contradicting barriers might be discovered. Similarly, through the choice of a different argumentative ground instead of the Capability Maturity Model, the current state of data-driven marketing processes might appear in a very different light. However, this research tried to actively reduce the impact of such changes on results by investing in the quality of documentation and an exhausting literature review. Nonetheless, this research leaves room for further epistemological substantiation, which cannot be achieved within the scope of a master's thesis research.

5.4 Recommendations for future research

This research is limited to the views of ten participants from the Finnish region. Hence, further studies on the subject would benefit from a more significant number of participants. Additionally, since this research is limited to Finnish participants, local cultural factors and possible background influences may apply. Such consideration was not taken into account further in this study, but their existence is acknowledged and highlighted as part of the study's limitations. Having participants from varying geographical, social and cultural environments would bring dimension to future studies in the matter. Along these lines, further examinations should test the Data-driven Marketing Capability Maturity Model created here with the goal that the model can be summed up and used to benchmark DMCMM capacities across different associations.

Moreover, gaining more knowledge of the specific capabilities linked to data-driven marketing would help establish a more robust base for future data-driven decision-making studies done in the marketing field. Day and Moorman (2016) expressed similar wishes for future research, as they urged researchers to study new capabilities and to discover and define other important new marketing capabilities that will probably emerge during this decade. Additionally, a more hands-on approach towards this subject in research context might prompt a more straightforward approach to the transition from research to practice. Thus, future research that would aim to provide more concrete examples on how to become a data-driven marketing professional, might influence and accelerate data-driven process adaptation by marketing professionals.

In the future, the possibility prevails that at some point, all marketers will have to adapt data and insights in their work. If this becomes a reality, maybe what will end up being the essential issue of separation is flightiness. Cukier and Mayer-Schoenberger (2013) describe this as the human component of intuition, risk-taking, mishaps, and probable blunder. Provided that this is true, at that point, there will be an exceptional need to cut out a spot for the human: to save space for instinct, good judgment, and luck to guarantee that they are not packed out by information and solutions generated by computers (Cukier & Mayer-Schoenberger 2013). Taking this into account, further studies into the importance (or lack of importance) of the human factor could be a potential research area. Conceptualizing the role and the influence of the human factor in data-driven decision-making is an essential research topic, especially since sophisticated and automated modeling continually evolves.

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APPENDIXES

APPENDIX 1 Interview structure

Warm up question

1. Who are you and where do you work?
2. What is your current role and main tasks?
3. How long have you worked in your current position?

Stating the current situation

4. What is the role of marketing in Your organization?
5. What are the main goals of marketing? Why?
6. What role do digital channels play in Your overall marketing strategy?
7. What are the most important activities of Your digital marketing efforts?
8. How do you measure marketing success?
9. What tools do you currently use to measure marketing efforts?
10. How does the measurement of marketing efforts affect the company performance? Why? Why not?
11. How do you optimize marketing effort based on data?
12. How do you utilize data in your decision-making process?
13. What sort of reporting do your process from marketing analytics and how often does such reporting happen?
14. Do other entities in your company utilize analytics for decision-making processes? If so, which ones and in what way?
15. What analysis, if any, do you outsource? Why? Why not?

Possibilities and barriers of marketing analytics

16. How was the set up for marketing analytics processes first established in Your organization?
17. When measuring and optimizing marketing performance, what do you find easy to quantify and understand? Why?
18. When measuring and optimizing marketing performance, what do you find challenging to quantify and understand? Why?
19. What marketing processes are not yet measured in your company?
20. What is hindering the quantifying of such resources and processes?

Ending questions

21. Was there anything else you would like to highlight that hasn't yet come up regarding your company's marketing analytics and data utilization?

APPENDIX 2 Invitation message to interviewees

Dear [recipient name],

This message was sent to remind you about our interview [interview time and date]. The interview will take around half an hour to complete. There are a few other things I would like to bring up prior to our meeting in order to make our time as efficient as possible.

Those points are:

- If appropriate, the interview will be recorded for myself, so that I am able to effectively get all points of the interview in the transcription phase. The audio recording of the interview will not be shared and will be deleted when the survey is complete. The names or companies of the interviewees are not listed in the master's thesis to ensure privacy of the interviewees.
- The purpose of this master's thesis for Digital Marketing and Corporate Communication is to examine the current state of the ways that organizations are utilizing marketing data, and thereby provide an indication of how and why this could and should be further developed.
- When the master's thesis is completed next spring, in addition to the finished product I will provide all companies with a small consultative recommendation on why, where and how marketing analytics can be developed in a towards a more strategic direction in their specific context, based on my research. The intention is that these recommendations could be of concrete benefit to companies.

Otherwise all is set. See you [interview time and date].

Thank you in advance for your contribution to my master's thesis.

Best regards,
Heidi Länsipuro
Digital Marketing and Corporate Communication student
Master's thesis worker at University of Jyväskylä, Finland