THE ROLE OF BIG DATA AND CAPABILITIES IN MARKETING COMMUNICATION: MANAGERIAL PERSPECTIVES ON DATA-DRIVEN DECISION-MAKING

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ABSTRACT

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The role of data in companies has been growing rapidly and marketing communication departments have access to various data sources. There is an increasing need to view business problems from a data perspective and companies are investing in data and analytics. However, marketing communication departments are struggling with data utilization and most of the big data initiatives fail due to lack of capabilities. Thus, examining the relationship between big data, data-driven decision-making and organizational capabilities is a current and important research topic.

The objective of the study is to examine how marketing communication departments use big data in data-driven decision-making and what kind of organizational capabilities it requires. The study was conducted by using qualitative research methods, and thematic analysis was applied to identify meaningful patterns from the data and draw conclusions. The focus of the study is on managerial perspectives, which was achieved by purposeful sampling and conducting nine semi-structured interviews with managers, head of marketing and communication departments and entrepreneurs who worked closely with data-driven initiatives and approaches.

The findings indicate that marketing communication departments have started to build data warehouses where they import and combine data from different sources in order to produce insights for decision-making. The study identified strategic, operative and process-related benefits of big data utilization while the challenges concern data dimensions, company's capabilities and privacy. The findings also point out what kind of organizational capabilities are required in each step of the data-driven decision-making process. Moreover, the results indicate what dynamic capabilities are in practice from marketing communication perspective and how companies can sense and seize opportunities as well as transform their capabilities in dynamic industries.

Altogether the study contributes to the knowledge of data-driven decision-making by adding big data perspective and dynamic capabilities into the process. The framework created from the main results clarifies the data-driven decision-making process by explaining what kind of data sources marketing communications departments collect, how they analyze data with different tools and apply insights in decision-making.

Keywords
Data-driven decision-making, Big data, Analytics, Organizational capabilities, Dynamic capabilities

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Datan rooli yrityksissä on kasvanut nopeasti ja erityisesti markkinointiviestinnän osastoilla on pääsy useisiin eri datalähteisiin. Yritysten liiketoimintoja tarkastellaan yhä useammin datan näkökulmasta ja investoinnit sekä dataan että analytiikkaan ovatkin kasvussa. Markkinointiviestinnän osastot kuitenkin kamppailevat datan hyödyntämisen kanssa ja valtaosa massadata (engl. big data) -aloitteista epäonnistuu riittämättömien kyvykkyyksien vuoksi. Tästä johtuen massadatan, dataohjatun päätöksenteon ja organisaation kyvykkyyksien välisen suhteen tarkastelu on ajankohtainen ja tärkeä tutkimusaihe.

Tämän tutkimuksen tavoitteena on selvittää, miten markkinointiviestinnän osastot käyttävät big dataa dataohjatussa päätöksenteossa ja millaisia organisaation kyvykkyyksiä se vaatii. Tutkimus toteutettiin kvalitatiivisilla tutkimusmenetelmillä ja teema-analyysiä hyödynnettiin tulosten analysoinnissa sekä johtopäätöksien luomisessa. Tutkimuksen painopiste on johdon näkökulmissa ja tämä saavutettiin roolipohjaisella otannalla sekä toteuttamalla yhdeksän puolistrukturoitua haastattelua päälliköiden, markkinointi- ja viestintäosaston johtajien sekä yrittäjien kanssa, jotka työskentelevät tiiviisti datan parissa.

Tulokset osoittavat, että markkinointiviestinnän osastot ovat alkaneet rakentaa datavarastoja, joihin ne tuovat ja yhdistävät dataa eri lähteistä tuottaakseen oivalluksia päätöksentekoon. Tutkimuksessa tunnistettiin massadatan strategisia, operatiivisia ja prosessiin liittyviä hyötyjä, kun taas haasteet liittyvät datan eri ulottuvuuksiin, yrityksen kyvykkyyksiin sekä yksityisyyteen. Tulokset myös selventävät millaisia organisaation kyvykkyyksiä tarvitaan dataohjatussa päätöksenteko prosessissa. Lisäksi tulokset osoittavat, mitä dynaamiset kyvyt tarkoittavat käytännössä markkinointiviestinnän näkökulmasta ja kuinka yritykset voivat tunnistaa ja hyödyntää mahdollisuuksia sekä muuttaa kyvykkyyksiään dynaamisilla toimialoilla.

Kaikkiaan tutkimus laajentaa olemassa olevaa viitekehystä dataohjatusta päätöksenteosta lisäämällä prosessiin massadata -näkökulman ja dynaamiset kyvykkyydet. Päätuloksista muodostettu viitekehys kehittää dataohjattua päätöksenteko prosessia tunnistamalla, millaisia datalähteitä markkinointiviestinnän osastot keräävät, miten dataa analysoidaan erilaisilla työkaluilla ja kuinka oivalluksia käytetään päätöksenteossa.

Asiasanat
Dataohjattu päätöksenteko, Massadata, Analytiikka, Organisaation kyvykkyydet, Dynaamiset kyvykkyydet

Säilytyspaikka
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1 INTRODUCTION

1.1 Research background

The amount of business data has been growing exponentially over the last decade due to advances in information and communication technology (ICT) (Chen, Chiang & Storey, 2012; Wang & Wang, 2020). Technological advances have made data collection less expensive while the growing number of analytics tools allows companies to take advantage of available information, which has driven companies to become increasingly customer-centric (Sleep, Hulland & Gooner, 2019). The growing amount of large and fast-moving data sources, which are often real-time and unstructured by nature, are often described by the term big data (Davenport, 2013; Fan, Lau & Zhao, 2015; McAfee & Brynjolfsson, 2012). Increasing interest towards big data is largely explained by its suitability for data-driven decision-making, business strategies (Barton & Court, 2012; Manyika et al., 2011; Sleep et al., 2019) and business value (Benoit, Lessmann & Verbeke, 2020). Big data has the potential to transform business processes and change the dynamics of competitive environment (Fosso Wamba, Akter, Edwards, Chopin & Gnanzou, 2015).

Especially marketing communication departments face high expectations of big data (Benoit et al., 2020; Gnizy, 2020). This is because marketing communication departments have access to large volumes and varieties of data (Johnson, Muzellec, Sihi & Zahay, 2019; Sleep et al., 2019), and these functions have traditionally been under pressure to demonstrate its value to top management (Court, Perrey, McGuire, Gordon & Spillecke, 2015). The rapid growth of user-driven technological changes has generated sophisticated customers, which changes the structure and content of marketing jobs (Germann, Lilien & Rangaswamy, 2013). Furthermore, the adoption of digital technologies has expanded the scope of marketing functions beyond advertising into an increasingly holistic, customer-centric and analytics-driven actions (Shah & Murthi, 2021). The growing amount of data and analytics possibilities has made marketing more a science than an art (Shah & Murthi, 2021). Marketing communication departments must convince to top management, why they should be invested in by driving growth, reducing costs and streamlining operations (Court et al., 2015).

There is an increasing need to view business problems from a data perspective and apply analytical thinking in daily business operations throughout the whole organization (Fitzgerald, 2015; Provost & Fawcett, 2013). While collecting data is important, companies also need tools and ways to analyze, understand and utilize the data (Erevelles, Fukawa & Swayne, 2016; Mikalef, Krogstie, Pappas & Pavlou, 2020). Big data enables more proactive and predictive approach to decision-making instead of reactively looking at the historical data (Cao, Duan & Banna, 2019; Erevelles et al., 2016; Sleep et al., 2019). The growth of data creates opportunities for marketing communication professionals to be an early adopter and forerunner of big data within the company (Johnson et al., 2019). If companies are able to proactively derive insights from detailed data, strategic decision-making is likely to improve (Davenport, 2014). In addition, rich and detailed data advances the understanding of marketing phenomena (Erevelles et al., 2016).

1.2 Problem setting and research questions

There is a lack of qualitative and B2B research linking big data, decision-making and organizational capabilities (Cao, Tian & Blankson, 2021). The focus of existing studies has mostly been on technological aspects (Mikalef, Pappas, Krogstie & Giannakos, 2018; Sleep et al., 2019) of data-driven decision-making and big data in B2C context (Troisi, Maione, Grimaldi & Loia, 2020). Further understanding should be developed on how big data analytics can reframe traditional marketing decision-making at a data-driven and strategic level (Troisi et al., 2020).

Current business literature of big data implies that all companies should be data-driven and adopt large volumes of data for decision-making (Sleep et al., 2019). Existing studies also suggest that the use of big data is quite massive and complex process (Erevelles et al., 2016) where companies need to build and invest in IT-infrastructures and skilled employees such as data scientists and business translators. However, less attention has been focused on managerial views of data-driven decision-making and best practices of how companies can truly become data-driven (Johnson et al., 2019).

It is unclear how data and business analytics can be used to improve decision-making and increase the competitiveness of a company (Cao et al., 2019; Suoniemi, Meyer-Waarden, Munzel, Zablah & Straub, 2020; Wedel & Kannan, 2016). Many studies provide correlational relationships but not causal evidence of how the use of data and analytics affect the company performance (Germann et al., 2013). There is a dearth of empirical knowledge on the business value of big data (Benoit et al., 2020; Fosso Wamba et al., 2015; Mikalef et al., 2020; Mikalef et al., 2018). In addition, it is not clear to what extent companies make marketing communication decisions and actions based on insights produced by big data (Erevelles et al., 2016; Mikalef et al., 2020). Therefore, a knowledge base should be increased on data-driven decision-making practices as well as challenges and opportunities (Grandhi, Patwa & Saleem, 2020). Researchers should identify and document use cases that explain how companies can use big data to support decision-making (Jeble, Kumari & Patil, 2018; Mikalef et al., 2020; Power, 2014).

The role of data in business will continue to grow and companies that succeed in leveraging data in decision-making will outperform others (Bean & Davenport, 2019). Improved use of data can help companies to generate more value for customers (Grandhi et al., 2020), however, currently most of the big data initiatives fail (Cao et al., 2021) and marketing communication departments often lack the expertise of how to utilize big data in decision-making (Sleep et al., 2019). The amount of data is considered somewhat overwhelming among marketers

(Branda, Lala & Gopalakrishna, 2018) and there is a clear gap between marketing capabilities and expectations (Day, 2011).

While several studies showcase the positive business effects of using big data (Ferraris, Mazzoleni, Devalle & Couturier, 2019; Cao et al., 2021; Court et al., 2015; Gnizy, 2020; Manyika et al., 2011), other studies demonstrate the challenges faced by companies (Barton & Court, 2012; De Luca, Herhasen, Troilo & Rossi, 2020; Johnson et al., 2019; McAfee & Brynjolfsson, 2012; Sleep et al., 2019; Troisi et al., 2020). In addition, some studies emphasize the role of company's culture (Bean & Davenport, 2019; Johnson et al., 2019; McAfee & Brynjolfsson, 2012) and state that incorporating data in decision-making is a management challenge (Davenport, 2014; Fitzgerald, 2015; Fosso Wamba et al., 2015). Evidently, big data brings both opportunities and promising new dimensions as well as challenges for companies in all levels and departments. Therefore, companies should focus on how data can provide value in their business (Davenport, 2013; Fan et al., 2015; Eletter, Yasmin & El Refae, 2019).

What the existing research has not profoundly studied is that how managers perceive the role of big data in marketing communication, how big data is used in data-driven decision-making and what kind of organizational capabilities it requires. Both practice and scholarly research urges for more information and knowledge into the gap between big data, decision-making and organizational capabilities. Hence, the objective of this research is to find out what kind of role big data have in marketing communication decision-making. Additionally, this thesis aims to discover what kind of organizational capabilities are needed in order to utilize data in decision-making. The focus of this work is on managerial perspectives of both B2B and B2C marketing communication departments.

Thus, the following research questions were created:

- How marketing communication departments use big data in data-driven decision-making?
- What kind of organizational capabilities are required in order to utilize data in decision-making?

1.3 Methodology and research structure

This thesis adopts a qualitative research method to address the research questions because vast majority of previous studies related to big data and marketing communication have used quantitative approaches. Therefore, qualitative research can add value by creating a unique understanding of the topic, which would be difficult to collect with a quantitative survey. Nine semi-structured interviews were conducted during 2/2022 – 3/2022. Interviewees were managers, head of marketing and communication departments and entrepreneurs from large companies from different industries including both B2B and B2C sectors.

Interviews were transcribed and data analysis was done by applying thematic analysis through the lens of theoretical framework and research questions.

The study contributes to existing research by extending the existing framework of data-driven decision-making (Tabesh, Mousavidin & Hasani, 2019) by adding big data perspective and dynamic capabilities into the process. Dynamic capabilities were chosen for the theoretical framework because the existing research has demonstrated its connection to big data (Cao et al., 2021; Erevelles et al., 2016; Johnson et al., 2019; Mikalef et al., 2020; van Rijmenam, Erekhinskaya, Schweitzer & Williams, 2019). The main results of the study develop the data-driven decision-making process and help managers to understand what kind of data sources marketing communication departments can collect, what kind of analytical tools can be used, how data can be analyzed and what kind of decisions can be made based on analyzed data.

The research consists of five main chapters illustrated in Figure 1. The second chapter introduces key concepts, existing literature review and theoretical framework used in the study. The third chapter presents the study method, data collection and data analysis. The fourth chapter reports the main results and findings of the study. The fifth and last chapter draws theoretical contributions and managerial implications from the results as well as presents limitations of the study and provides recommendations for future research.

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FIGURE 1 Structure of the study

2 LITERATURE REVIEW

This chapter introduces the key concepts that have been identified as imperative parts of the study. First, the definitions of data-driven decision-making, big data and analytics are provided in order to achieve a comprehensive understanding of the topic. In addition, related concepts are explained that are used in similar studies. This is followed by an introduction of the organizational capabilities. Finally, theoretical framework of the study is presented.

2.1 Key concepts

2.1.1 Data-driven decision-making

According to Brynjolfsson, Hitt & Kim (2011, p. 5), data-driven decision-making "captures business practices surrounding the collection and analysis of external and internal data". The definition of Brynjolfsson et al. (2011) acknowledges data-driven decision-making as an ideology and strategic resource, which emphasizes the role of leadership in fostering a data-driven culture (Troisi et al., 2020). In general, decision-making is connected and integrated in all levels of management functions, therefore, the managers ability to make decisions is critical for the success of the company (Intezari & Gressel, 2016).

Similar term to data-driven decision-making is data-driven marketing, which refers to data collection from variety of channels and analyzing the data in order to identify patterns that can be used in marketing decision-making and strategy (Grandhi et al., 2020). However, this research applies the term data-driven decision-making because it views the topic more from a process perspective highlighting the decision-making process itself and how decisions are made. Therefore, it is not limited to how data is used in marketing.

This study adopts a definition made by Provost & Fawcett (2013, p. 53), which defines data-driven decision-making as a "practice of basing decisions on the analysis of data rather than purely on intuition". This definition is relevant to this work because it emphasizes the need to justify and support decisions with data and evidence. In addition, the definition considers the different dimensions of data and the role of analysis in decision-making process. Moreover, it highlights that evidence-based decision-making is a strategic approach for business decisions (Provost & Fawcett, 2013). The definition also includes the assumption that data should be used as a foundation of decision-making instead of intuition or experience.

One of the driving forces behind data-driven decision-making is the need to demonstrate the accountability of actions and link outputs with company's overall goals (Shah & Murthi, 2021). This is especially relevant and topical in modern marketing communication departments (Johnson et al., 2019). Data-driven applications are also strongly associated with digitalization and enabled by new digital technologies (Shah & Murthi, 2021). Therefore, data-based decision-making is applied under constantly changing environments, which requires certain capabilities and skills from the organizations.

2.1.2 Big data

Big data is usually described as large quantity (Agrawal 2014), volume (Grandhi et al., 2020) and size (Carillo, Galy, Guthrie & Vanhems, 2019; Davenport, 2014; Manyika et al., 2011) of structured and unstructured data emphasizing the latter (Agrawal 2014; Chen et al., 2012; Weinberg, Davis & Berger, 2013). The nature of big data is usually complex (Agrawal 2014; Carillo et al., 2019; Chen et al., 2012) including real-time data (Agrawal 2014) from variety of sources (Chen et al., 2012; Weinberg et al., 2013). Boyd & Crawford (2012, p. 663) defined big data "as a cultural, technological, and scholarly phenomenon", which is based on the interaction of technology, analysis and mythology. This definition is not so much about the size of the data than it is about the ability to search, compile and compare large sets of data (Boyd & Crawford, 2012). Also, Bumblauskas, Nold & Bumblauskas (2017) stated that big data should not be defined solely based on the actual size and scope of the data, rather it should be integrated around the analysis and organization's ability to use those insights in decision-making.

Big data is a trendy concept (Rejeb, Rejeb & Keogh, 2020) and many existing definitions especially from information technology perspective emphasize the technological aspects of data (Rejeb et al., 2020; Weinberg et al., 2013). However, Power (2014) states that big data is a marketing term and Weinberg et al. (2013) adds that marketing departments should view big data from a managerial and decision-making perspective.

Laney (2001) introduced 3 V's of big data, namely, volume, variety and velocity, which has been adopted commonly as a definition of big data (Cao et al., 2021; Chen et al., 2012; Fan et al., 2015; McAfee & Brynjolfsson, 2012; Manyika et al., 2011). Recently two other V's, veracity and value, have been added to the definition. These 5 V's refer to the dimensions and characteristics of big data (Ferraris et al., 2019; Fosso Wamba et al., 2015; Gnizy, 2020; Song & Zhu, 2016; Wedel & Kannan, 2016):

1. Volume (refers to the size, amount and quantity of data from terabytes to petabytes)
2. Variety (refers to the sources, formats, types and diversity of data)
3. Velocity (refers to the speed, flow and frequency of data e.g. streaming)
4. Veracity (refers to the quality, reliability, validity, accuracy and uncertainty of data)
5. Value (refers to the economic benefits and business view of big data, linked to decision-making capabilities)

According to Wedel & Kannan (2016), the volume and velocity of data are important from a technical and computing point of view, variety and veracity are important from analytics perspective while value of data is important from business standpoint.

Since this research focus on how marketing communication departments perceive and use big data in decision-making, and all the 5V's are relevant for marketing communication departments, the definition of big data should not be defined too narrowly. Therefore, this study embraces big data as a combination of presented 5V's, which considers the different dimensions of big data such as its unstructured and real-time nature, large size, different sources and formats as well as business value.

Driving forces of big data include social media, social networks, websites, online communities (Ferraris et al., 2019; Wang & Wang, 2020), e-commerce, online transactions, the growth of analytics (Agrawal, 2014), programmatic advertising (Johnson et al., 2019), IOT devices, applications, (Suoniemi et al., 2020; Wang & Wang, 2020), customer databases such as CRM and ERP (Agrawal, 2014; Brynjolfsson et al., 2011), sensor data and GPS signals from smartphones and smartwatches (Bumblauskas et al., 2017; Ferraris et al., 2019; Mikalef et al., 2018).

Big data is often associated with proactive, predictive and strategic approach of business decisions (Cao et al., 2019; Sleep et al., 2019). Big data can be used for multiple business purposes such as customer satisfaction, segmentation, competitive intelligence and supply chains (Court et al., 2015; Davenport, 2014). It can also be applied in forecasting trends like sales, revenues, production (Bumblauskas et al., 2017) and customer churn as well as personalization (Benoit et al., 2020), pricing, text mining and product development (Johnson et al., 2019). In addition, big data can be harnessed to examine customer needs and correlations such as do consumers who buy product X tend to buy product Y. For instance, Netflix uses big data to recommend movies and series to its customers while banking industry uses big data to recognize fraudulent transactions (Agrawal, 2014).

2.1.3 Analytics

In general, analytics can be divided into descriptive, predictive and prescriptive approaches (Jeble et al., 2015; van Rijmenam et al., 2019; Wedel & Kannan, 2016). Descriptive analytics focus on historical events and describes what has happened in the past (van Rijmenam et al., 2019; Wedel & Kannan, 2016) while predictive analytics seeks to answer the question what will probably happen in the future (Intezari & Gressel, 2016; Wedel & Kannan, 2016). Prescriptive analytics takes a step further towards advanced analytics and aim to discover what should happen in the future (Intezari & Gressel, 2016; Wedel & Kannan, 2016).

From business perspective, analytics is closely connected to the use of data. Companies need ways to utilize analytics in order to leverage big data in decision-making (Cao et al., 2021). As Day (2011, p. 28) stated: "Big data without analytics is just a massive amount of data. At the same time, analytics without big data are simply mathematical and statistical tools and applications". According to Agrawal (2014), analytics enables and harnesses the true power of data, which are information and knowledge. The study made by Cao et al. (2021) suggested that companies should view and use big data and marketing analytics together in order to maximize the potential business value. Following table (Table 1) describes similar concepts which are relevant to this work.

TABLE 1 Definitions of corresponding concepts

Concept	**Definition**
Big data analytics	Big data analytics (BDA) is a comprehensive approach to manage, process and analyze the different characteristics (5V's) of big data (Fosso Wamba et al., 2015, Bumblauskas et al., 2017). BDA refers to the technologies used to create understanding of useful interpretations about customers, competitors and environment (Johnson et al., 2019). Chen et al. (2012) and Ferraris et al. (2019) takes a value-based approach where big data is transformed into useful information and knowledge in order to improve company's performance. Wedel & Kannan (2016) recognizes BDA's effect on decision-making while Erevelles et al. (2016) states that it extends our understanding of marketing phenomena with advanced analytic techniques. Big data analytics techniques for both structured and unstructured data include text analytics, audio analytics, video analytics, social media analytics and predictive analytics (Gandomi & Haider, 2015).
Advanced analytics	In traditional analytics, a set of data is analyzed in order to find insights and support internal business decisions (Agrawal, 2014; Davenport, 2014) usually focusing on descriptive analytics describing historical events (Wedel & Kannan, 2016). Advanced analytics apply new techniques such as machine learning, data mining, artificial intelligence (AI), natural language processing (NLP), neural networks and speech recognition (Agrawal, 2014; Intezari & Gressel, 2016), which aims to predict, optimize and discover answers and solve problems while focusing mainly on predictive and prescriptive approaches (Intezari & Gressel, 2016; Wedel & Kannan, 2016). Barton & Court (2012) describes advanced analytics as a pivotal competitive asset recognizing its connection to business performance.
The difference between advanced analytics and big data analytics	The meaning of advanced analytics is usually understood as new technologies, tools and techniques such as data mining and machine learning, which are developed to analyze large and complex sets of data (Intezari & Gressel, 2016). These advanced analytic techniques can be utilized in big data analytics, which deals specifically with big data and is used to extract information by discovering hidden patterns and trends from big data (Chen et al., 2012; IBM, 2017; Jeble et al., 2018).

Marketing analytics	Marketing analytics is a domain of business analytics referring to the collection, management and analysis of data in order to derive insights and useful knowledge about marketing performance, which can be further utilized in marketing decision making (Cao et al., 2019; Wedel & Kannan, 2016). It refers to the extensive use of people, processes and technology with the goal of bringing information to marketing operations and decision-making (Branda et al., 2018). Marketing analytics usually aims to demonstrate the return of investments (ROI), marketing attribution and the effectiveness of actions with the goal of optimizing marketing activities and results based on data (Johnson et al., 2019; Wedel & Kannan, 2016).
Business intelligence	Business Intelligence (BI) is an umbrella term that refers to companies' capabilities, technologies and information systems with the purpose of supporting decision-making (Chen et al., 2012; Eletter et al., 2019). Business Intelligence is a closely related concept to big data and analytics as it combines the extensive use of data together with statistical methods and analytics empowering companies to gather insights for decision-making (Chen et al., 2012; Frisk & Bannister, 2017). BI deals mainly with structured data and answer basic questions of business performance (Eletter et al., 2019).

2.1.4 Organizational capabilities

Organizational capabilities refer to collective skills, processes, abilities and competence that are intangible assets of an organization (Smallwood & Ulrich, 2004). They are seen as company-wide assets rather than expertise of individual employees (Helfat & Winter, 2011). Capabilities refer to ability to perform and execute tasks, put knowledge into practice and innovate (Smallwood & Ulrich, 2004). Product development and adaptability are often associated with organizational capabilities (Teece, 2007). When market faces a technological disruption, organizations need capabilities to adapt to a changing market situation (Smallwood & Ulrich, 2004). Organizational capabilities are repeatable and have specific purposes, hence it is patterned and not just temporary behavior (Helfat & Winter, 2011). Organizational capabilities reflect the identity of the organization (Smallwood & Ulrich, 2004), drive company performance (Teece, 2014) and they are usually difficult to copy and measure (Day, 2011; Smallwood & Ulrich, 2004). Organizations needs different type of capabilities to succeed (Teece, 2007) and these capabilities can be broadly divided into operational and dynamic capabilities (Cao et al., 2021; Helfat & Winter, 2011; Kachouie, Mavondo & Sands, 2018) which are elaborated more detail in chapter 2.2.3.

2.2 Towards data-driven decision-making

Decision-making is an integral part of business operations and the responsibility for decision-making is increasingly shared among individuals in modern organizations (Grandhi et al., 2020). Although decision-making in business context is usually considered rational, this is not often the case since there are certain biases that affect decision-making (Frisk & Bannister, 2017). According to Kahneman, Lovallo & Sibony (2011), decisions are often done unconsciously based on gut feeling. van Rijmenam et al. (2019) continue that human are not very good at imagining future events and they tend to overestimate their own capabilities and focus on what they already know or think they know, which lead to tunnel vision and illusions of non-existent patterns. When companies make business decisions, they might be tempted to choose the most convenient option and seek evidence that support this (Day, 2011).

Rational decision-making includes the assumption that decision-maker has the correct information and mindset that allows to make a clear and justified decision (Frisk & Bannister, 2017). In order to avoid biases in decision-making, there is a need for data (Grandhi et al., 2020). Data-driven decision-making enables more informed decisions instead of relying on managerial expertise or intuition (Sleep et al., 2019). Existing studies suggest that data-driven organizations are in a better position to cope with changes in fast-moving environments (van Rijmenam et al., 2019). However, it is good to notice that data-driven decision-making is not either-or approach and both data as well as employee's expertise can be used as a basis of decision-making (Provost & Fawcett, 2013).

Traditionally, business decisions have been based on historical data where managers look for information that has been produced backwards, is manually coded and presented in a standardized manner (Sleep et al., 2019). Similar decision-making is evident in marketing where customer intelligence is traditionally based on market surveys and panels about customer attitudes, behavior and product design (Benoit et al., 2020; Fan et al., 2015). This kind of decision-making is mostly reactive instead of being proactive (Sleep et al., 2019). Big data is connected to decision-making in a way that it provides more proactive and predictive approach for decision-making (McAfee & Brynjolfsson, 2012). Data-driven decision-making is used to manage big data, which can be utilized to predict future behavior and customer needs (Troisi et al., 2020). The predictive nature of big data brings new dimensions and a more strategic approach to decision-making (Bumblauskas et al., 2017), for example, customer opinions and behavior can be tracked automatically by mining social media data (Fan et al., 2015). Therefore, advanced analytics can be utilized to automate the analysis of big data replacing the traditional manual coding (Bumblauskas et al., 2017).

The popularity of big data is growing largely because it can be used for decision-making in firm strategies (Brynjolfsson et al., 2011; Manyika et al., 2011; Sleep et al., 2019). Intezari & Gressel (2016) elaborated the common typology of structured and unstructured decision-making by identifying four major types of data-based decisions: structured decisions based on structured (SD-SD) or unstructured data (SD-UD) and unstructured decisions based on structured (UD-SD) or unstructured data (UD-UD). Structured decisions refer to simple, clear and systematic processes where decisions are made automatically based on existing models and knowledge, whereas unstructured decisions refer to complex processes and uncertain situations where decisions rely on humans and there is no standard procedures or methods on how to act (Intezari & Gressel, 2016). Structured data is usually in standardized and organized row-column format such as financial figures and employee information, while unstructured data often refers to social media data in different formats such as text, images, videos, audio and signals (Intezari & Gressel, 2016). External trends such as social media tracking, e-commerce, programmatic advertising and IOT devices create large streams of mostly unstructured data forcing companies and especially marketing departments to become increasingly data-driven (Johnson et al., 2019). These emerging trends and the growing importance of big data are setting new requirements for decision-making as well as marketing professionals (Davenport, 2013).

While data can provide useful insights and knowledge for businesses, insights provide only limited value if they are not used for decision-making and actions (Tabesh et al., 2019). General issue is that reports and analysis are made, managers view them, but no decisions or actions are made based on insights (Davenport, 2014). In continuous measurement, companies should have guidelines on when and what kind of situations decisions and actions are necessary (Davenport, 2014). The value of data ultimately derives from the ability to inform decision-making and implement actions (Bumblauskas et al., 2017; Weinberg et al., 2013). Grandhi et al. (2020) continues that successful integration of data in decision-making is based on the extent that organization is capable to embrace the practice. De Luca et al. (2020) encourage companies to shift their efforts from data to actions and build models that predict the return of investments.

Using data and insights to support decision-making is not a new phenomenon. According to Davenport (2014, p. 45), interpretation of data has evolved during the last 50 years from "decision support to executive support, to online analytical processing, to business intelligence, to analytics and now to big data", which is the era we are living today. Bumblauskas et al. (2017) states that the amount of data started causing information overload during 1970-1980 when technology was lagging and there was a limited ability to turn data into information and knowledge. According to Van Auken (2015), consumer panels were big data at the time. During 1990's the Customer Relationship Management (CRM) as well as Enterprise Resource Planning (ERP) systems made data collection and analysis easier, however, in the mid of 1990's, the Internet and ecommerce started to enable real-time data collection setting new demands for data processing (Agrawal, 2014). In the early 2000s, the growth of mobile phones accelerated the existing trend and further increased the amount of data and raised the need for data analysis (Benoit et al., 2020; Bumblauskas et al., 2017). Eventually, the proliferation of smartphones, increasing usage of social media and streaming data from IOT devices started to generate big data, which sets growing needs for advanced analytics systems (Agrawal, 2014).

2.2.1 Business benefits of data utilization

Existing research has shown business benefits of data-driven decision-making and big data. Based on extensive research, Brynjolfsson et al. (2011) found evidence between data-driven decision-making and better company performance in measures such as market value, return on equity and asset utilization. Firms that adopted data-driven decision-making had 5-6% higher output and productivity than expected based on their investments and technology usage (Brynjolfsson et al., 2011).

The study findings of Cao et al. (2019) demonstrated the positive effects of marketing analytics on decision-making as well as firm competence. Also, the deployment of marketing analytics has a positive effect on company performance especially in highly competitive industries (Germann et al., 2013). Similar results can be seen from a study made by Gnizy (2020), which found a connection between the use of big data and firms' competitive advantage. Troisi et al. (2020) identified the impact of data-driven decision-making on the company performance and on the achievement of marketing objectives.

Big data is often associated with high expectations and current research has indeed found a connection between big data and competitive advantage (Fosso Wamba et al., 2015; Mikalef et al., 2020; van Rijmenam et al., 2019), firm performance (Ferraris et al., 2019), productivity (Manyika et al., 2011), differentiation (Barton & Court, 2012) and cost reduction (Benoit et al., 2020). In addition, some studies have focused on the fifth V, business value of big data (Fosso Wamba et al., 2015; Forrester, 2012; Song & Zhu, 2016). Song & Zhu (2016) states that the business value of big data is the most important but also the most challenging dimension to study. Fosso Wamba et al. (2015) found that access to real-time data can improve information sharing and decision-making across departments. Bumblauskas et al. (2017) and Davenport (2014) continue that the added value of big data derives from the findings of data and connecting these insights into decision-making and actions in organizations.

According to Benoit et al. (2020), the business benefits are often divided into customer value and company value. He continue that companies who are seeking to gain strategic advantage should focus on the synergy between both customer value as well as company value. According to Sleep et al. (2019) data-driven decision-making increase the understanding of customers and therefore helps to create value for relevant stakeholders. The empirical study made by Hallikainen, Savimäki & Laukkanen (2020) showed that the adoption of customer big data fosters sales growth of B2B companies and enhances the customer relationship performance. Study made by Suoniemi et al. (2020) indicate that companies who pursue differentiation as a business strategy are more likely to benefit from big data investments compared to companies who apply cost-leadership strategy.

2.2.2 Data utilization challenges

While data-driven decision-making and big data seems promising drivers of company performance, many organizations fail to achieve the expected benefits (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Barton & Court, 2012; Cao et al., 2021; Court et al., 2015; De Luca et al., 2020; Sleep et al., 2019; Tabesh et al., 2019). Jobs, Gilfoil & Aukers (2016) highlight that the key challenge is to integrate big data into company's overall strategy. In addition, Johnson et al. (2019) states that companies have difficulties in integrating analytics into strategic decision-making processes. Intezari & Gressel (2016) continue that the amount, sources and speed of data has made strategic decision-making processes more complex.

Big data can take variety of forms including text data, numeric data, images, audio and video (Agrawal, 2014; Bumblauskas et al., 2017; Ferraris et al., 2019; Wedel & Kannan, 2016). According to Intezari & Gressel (2016) and Sleep et al. (2019), the variety of data sources and formats as well as the nature of structured and unstructured data is one of the biggest challenges for companies who want to leverage big data in decision-making. In addition, existing studies have reported the lack of talented employees (Erevelles et al., 2016; Johnson et al., 2019), information chaos caused by large amounts of data (Grandhi et al., 2020; Troisi et al., 2020), poor data quality (Fosso Wamba et al., 2015; Janssen, van der Voort & Wahyudi, 2017; Shah, Horne & Capellá, 2012), difficulties to combine online and offline data (Van Auken, 2015), cultural challenges (Johnson et al., 2019; Sleep et al., 2019), data silos between departments (Johnson et al., 2019; Janssen et al., 2017), privacy concerns (Benoit et al., 2020) and lack of capabilities to collect, use and manage the data (Barton & Court, 2012; Sleep et al., 2019; Shah et al., 2012). According to Johnson et al. (2019), these challenges are especially relevant for marketing departments who face expectations of data-driven decisions and results.

Bean and Davenport (2019) reported that while companies are increasingly investing in big data and analytics, becoming data-driven and adopting big data analytics is rather slow process and companies do not treat data as a business asset. Some managers are skeptical towards big data and data-driven decision-making (Barton & Court, 2012; Sleep et al., 2019). More data does not necessarily mean smarter insights and better decisions, instead, it can lead to analysis paralysis and inability to make actions (Sleep et al., 2019). This emphasizes in situations where one department creates the insights whereas another department uses the information to make decisions (Bumblauskas et al., 2017). According to Germann et al. (2013), people who produce the insights are usually not those who implement the decisions. Excessive amount of information can be frustrating to managers (Gnizy, 2020), and sometimes data is only used to reinforce existing beliefs in which case it provides only minimal additional value (Sleep et al., 2019). In addition, complexity of firms affects the level of data integration in businesses (Sleep et al., 2019).

Bumblauskas et al. (2017) and McAfee & Brynjolfsson (2012) state that big data and data-driven decision-making do not erase the need for human creativity, vision and interaction. McAfee & Brynjolfsson (2012) continue that utilizing information and big data can improve company's performance but in order to do that companies need to change their decision-making culture. Johnson et al. (2019) and Hallikainen et al. (2020) also highlight the role of company's culture in big data analytics implementation process. Since company culture is a major factor in data-driven decision-making, utilizing big data becomes a management challenge, which according to Davenport (2014), requires new ways of decision-making. Companies are reorganizing management across the board to work with data, analytics and digitalization (Fitzgerald, 2015). A study made by Carillo et al. (2019) emphasize that attitudes and mindsets of managers towards analytics should become more positive in order to make better use of data-driven approaches. According to Fosso Wamba et al. (2015), executives should be committed to decision-making practices where data is a fundamental part of the process.

Integrating data-driven decision-making is a complex strategic decision which requires understanding of the company's current capabilities (Sleep et al., 2019). Barton & Court (2012) found out that companies need to develop strengths in three areas in order to exploit big data in decision-making: (1) creative use of multiple internal and external data sources, (2) build advanced prediction and optimization models that focus on key performance drivers, (3) transform the company's capabilities by updating decision-making processes and developing easy-to-use tools and models. Barton & Court (2012) continue that company's capabilities can be transformed by developing analytics that is synchronized with decision-making and day-to-day operations, creating simple tools for frontline managers and reinforcing capabilities to exploit and make use of big data.

Information technology architecture is an integral part of the process where data is utilized in daily operations and decision-making (Barton & Court, 2012). According to Sleep et al. (2019), marketing and data functions should be integrated in order to use big data in decision-making. Benoit et al. (2020) continue that aligning business with IT-based solutions such as big data analytics is challenging for companies. Consistent communication across different departments is a key in advanced use of data (Sleep et al., 2019). Barton & Court (2012) encourage companies to focus on targeted and experimental efforts instead of rushing into immediate large investments. Also, Day (2011) recommends that companies should start with small investments and aim to develop processes around data-driven decision-making that can generate new insights. Benoit et al. (2020) agree that long-term benefits are most likely to be achieved by examining specific short-term challenges.

2.2.3 Dynamic capabilities

Organizational capabilities can be divided into dynamic and operational capabilities (Cao et al., 2021; Helfat & Winter, 2011; Kachouie et al. 2018). Operational capabilities refer to a company's skills, processes, and competencies in daily and recurring activities often in the short them (Helfat & Winter, 2011; Teece, 2014), which are used to maintain the status quo of the company (Winter, 2003). In contrast, dynamic capabilities refer to company's capabilities to modify or extend the current status quo (Helfat & Winter, 2011). The concept of dynamic capabilities extends the theory of resource-based view by focusing on how companies can achieve sustainable competitive advantage in fast-moving and changing market circumstances where rapid technological changes are present (Day, 2011; Teece, 2007). Compared to operational capabilities, dynamic capabilities are often perceived more strategic (Kachouie et al., 2018), innovative (Teece, 2014) and long-term (Teece, 2007). Following table (Table 2) summarizes the main differences between operational and dynamic capabilities.

TABLE 2 The main differences between operational and dynamic capabilities

Operational capabilities	**Dynamic capabilities**
maintain status quo (Helfat & Winter, 2011; Winter, 2003)	modify and/or extend status quo (Helfat & Winter, 2011)
static (Teece, 2014), stable (Day, 2011) functional and tactic (Kachouie et al., 2018)	strategic and adaptive (Kachouie et al., 2018; Teece, 2007)
short-term (Helfat & Winter, 2011; Teece, 2007)	long-term (Helfat & Winter, 2011; Teece, 2007)
day-to-day and recurring activities (Helfat & Winter, 2011)	ongoing changes in market circumstances (Helfat & Winter, 2011)
efficiency (Teece, 2014) and routines (Teece, 2007)	innovative and entrepreneurial (Teece, 2007)
doing things right (Teece, 2014)	doing the right things at the right time (Teece, 2014)

In practice, it can be difficult to draw boundaries between dynamic and operational capabilities (Helfat & Winter, 2011). In terms of marketing communication, dynamic capabilities may refer to any type of activity such as planning, implementation, brand management, customer relationship management or product development (Cao et al., 2021) that focus on strategic side of marketing communication and aim to create competitive advantage in the long-term (Helfat & Winter, 2011; Kachouie et al., 2018). Dynamic marketing communication skills aim to enhance current market and customer knowledge as well as resources to generate superior value to customers or other stakeholders (Cao et al., 2021; Kachouie et al., 2018). These innovative skills and ways of working (Kachouie et al., 2018; Teece, 2007) are usually internal (not outsourced) competence related to business development, information technologies and technological change (Day, 2011).

Much like big data and data-driven decision-making, dynamic capabilities are often linked to competitive advantage, strategic competence and superior company performance (Erevelles et al., 2016; Teece, 2007; van Rijmenam et al., 2019). According to van Rijmenam et al. (2019), big data analytics is a dynamic organizational capability that endorses strategic decision-making in environments with uncertainty and rapidly changing conditions. Dynamic capabilities can be used to (1) sense opportunities and threats, (2) seize opportunities and (3) maintain competitiveness by reconfiguring the company's existing assets (Teece, 2007). Sensing opportunities and threats refer to scanning the environment, identifying new types of information or knowledge, and interpreting if and how the findings should be reacted (Teece, 2007). Research and learning are usually involved in the process of discovering new opportunities (Teece, 2007). In turn, seizing opportunities refer to pursuing and using the sensed information to create new products, services or processes (Teece, 2007). Therefore, seizing are attempts to capture value from sensed opportunities which usually requires investments and commercialism (Teece, 2007). Maintaining competitiveness in this context means enhancing, reconfiguring or protecting the company's capabilities and competence (Teece, 2007). Companies build necessary routines in order to achieve operational efficiency, however maintaining the competitiveness of the company is solely not enough to provide competitive advantage (Teece, 2007).

2.3 Theoretical framework

This study applies a theoretical framework described by Tabesh et al. (2019) and adds different dimensions of big data (Ferraris et al., 2019; Fosso Wamba et al., 2015; Gnizy, 2020; Song & Zhu, 2016; Wedel & Kannan, 2016) and dynamic capabilities (Teece, 2007), to the process (Figure 2). The purpose of the framework is to identify a meaningful way to describe the role of big data and dynamic capabilities in data-driven decision-making. This framework considers data-driven decision-making as an informed and continuous process which consists of three phases: data collection, turning data into insights, and applying insights in decision-making. Big data is an integral part of the data-driven decision-making process and different data dimensions produces both opportunities and challenges for data-driven decision-making. Previous research has linked dynamic capabilities with big data (Cao et al., 2021; Erevelles et al., 2016; Johnson et al., 2019; Mikalef et al., 2020; van Rijmenam et al., 2019) and dynamic capabilities enable companies to sense opportunities and threats, seize opportunities and transform company's capabilities in a dynamic environment. This study views the framework as a lens to the research which guides the data collection and analysis phase.

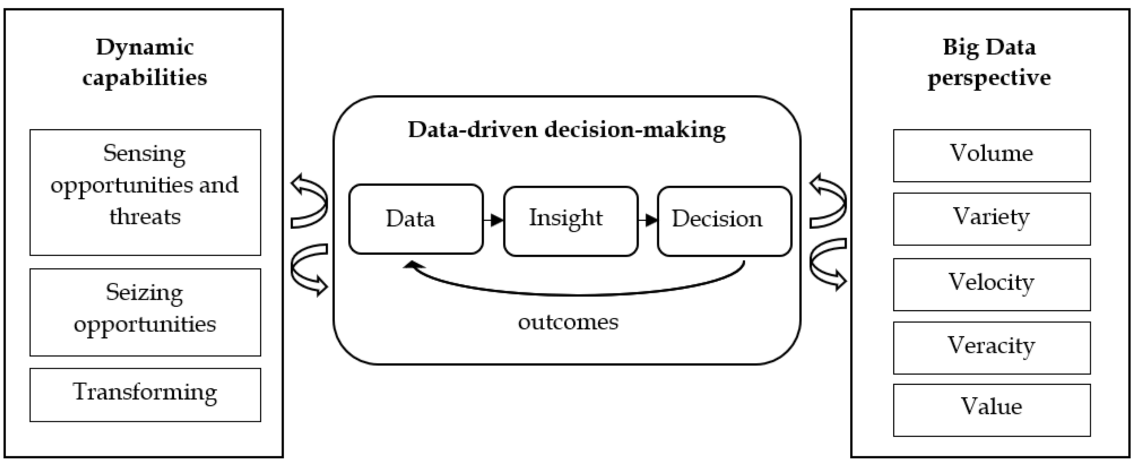

FIGURE 2 The role of big data and dynamic capabilities in data-driven decision-making (adapted from Tabesh et al. 2019)

2.3.1 From data to insight

Converting data to insight starts from developing relevant data sources depending on the company's business model and establishing information system infrastructure in order to collect data (Jeble et al., 2018). Then, data can be gathered from variety of sources and in different formats (Tabesh et al., 2019). Data is usually in structured or unstructured form (Gandomi & Haider, 2015). Structured data refers to data that is in specific format, easy to process and often stored in a database while unstructured data is undefined as it may contain images, videos, text, audio, location information or information generated by social media (Gandomi & Haider, 2015). After the data has been collected, the next step is to clean and organize the data, which makes it more manageable and facilitate the data analysis phase (Tabesh et al., 2019).

Data analysis usually refers to interpreting the data and identifying patterns and their meanings in order to discover useful information (Boyd & Crawford, 2012). What separates data from information is that data is unorganized raw facts and is not dependent on the information (Bumblauskas et al., 2017). When data is organized and given a meaning in a particular context, it becomes information and is therefore dependent on the data (Bumblauskas et al., 2017). Knowledge, in turn, requires human interaction and is based on values and experiences emerging in the minds of human (Intezari & Gressel, 2016). Since data itself has no meaning before it is organized (Sleep et al., 2019), analysis is needed to extract information from data (Eletter et al., 2019). Data is analyzed by using different types of analytical tools and methods with the purpose of generating insights for decision-makers (Tabesh et al., 2019). The focus of data analysis should not be on collecting as much data as possible, instead companies should focus on developing meaningful and valuable analytics practices and processes, which are able to generate insights from data (Jeble et al., 2018). Technical and analytics departments are usually responsible for data collection and turning data into insight (Tabesh et al., 2019). This process is demonstrated in Figure 3.

Data mining is a term often used in this context and it usually refers to advanced analytics techniques that discover patterns from the data sets in order to find and extract meaningful information (Eletter et al., 2019; Jeble et al., 2018). It is a method of data analysis that uses several different techniques such as clustering, regression and classification (Agrawal, 2014; Eletter et al., 2019). Data mining is used specifically to uncover information of big data and it differs from data analysis in a sense that data analysis test models and hypotheses while data mining seeks to find previously unknown connections and patterns from data sets (Eletter et al., 2019).

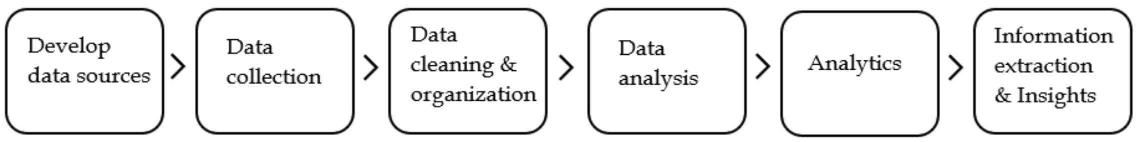

FIGURE 3 From data to insight process (adapted from Jeble et al. 2018)

Troisi et al. (2020) introduced a similar process of extracting insights from big data. The main steps of the process are (1) data collection, (2) data organization, (3) data extraction, (4) data integration, (5) data analysis, (6) data sharing, (7) data storage and (8) data reuse (Troisi et al., 2020). The first four steps are related to data management processes and technologies to acquire, store and organize data for analysis (Gandomi & Haider, 2015). Then, analytics is used to interpret and analyze the data in order to uncover insights (Gandomi & Haider, 2015). Eventually, insights are shared, stored and reused (Troisi et al., 2020).

The role of big data when turning data to insight

Big data brings additional challenges when converting data to insights because in addition to the volume of data, variety and velocity of the data present challenges in collecting, organizing and analyzing the data (Bumblauskas et al., 2017; Jabbar, Akhtar & Dani, 2020; Jeble et al., 2018; Troisi et al., 2020). In addition, poor data quality can lead to biases in algorithms and decision-making (Jabbar et al., 2020; van Rijmenam et al., 2019). Therefore, it should be noted that the insights derived from big data are dependent on the different dimensions of available data (Mikalef et al., 2018), which are often in unstructured and digital form (Gandomi & Haider, 2015; Van Auken, 2015).

Data collection is often spread over several parties and partnerships, which brings an additional challenge when analyzing big data and using it for decision-making (Janssen et al., 2017). Big data must be converted to rows and columns in order to be analyzed and this is often done with advanced analytics (Van Auken, 2015), which can be a lengthy process (Suoniemi et al., 2020). According to Sheth & Kellstadt (2021), data curation and analysis are one of the biggest challenges of data-driven approaches. They continue that there is an increasing need for new techniques to process big data. However, Mikalef et al. (2020) emphasize that the biggest challenges for most companies are not related to the technologies but rather to organizational capabilities.

Existing research has shown that big data offers promising opportunities for companies to discover new insights, which can be used in decision-making or to enhance internal or external processes (De Luca et al., 2020; Ferraris et al., 2019; Fosso Wamba et al., 2015; Janssen et al., 2017; Manyika et al., 2011; Mikalef et al., 2020). According to van Rijmenam et al. (2019), big data analytics can provide new insights by turning unstructured data to structured information with the use of new technologies such as natural language processing (NLP). These insights provided by big data analytics can support strategy making (van Rijmenam et al., 2019).

Leveraging internal and external data sources can help companies to understand their environment and customers (Jeble et al., 2018; van Rijmenam et al., 2019). According to Ferraris et al. (2019), the power of big data derives from harnessing advanced analytics with large data sets, which may produce insights beyond human mental capabilities. These insights may reveal previously hidden patterns or completely new insights regarding business environment or customers (Ferraris et al., 2019). For example, mining social media data may provide new insights about customers and consumer behavior (Davenport, 2014; Gandomi & Raider, 2015; van Rijmenam et al., 2019), which can help to create a more comprehensive customer profile (Jeble et al., 2018). From corporate communication perspective, big data analytics enhance storytelling (Boldosova, 2020) and can be used to measure company reputation in order to understand stakeholders' views (Westermann & Forthmann, 2020). Analyzing big data with predictive analytics can help to identify future customer needs and the real-time nature of big data is especially useful in businesses that require agile decision-making (Jeble et al., 2018; Van Auken, 2015). According to Janssen et al. (2017) combining data from different sources to provide new insights can improve decision-making, however, this requires clear processes. Gandomi & Haider (2015) also emphasize the role of efficient processes when turning fast-moving data sets into meaningful insights.

The role of dynamic capabilities when turning data to insight

The process of turning data to insights is a similar concept than dynamic capabilities and sensing opportunities and threats. Sensing opportunities also aims to identify and interpret new information by scanning the environment (Teece, 2007). Existing research studies Cao et al., 2021; Erevelles et al., 2016; Johnson et al., 2019; Mikalef et al., 2020; van Rijmenam et al., 2019) has demonstrated the connection between dynamic capabilities and big data. Mikalef et al. (2020) found out that companies are able to strengthen dynamic capabilities by generating insights from big data analytics. Furthermore, big data analytics has a positive effect especially on company's marketing and technological capabilities (Mikalef et al., 2020; Suoniemi et al., 2020). According to Suoniemi et al. (2020), companies should align big data efforts with their marketing processes.

In line with these results, the study made by Erevelles et al. (2016) states that customer insight extracted from big data enhances dynamic capabilities of a company. Moreover, insights derived from big data together with dynamic capabilities can create value especially when they are used for strategic decision-making (Erevelles et al., 2016). Cao et al. 2021 also stated that insights from big data can be used to enhance and develop sensing capabilities, which enable companies to reinforce their dynamic marketing capabilities and seizing opportunities. According to Johnson et al. (2019), big data analytics implementation utilizes different types of dynamic sensing capabilities. Insights gained from big data should serve as a foundation for developing marketing capabilities (Cao et al., 2021).

Descriptive analytics is a commonly used technique for processing big data (Gandomi & Haider, 2015). Study made by van Rijmenam et al. (2019) found out that especially descriptive analytics, but also predictive analytics empower companies to sense opportunities and threats allowing them to turn data into information. Descriptive analytics are widely used among companies to sense and explore their environment and customer needs, however it can only provide insights in a historical context and does not provide recommendations on what should be done in the future (van Rijmenam et al., 2019). In addition to big data analytics, marketing analytics enable companies to sense opportunities and threats, which according to Cao et al. (2019), help companies to develop competitive advantage. Sensing capabilities in practice refers to understanding market trends and technological changes (van Rijmenam et al., 2019) as well as learning about customers (Cao et al., 2019).

One of the driving forces behind dynamic capabilities is that companies need continuous renewal in competitive environments (Teece, 2007). Organizations who turn data into insights are more likely to recognize unusual events or threats (van Rijmenam et al., 2019). Therefore, companies should focus not only on what is known but also on what is not known (Erevelles et al., 2016). Dynamic capabilities help to understand how big data can be used to scan, anticipate, learn and respond to new opportunities and threats in environment (van Rijmenam et al., 2019). According to Day (2011), companies should sense market information proactively by establishing processes in order to effectively utilize insights from data.

2.3.2 From insight to decision

When insights have been produced, the next step of the framework is interpretation of insights (Tabesh et al., 2019). Insights are further processed into information and transformed into decisions (Tabesh et al., 2019). Companies must decide if and how they are going to use the information produced from data (Jeble et al., 2018). Main task of the phase is decision execution, where decisions are transformed into usable actions and executed (Tabesh et al., 2019). The main objective of insights is to support decision-makers in the decision-making process (Jeble et al., 2018). This requires information sharing where the role of company culture and managers emphasize (Troisi et al., 2020).

Eventually the decisions lead to actions, which produce outcomes and creates more data leading back to the data collection and storage phase (Tabesh et al., 2019). Therefore, turning data to insights and further into decisions is an ongoing process where decisions are made based on evidence rather than intuition (Tabesh et al., 2019). When technical and analytics departments are mostly responsible for turning data into insight, the role of managers emphasize when decisions are made based on insights (Tabesh et al., 2019). According to Janssen et al. (2017), the quality of decision-making is affected not only by the quality of data but also by the process in which the data is collected and the way the data is analyzed. Day (2011) adds that the decision-making should be driven by proactive approaches of sensing market information and insights.

The role of big data when turning insight to decision

The essential difference between traditional data and big data is the transition from structured data which are in clear databases to unstructured behavioral data (Erevelles et al., 2016). The typical use of insights derived from big data in decision-making is to predict product demands and customer needs, offer product recommendations, design strategies (Jeble et al., 2018; Van Auken, 2015) and improve product development (Davenport, 2014). By predicting customer behavior companies can influence customer decisions (Erevelles et al., 2016; Suoniemi et al., 2020). According to Davenport (2014), big data is used particularly to optimize and improve customer-facing products and services, and to create value for customers. The study made by van Rijmenam et al. (2019) suggest that predictive analytics can improve decision-making processes across the organization by focusing on not only historical events but by producing data on future needs and actions. Predictive analytics uses algorithms and advanced analytic techniques such as machine learning to identify patterns and relationships from large sets of (un)structured data from different sources to create insights for decision-making (Gandomi and Haider, 2015).

In traditional decision-making, the responsibility often lies with those with the most experience and expertise (Sleep al. 2019). However, big data analytics allows real-time data sharing across the organization empowering companies and changing the nature of decision-making, which becomes more decentralized leading to more agile companies (van Rijmenam et al., 2019). According to Jabbar et al. (2020), big data is used for real-time decision-making in programmatic marketing. van Rijmenam et al. (2019) argue that predictive and descriptive analytics allow companies to change their focus from traditional decision-making to data-driven decision-making, where decisions are based on evidence and insights produced by data rather than intuition. Erevelles et al. (2016) states that the use of big data can improve decision-making process by creating additional value. Bumblauskas et al. (2017) continue that exploiting big data to maximize business value requires human interaction since insights produced by big data need to be further processed into knowledge which can be used in decisions and actions.

The role of dynamic capabilities when turning insight to decision

The process of making decisions based on insights has similar dimensions than dynamic capabilities and seizing opportunities. The use of big data analytics can help firms to create new products and services, streamline operations, automate processes and enhance product development (Benoit et al., 2020; Manyika et al., 2011). Similarly, seizing opportunities in dynamic capabilities refers to creating new products, services and processes as well as their commercialization (Teece, 2007). Companies aim to seize value from opportunities they have identified by scanning and sensing the environment (Teece, 2007). According to Day (2011), companies should establish processes after they have sensed opportunities or threats in order to utilize those recognized insights (Day, 2011).

Existing research studies shows that dynamic capabilities are closely linked to big data analytics capabilities and insights generated from big data does not only enhance sensing of opportunities and threats but also informs decision-making (Mikalef et al., 2020). Sensing capabilities together with decision-making has a significant impact on the competitiveness of the company (Cao et al., 2019). According to van Rijmenam et al. (2019), companies can develop dynamic capabilities to seize the opportunities that have been sensed by aligning decision-making with internal processes such as product development. The study made by van Rijmenam et al. (2019) found out that especially predictive analytics improve company's ability to seize opportunities and make decisions based on insights. More specifically, companies are using predictive analytics to improve decision-making protocols and processes as well as to foster data-driven organizational culture (van Rijmenam et al., 2019). Predictive analytics allows companies to test and build new models that focus on market events which may occur in the future (Ferraris et al., 2019). Predictive analytics also help companies to understand which opportunities should be seized (van Rijmenam et al., 2019).

In addition to predictive analytics, also descriptive analytics (van Rijmenam et al., 2019) and marketing analytics (Cao et al., 2019) can be used to systematically sense and seize opportunities by combining historical data with other data sources to improve internal processes and produce insights for decision-making and strategy. Mikalef et al. (2020) adds that insights generated from big data reinforce managers decisions to seize the opportunities. Janssen et al. (2017) continue that the extent to which companies take advantage of big data insights depends largely on the company's capabilities to seize opportunities with big data analytics.

When opportunities are seized, the role of leadership, communication and organizational culture emphasize (van Rijmenam et al., 2019). Managers should align organizational culture and develop data-driven capabilities and practices across the company (Ferraris et al., 2019). Janssen et al. (2017) emphasize the importance of efficient processes in order to achieve the benefits of data-driven decision-making. Communication is a key for the efficiency of the process and according to Day (2011), opportunities and threats are sensed in several departments within the organization or its partner network, and new insights do not always reach out to managers. Erevelles et al. (2016) and Day (2011) states that companies should proactively strive to identify weak signals from the external environment. Even though insights are found, and they get the attention of managers, companies may still fail to streamline its operations and educate its employees of how to use those insights to improve company's capabilities (Erevelles et al., 2016).

According to Mikalef et al. (2020), the business value of data-driven insight is not automatically achieved without taking actions. He continues (p. 12) that "data-driven insight is only a component of a firm's ability to sense and seize", therefore, seizing data-driven insight requires flexibility and capabilities from a company. The value of big data derives when it is utilized in decision-making (Gandomi & Haider, 2015). Marketers should turn behavioral insights found from the data into market intelligence and base their decisions on evidence rather than intuition (Erevelles et al., 2016).

Decision-making quality of big data is affected by several things such as the quality of data sources, the quality of analytics process, big data infrastructure and the organizational capabilities to collect and process the data (Janssen et al., 2017). Moreover, the capability of decision-makers to understand data and the process itself is directly reflected in the quality of decision-making (Janssen et al., 2017). In order to utilize big data in decision-making, companies need to be able to analyze the data and develop sophisticated processes to extract meaningful information (Janssen et al., 2017). Since the ability to make decisions based on big data relies on the process that transforms data into insights, companies should focus on how to build those necessary capabilities and align analytics with business strategy and decision-making (Mikalef et al., 2020).

In changing business environments, companies should continuously sense the environment, create insights from the data and evaluate the importance of findings to decision-making (Bumblauskas et al., 2017). This is a challenging and continuous process where new data is generated exponentially, and the previous information and knowledge may become obsolete (Bumblauskas et al., 2017). Companies who apply big data to enhance dynamic capabilities are in a better position to compete and create value for customers (Day, 2011; Erevelles et al., 2016; van Rijmenam et al., 2019).

3 METHODOLOGY

The purpose of research is to develop an understanding and knowledge of selected phenomenon (Adams, Khan, Raeside, 2014, p. 6). Research objectives define and guide the methodological choices (Adams et al., 2014, p. 5). Methodology is associated with "the science and philosophy behind all research" (Adams et al., 2014, p. 5). Methodology deals with the research strategy and logic of science (Grix, 2002), which allows us to be critical towards what knowledge is and how it is created (Adams et al., 2014, p. 5). Research methods refer to the techniques derived from the research questions that are used to conduct and implement the study (Grix, 2002).

This chapter introduces the methodological choices that are considered the most appropriate for the study. First, qualitative research method is presented. Secondly, the data collection is reviewed. Lastly, the data analysis process is discussed.

3.1 Qualitative research

This study applies qualitative research method since previous research regarding big data, data-driven decision-making and organizational capabilities focus on quantitative approaches. Qualitative research aims to explore the studied phenomenon holistically and describe the reality of respondents (Adams et al., 2014, p. 6). It is widely used to understand, describe and interpret business-related issues in their own context (Eriksson & Kovalainen, 2008, p. 2). In general, qualitative research focus on developing theories and hypotheses while quantitative research focus on explaining and testing them (Hair, Money, Samouel & Page, 2015, p. 296). Eriksson & Kovalainen (2008, p. 3) adds that in qualitative research the data collection and analysis are context dependent whereas in quantitative research the data collection and analysis are more structured and organized.

Eriksson & Kovalainen (2008, p. 4) continue that qualitative research approaches are especially used in situations where the previous knowledge of the topic is modest, therefore interpretation and creating an understanding are key elements of the process. Also, Hair et al. (2015, p. 296) states that qualitative research exploits several different methods that are often used in situation where "…little is known about a research problem or opportunity, previous research only partially or incompletely explains the research question", and "… if the primary purpose of the research is to propose new ideas and hypotheses that can eventually be tested with quantitative research". Qualitative research field with vast number of methods can produce rich insights, however, the study implementation should be adapted according to the research context and objectives (Eriksson & Kovalainen, 2008, p. 6).

Qualitative research has also faced some criticism due to lack of clear procedures on how to collect and analyze data (Hair et al., 2015, p. 295). According to Adams et al. (2014, p. 97), small sample sizes may lead to poor generalization. He continues that the interpretations of qualitative research are more assertions than findings. However, the focus of qualitative research is often to create understanding of the phenomena rather than statistical generalization (Eriksson & Kovalainen, 2008, p. 3). Hair et al. (2015, p. 295) continue that quantification of the research does not guarantee relevance of study results.

The role of researcher usually emphasizes in qualitative research (Hair et al., 2015, p. 297) since the data collection and analysis are sensitive to the context (Eriksson & Kovalainen, 2008, p. 3). Researcher must acknowledge that the decisions and choices made during the research process affect the end results (Eriksson & Kovalainen, 2008, p. 2). Therefore, it is increasingly important to communicate transparently on which research methods have been chosen and why and how the data has been collected and analyzed in order to improve the reliability and validity of the results.

3.2 Data collection

There are a lot of different techniques and methods to collect data for qualitative research such as interviews, focus groups, observation, field notes or online reviews (Hair et al., 2015, p. 296). This research collects data through interviews. Interviews are often used in business and management research and are an effective technique to gather in-depth information of respondents' perceptions, motivations and behavior (Adams et al., 2014, p. 97). Although interviews are quite time-consuming and one may question their generalizability, they help to create an understanding of the phenomenon by finding out what kind of presumptions the interviewees hold and what is important for relevant stakeholders (Adams et al., 2014, p. 143). In addition, interviews are especially useful when dealing with complex issues and trying to develop an understanding of why something is happening, which usually require open-ended questions to collect the data (Hair et al., 2015, p. 200).

The structure of interviews can vary from highly structured into completely unstructured. Structured interviews consist of predetermined questions asked in a specific order while unstructured interviews proceed more freely according to the defined themes (Hair et al., 2015, p. 200-201). This study applies semi-structured interviews, which means that a set of 'road map' questions are created in order to lead and guide through the interview (Adams et al., 2014, p. 144). Semi-structured interviews were chosen due to the method's flexibility allowing the interviewer to ask additional questions or change the order of the questions if needed. In addition, semi-structured interviews often focus on 'what' and 'how' questions (Eriksson & Kovalainen, 2008, p. 81), which are also the focus of the research questions. Moreover, the concepts of this research may mean different things to different people so semi-structured interviews allows the interviewer to create meanings to the phenomenon. The challenge of semi-structured interviews is that the interviewer should be well versed in the research topic to make sure that all the relevant topics are covered and follow-up questions can be asked (Eriksson & Kovalainen, 2008, p. 83).

Interview questions

According to Eriksson & Kovalainen (2008, p. 80), it is important to distinguish interview questions from research questions. They continue that interview questions should be related to research questions and provide data that help researcher to answer the research questions through data analysis. This research aims to apply this principle by collecting relevant data and implementing comprehensive data analysis to answer the research questions.

Interviews started with a few warm-up questions followed by the three main sections based on the key concepts and theories of data-driven decision-making, big data and organizational capabilities. Follow-up questions were frequently asked in order to continue discussion and develop further understanding of the topic. The interviews included mostly open questions that encouraged respondents to speak and explain their views (Eriksson & Kovalainen, 2008, p. 84). In addition, the aim was to create straightforward questions because the topic of the research is somewhat complex and according to Eriksson & Kovalainen (2008, p. 84), several simple questions work better than one complex question. However, excessive simplification was avoided so that the meaning of concepts did not change. The preliminary interview questions can be seen in Appendix 1.

Most of the questions were neutral in a sense that they avoid presumptions (Eriksson & Kovalainen, 2008, p. 85), however, the key concepts and terms are being discussed with the interviewees to avoid misunderstandings. In addition to being neutral, most of the questions were direct and straightforward in nature with the aim of making the interview conversational. Researcher also utilized a series of introductory questions which led the interviewees towards the main topics (Eriksson & Kovalainen, 2008, p. 85).

Interviewees

It was important that the interviewees were able to provide insights on the research topic. This required experience and expertise in applying data to marketing communication decision-making. Thus, purposeful sampling (Suri, 2011) was applied. Interviewee selection started by identifying large companies that have data-oriented roles in marketing communication departments. Large companies were targeted because they often have the resources to invest in data utilization. Then, possible interview candidates were approached via email, LinkedIn or telephone. The interview requests described the main themes of the interview questions in order to ensure that the possible interviewees had knowledge regarding them. In some cases, this was followed by a telephone call to confirm the suitability of the potential interviewee while in other cases, the interview candidates suggested another person or their colleague who has knowledge about the interview topics. These activities aimed to ensure that the interviewees were able to provide information-rich interviews in relation to the interview questions.

In total, nine interviews were conducted during February and March of 2022 (see Table 3). Nine interviews were considered enough because last interviews repeated the same themes and provided limited additional insights. The interviewees were managers, head of marketing or communication departments and entrepreneurs who worked closely with data-driven initiatives and approaches. Most of the interviewees had worked in several data-oriented roles in different companies and they were able to provide insights of data utilization among different companies. The work experience of interviewees regarding marketing or communication positions was between 5 and 22 years. Interviewees were selected from multiple industries both from B2B and B2C sectors in order to gain comprehensive view of the role of big data in marketing communication decision-making. Different industries were expected to provide holistic understanding of the topic. All the interviewed companies were Finnish, however, most of them have international businesses as well. In addition, all companies have more than 300 employees and most of them have 1000-6500 employees, except one interviewee who was an entrepreneur, although the interviewee had extensive work experience in both large and small firms.

TABLE 3 List of interviewees

Interviewee	Marketing communication experience in years	Field of expertise	Industry
Interviewee A	5+	Growth marketing, digital marketing	Consumer services
Interviewee B	18+	Marketing and communication	Entrepreneur
Interviewee C	14+	Marketing data, insight and development	Industrial products
Interviewee D	18+	Communication	IT software and engineering
Interviewee E	13+	Marketing and communication	Consumer services
Interviewee F	17+	Marketing and communication	Manufacturing
Interviewee G	22+	Online growth, marketing technology	ICT
Interviewee H	7+	Performance marketing, analytics	Transportation
Interviewee I	16+	Marketing development and insight	ICT

Interviews were conducted in Finnish, recorded and translated into English. Duration of interviews were approximately between 35-55min, and they were held one by one via Microsoft Teams and Google Meets. One important tactic in this research was to create safe and reliable interview environment for the interviewees in order to enable transparency and minimize research biases. This was done by communicating the interviewees at an early stage that the results of the interviews are anonymized, and the names of the interviewees or companies are not mentioned in the study.

3.3 Data analysis

Data analysis in qualitative research aims to identify and interpret patterns in the data (Adams et al., 2014, p. 152; Belk, Fischer & Kozinets, 2013, p. 138; Hair et al., 2015, p. 301). While quantitative data analysis usually follows certain structured steps, qualitative data analysis is an iterative process in which the data is revisited when new questions and relationships arise or when a general understanding of the research situation evolves (Hair et al., 2015, p. 302). In data analysis phase, researchers should continuously ask what themes and patterns are emerging from the data related to the research questions and consider if there are any inconsistencies between the observations (Hair et al., 2015, p. 302).

The process of collecting and analyzing qualitative data are deeply intertwined (Belk et al., 2013, p. 138; Hair et al., 2015, p. 302) and according to Belk et al. (2013, p. 138) researchers should start analyzing the data at the same time data collection starts. When data collection has started, textual analysis is often used to identify and understand the patterns found in the data (Hair et al., 2015, p. 296). By analyzing these patterns, meaningful insights can be found and used to compile findings and draw conclusions (Hair et al., 2015, p. 296).

The process of qualitative data analysis is illustrated in Figure 4. After the data has been collected, it needs to be reduced and organized into more understandable and manageable form (Hair et al., 2015, p. 303). Data reduction requires constant search for new meanings and relationships as well as decisions about what is important in the data with respect to the research questions (Hair et al., 2015, p. 303). It may pose challenges of how not to reduce relevant information (Adams et al., 2014, p. 152). Data reduction in qualitative interview data usually include interview transcriptions, however, Adams et al. (2014, p. 153) and Hair et al. (2015, p. 300) point out that translating all data is not necessary if it is not relevant to the research. Organizing data into themes is often an effective way to view the data and understand what is relevant (Adams et al., 2014, p. 159).

After the data reduction, the data should be displayed in a form that facilitates drawing findings and conclusions (Hair et al., 2015, p. 305). In data display, higher-order themes are often extracted from lower-order themes and patterns (Hair et al., 2015, p. 305). Here the perspective shifts from identifying patterns to understanding their meanings (Belk et al., 2013, p. 147). This can be done by looking for variations and relationships between the recognized patterns (Belk et al., 2013, p. 148-149).

The final step of the qualitative data analysis process is to draw conclusions based on the patterns and meanings identified from the data (Hair et al., 2015, p. 308). If the data has been collected through interviews, conclusions can be made after every interview (Hair et al., 2015, p. 308). In this stage, researchers are making assertions based on the data that help to understand and explain the studied phenomenon (Adams et al., 2014, p. 159). Rechecking and verification are part of the process in order to make the conclusions reliable (Hair et al., 2015, p. 308). Patterns assigned with meanings help to create conclusions and answer the research questions (Hair et al., 2015, p. 308).

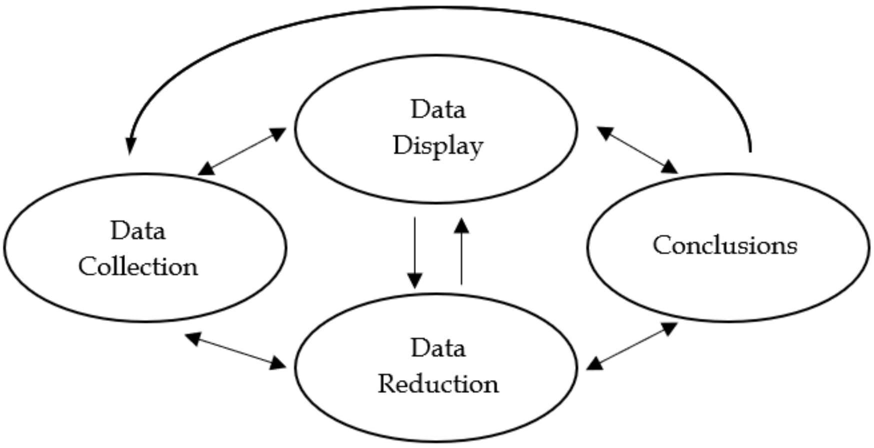

FIGURE 4 Steps in Qualitative Data Analysis (Hair et al., 2015, p. 303)

The process of data analysis in this research was similar to qualitative data analysis provided by Hair et al., (2015, p. 303) in Figure 4. The interview questions aimed to produce information that helped the researcher to answer the research questions, and the data analysis was done through the lens of theoretical framework and research questions. Transcribed interviews were analyzed by thematic analysis in order to reduce the data and identify meaningful patterns. Thematic analysis is a qualitative analysis method for identifying patterns and themes from the data and analyzing their meanings (Braun & Clarke, 2006). Thematic analysis method was chosen due to its flexibility and suitability for qualitative semi-structured interviews data (Braun & Clarke, 2006).

Data analysis started after the first interview and continued during and after the other interviews. First, each answer to each interview question was summarized in order to reduce the data. Then, summarized interviews were analyzed while looking for lower-order themes and patterns from the data. Themes are central topics of the data in relation to the research questions (Braun & Clarke, 2006). Organizing data into themes helped to reduce the data into more understandable form and link the preliminary interview topics with existing theory. Themes also helped to display the data and understand which topics are relevant.

Higher-order themes are created from the lower-order themes and compared to existing research. Illustration of finding themes is demonstrated in Figure 5.

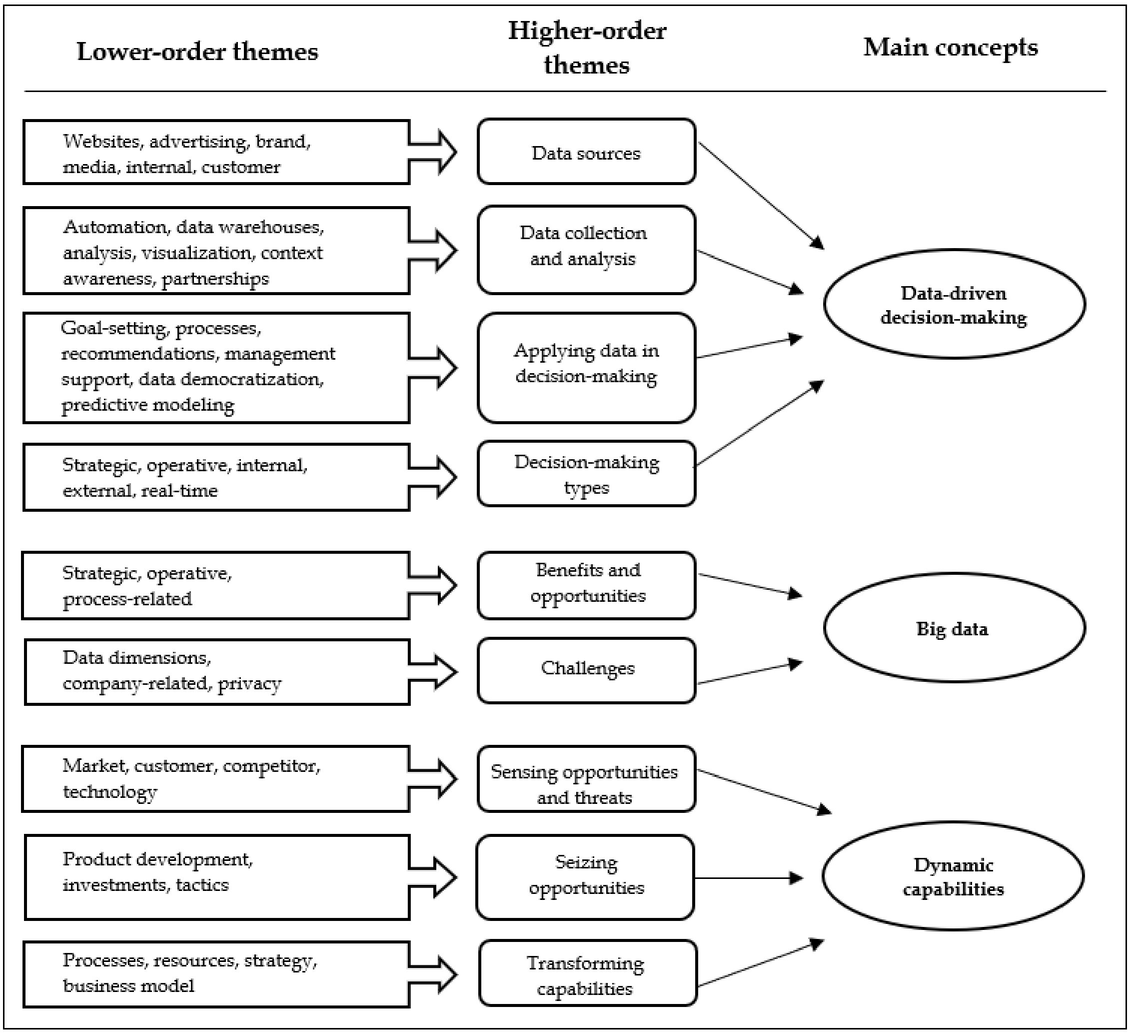

FIGURE 5 Data structure

Finally, after the lower-order themes and repeated patterns were identified, conclusions could be drawn with respect to the theoretical framework and research questions. All the relevant themes were named and these are discussed in more detail in the results section. Data analysis was a back-and-forth process where each interview provided either new insights or confirming information to the research questions.

4 RESEARCH FINDINGS

This chapter presents the results of the study. First, the main results of the interviews are presented in the form of a framework. This is followed by a more detailed analysis of each finding.

4.1 Main results

The main results of the study are built around the process of data-driven decision-making and presented in Figure 6. Marketing communication departments collect data from a variety of sources and one of the key findings of the study was that marketing communication departments have started to invest and build data warehouses where they import and combine data from different sources. The purpose of combining different data sources is to turn data into insights and expand the use of data-driven decision-making. Data collection and analysis are automated as far as possible and different analytical tools are used to visualize the data in order to create insights and recommendations for decision-making. Data collection requires technical knowledge, data analysis analytical competence, and applying insights in decision-making requires goal-setting, clear processes and management support. Data visualization through data warehouses democratizes the use of data and big data enables predictive modeling and real-time decision-making. Companies aim to achieve holistic understanding of the data, which is used both in strategic and operative as well as internal and external decisions.

Big data is an integral part of the data-driven decision-making process, and it brings both benefits and opportunities as well as challenges for data utilization. Benefits and opportunities can be divided into strategic, operative and process-related while the challenges focus on different data dimensions, company's capabilities and privacy. Especially data veracity and variety are ongoing challenges for marketing communication departments. Dynamic capabilities are linked to big data and emphasize in rapidly changing market environments. Companies sense opportunities and threats by following markets, customers and competitors as well as new technologies. Identified opportunities are then seized by product development, investments and change of tactics. Finally, companies aim to maintain and improve their competitiveness by transforming processes, resources, strategy or even business model.

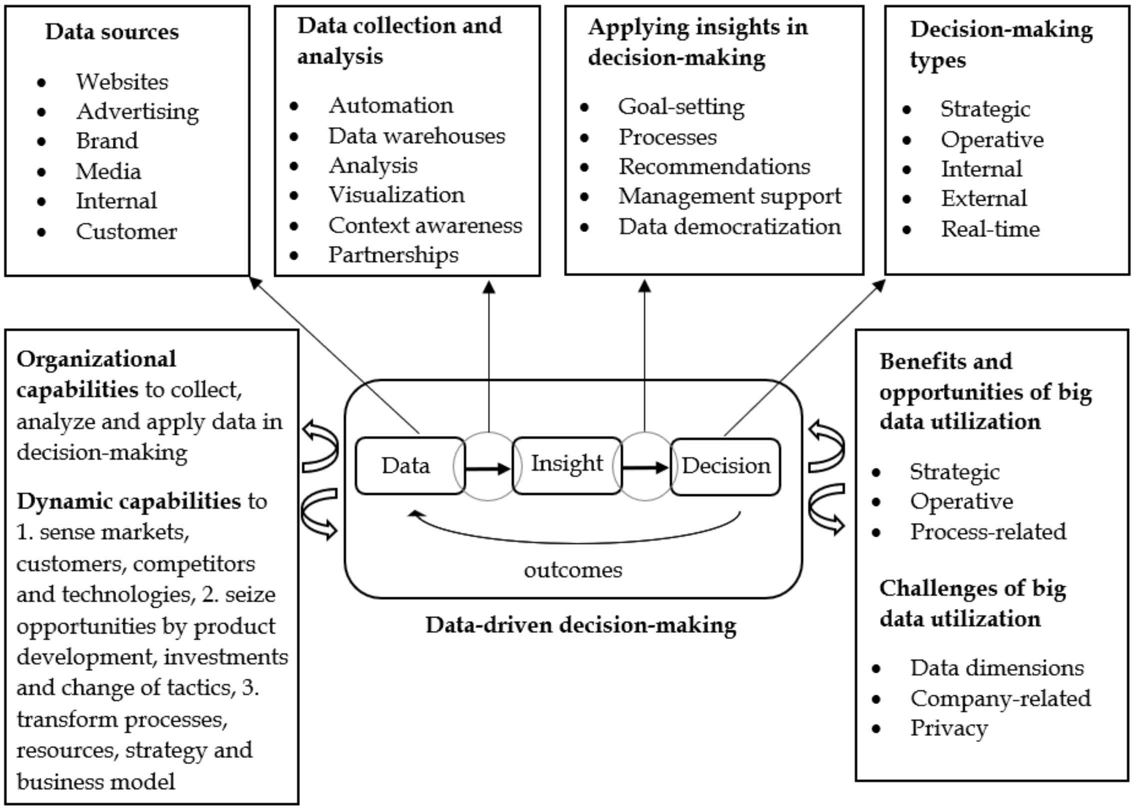

FIGURE 6 Main results of the study

4.2 Data-driven decision-making in marketing communication

4.2.1 Data sources

Marketing communication departments collect and use a lot of different data sources, however, the availability of data sources depends on the company. Six different themes were identified among data sources and these are summarized in Table 4. The first four themes are marketing communication related data sources, fifth is related to internal data sources while the sixth consists of customer data sources. Interviewees emphasized that there are a lot of different data sources and not all of them can be exploited, therefore, companies need to decide which are the most important and relevant data sources for them to collect and utilize in decision-making.

TABLE 4 Data sources that marketing communication departments collect

Website data	- traffic - session - paid - organic - e-commerce
Advertising data	- digital performance (view, clicks, conversions) - channel specific (e.g. display, video, programmatic, Facebook, Google, tv, outdoor, newspapers, radio) - advertising platforms - campaign measurements - marketing automation - influencers
Brand metrics	- awareness - consideration - preference - image - brand attitudes
Media monitoring	- traditional media monitoring - social media monitoring - social listening data - earned media visibility - own media and channels
Internal data	- sales - media investments - market shares - price - weather - location - stock & supply - competitor - hr data - event & registration data - data that is not in digital form
Customer data	- CRM - customer surveys - customer satisfaction - app data - demographic data - customer segments

The most common data sources for marketing departments are website and advertising data. Companies collect data from web analytics including both paid and organic data as well as data related to traffic, sessions and e-commerce. Advertising effectiveness is mostly measured with digital performance data and channel-specific data including digital and traditional media as well as online and offline media. Campaign measurements and data from advertising platforms are also used to evaluate the effectiveness of actions. Other data types related to advertising that the interviewees mentioned were marketing automation and influencers data. Most of the data sources related to advertising are operative and campaign level data. One interviewee also pointed out that the data also moves in another direction and companies not only collect data but also export data to advertising management systems where they can utilize for example own target groups in paid media.

> Interviewee E: "If we think about marketing, there are different types of data sources. One is related to data from digital platforms where we can see the number of views, clicks and actions. Then, there is website analytics data."

> Interviewee B: "…one perspective is to look at advertising effectiveness. With digital marketing it is easier and it certainly is one of the reasons why digital marketing has increased so strongly since there is an illusion that it would be more effective than other forms of advertising due to the fact that it is more measurable."

> Interviewee I: "From digital marketing we collect display, video and programmatic data. Then data from Google and Facebook… Campaign surveys measure the effectiveness of different activities, so, not just digital marketing but all relevant channels."

Brand tracking is a common way to measure company's awareness, consideration, preference, image and brand attributes. According to the interviewees, brand metrics are often measured by research companies or media agencies and used in customer path framework modeling.

> Interviewee B: "…brand metrics is its own area of measurement where awareness, preference or certain brand attributes can be measured. The development of these metrics is measured over a certain period of time or continuously."

Media monitoring data is important data source especially for communication departments. It consists of traditional media monitoring and social media monitoring. Social listening is also a term often used in this context. Traditional media monitoring covers print, online and broadcast media sources while social media monitoring covers mentions in earned and owned media. Some of the interviewees emphasized that communication measurement from a commercial perspective is more difficult compared to marketing measurement. Communication measurement was also perceived similar to brand measurement.

> Interviewee D: "For communication, it is easiest to start with media and social media monitoring and then move on to the website analytics, marketing analytics, marketing automation, CRM, event data etc."

> Interviewee B: "If we think about communication measurement, it is on a much lighter level and early stage. Perhaps communication measurement can be compared to brand measurement for example how many contacts have been made with outdoor advertising or TV since communication can also measure how many contacts have been achieved with communication."

Companies have variety of internal data sources that they can measure and use in marketing communication decision-making. Interviewees told that they measure business data such as sales, media investments and market shares. Price data is relevant especially for e-commerce and application businesses. Other internal data sources mentioned were weather and location data, stock and supply, competitor, hr data and event data. In addition, companies have discussions with relevant stakeholders, which produce data that is not in digital form.

> Interviewee B: "I would say that for all markets, sales data is really important when you think about the purpose of marketing which is to increase sales."

> Interviewee F: "One thing that can't be underestimated by any means, even though it may not be numerical data, is the silent knowledge of our sales and marketing people around the world, so what they say, what they see on the field, what customers say..."

Customer data is important source for marketing communication departments. Companies often collect customer data to CRM systems, which are important data sources for marketing automation. Interviewees emphasized that they need to have permissions from customers to collect the data. Customer data is also collected through surveys and satisfaction studies. Customer data helps companies to create customer segments which may contain information about demographic information, buying habits, points of interest etc. A few interviewees also stated that app data is a major source of customer data for them.

> Interviewee E: "And then big part of marketing is customer marketing, which means that a company has, for example, 200,000 people who have given a marketing permission so companies are able to do various things such as personalization."

> Interviewee G: "…marketing automation, which is based on sending messages to customers and therefore, CRM is an important data source."

> Interviewee A: "Customer satisfaction is a big source of data for us, and we use it as the basis of decisions for example what is our net promoter score and how it evolves as a result of our actions."

4.2.2 Data collection and analysis

Data collection and integration are usually done by tech or IT team, however, it requires information from experts in different fields who are able to tell what kind of data they need and find useful. In some companies, analysts are also part of the data collection process and have a role in monitoring, processing, cleaning and managing the data. Data collection is mostly automated these days with different API interface solutions while some data sets need to be manually imported into the data systems. Marketing communication departments are increasingly collecting the data into a single warehouse behind a single tool. Companies are moving data warehouses to the cloud, which makes it easier to implement and manage big data in cloud systems such as Snowflake.

> Interviewee I: "…we have IT team where we have own analytic team of data scientists and architects who help to build integration, so we automatically get the data."

> Interviewee E: "In today's world, data collection is mostly automated. Usually at the beginning of the project you think about what kind of tools are needed and then that tool is installed on the site and automatically starts to collect data whether it is about views or ad clicks or whatever."

> Interviewee C: "Recently we had this big IT project when the marketing data warehouse was established. Individual survey data is exported there as data dumps, but everything else we have tried to automate as far as possible."

While data collection is usually done by company's IT department, basic data analysis is increasingly done by everyone who works with marketing or communication related positions. Interviewees told that even creative teams can see the impact of different messages. Customer and campaign level data are analyzed continuously while more in-depth analysis is usually done by dedicated analysts. The role of analysts is usually to process the data in a form that is easy to interpret, and this requires specific knowledge that can be in-house or outsourced depending on the company's resources.

> Interviewee E: "...our creative team can also see the impact of different messages... if we think about more in-depth analysis such as sales modeling and attribution, then it usually requires web analysts or analysts."

> Interviewee G: "Data analysis is done by everyone, however, we have a dedicated analyst for this. We have tried to make and build the dashboards as easy as possible so everyone could analyze and interpret the data related to their own responsibilities and actions."

> Interviewee I: "Analysts visualize and update dashboards in Tableau almost in real-time. Almost everyone who do and plan marketing utilize the dashboards and can interpret the data, however, bigger analysis is made by analysts."

Similar to data collection, companies also aim to automate the data analysis process as far as possible in order to reduce the manual work. Relevant experts from different fields should be involved in the analysis process because they have the context awareness of different data sources. Partnerships such as media agencies can also help to analyze media-specific data, therefore, data analysis is often a teamwork.

> Interviewee I: "…we aim to have automatized analysis so manual work should not be needed... Ultimately, the final analysis is formed based on a dialogue with all the relevant stakeholders. It does not work so that a ready-made report and

conclusions are given because teams who do the decisions have specific context knowledge, so the discussions are key."

> Interviewee D: "At the moment, the question is how to automate data collection and analysis as much as possible."

> Interviewee D: "…those who really understand the data should be closely involved in the process at least in the early stages. So, if a specific number rises by 0.01 units, does it mean anything."

One of the key findings of the study was that marketing communication departments are building their own data warehouses where they collect data from different sources in order to analyze data and turn it into insights. Different data sources are combined and tools such as BigQuery is used to process and manipulate the data, which is then visualized in tools such as PowerBI or Tableau. Marketing performance data is often combined with investments and sales data, however, most of the respondents emphasized that combining different data sources is challenging because they are not automatically linked.

> Interviewee C: "Now that we have built our own marketing data warehouse which is automated from several different data sources through different API interface solutions, we utilize BigQuery to build various tables and visualize the data in PowerBI."

> Interviewee B: "One of the things that has developed strongly is that companies use their own tools and import marketing data into it, such as PowerBI, where you can import, for example sales and marketing data."

> Interviewee D: "...the best scenario is that all the data sources are in one place where they can be analyzed."

> Interviewee I: "We collect different data sources and combine them in a single view so that we get all the digital data into one dashboard."

There are a lot of different data sources and analytical tools that marketing communication departments can use in decision-making. Analytical tools vary between companies and are summarized in Table 5. Different tools have different purposes and they are usually used by a certain group of experts. Some tools have ready-made graphical interfaces where the data is already presented in a format that help to draw some conclusions. The purpose of data visualization tools is to present the data in an easy-to-understand format and visualize the development of chosen metrics. Then, there are also various advertising management tools which bring together data from different sources.

> Interviewee H: "…we use Supermetrics and funnel.io to combine different data sources."

> Interviewee C: “PowerBI has a clearly larger capacity compared to Google data studio, which may be enough to visualize Google Analytics data, but when you want to combine different data sources, then downloading gets slower and it becomes almost impossible to work with. We use BigQuery to visualize the data in PowerBI and this has been a good solution for us.”

> Interviewee E: “A lot of companies in Finland use Google Analytics, which is probably the most used analytics tool when it comes to websites.”

TABLE 5 Analytical tools used by marketing communication departments

Analytical tools	Purpose
BigQuery	Process, handle and manipulate data
Google Analytics Adobe Analytics	Web analytics
Google Data studio Tableau PowerBI	Data visualization, data sharing
Supermetrics funnel.io	Combine data sources
Hotjar	Website behavior
Meltwater	Media monitoring
Net Promoter Score Trustpilot	Customer satisfaction
Social media analytics	Own media and channels
Analytics and graphical interfaces of different platforms	e.g., Google and Facebook data App analytics Internal intra-system
segment.io own attribution tools and models	Attribution modeling

4.2.3 Applying insights in decision-making

Data-driven decision-making process is strongly linked to capabilities and resources of a company. Once the data has been collected and analyzed, companies evaluate insights and determine whether there is a need for action. Applying insights in decision-making requires, above all, goal setting, clear processes and management support. Companies should measure the fulfillment of the goals with relevant KPI's in order to benefit from the data. This requires companies to have discussions on what kind of things they can and should measure, and how do they determine success. Another major factor that interviewees emphasized was clear responsibilities and systematic processes. Companies should have guidelines of what data top management views, what data operational management views and what data is viewed at the campaign level.

> Interviewee F: “...the use of data should always be based on a clear strategy. Otherwise, you have data points here and there, which is not useful without consistency.”

> Interviewee E: "This (applying insights in decision-making) requires systematicity and there needs to be some kind of plan on how to use the data."

The role of management emphasizes when applying insights in decision-making. According to the interviewees, managers and leaders need to be data- and analytics oriented and capable to analyze data independently, however, they need to prioritize their time and knowledge, and focus on the big picture instead of all the specific details. While operative management usually focus on executing certain tasks, top management should be capable of asking the right questions, which may help to reveal insights. Data-driven initiatives require management sponsor in order to increase its acceptance.

> Interviewee E: "Quite many have most likely an illusion that managers do not independently process and utilize data. In reality, this is the opposite, and management team members spend a lot of time on dashboards and analysis."

> Interviewee F: "As a leader, it is typical that we have short of time and knowledge, and we can't know or do everything at detail level. I think it may be more crucial as a leader to understand what we need and build a team that can harness the use of data."

The role of data-driven decision-making in general has been increasing during the last years because it democratizes the use of data in companies. Data visualization methods have evolved and with the use of dashboards, decision-making is increasingly shared among employees.

> Interviewee C: "Data democratization is something that we will be better able to do in the future since all of our data sources go to the same warehouse and are visualized through a tool."

4.2.4 Decision-making types

According to the interviewees, marketing communication departments use analyzed data in all kinds of decisions, both strategic and operative, internal and external, and from roof top level decisions to individual campaigns. These decision-making types are divided into strategic and operative decisions (Table 6). The role of marketing communication varies across companies, which affects the level and purpose of decision-making.

TABLE 6 Decision-making based on analyzed data

Strategic	Operative
• Long-term • External • Resource utilization • Reviewing and approving marketing strategy • Goal-setting and KPI's • Product development • Predictive • Real-time	• Short-term • Internal • Campaign level decisions • Optimization of actions • Targeting and personalization • Content creation • Campaign timings • Testing • Pricing

At strategic level, analyzed data guides the resource utilization of what can be invested in and where companies should invest at channel- and media level but also by industry. Strategic decision-making is often considered long-term and external where data helps to decide how to allocate the company's resources such as budget and use it as efficiently as possible. Analyzed data is also important part of marketing strategies when creating goals and choosing markets, target groups and tactics. Applying data in decision-making is strongly related to goal-setting, what KPIs companies should set and why, and how to measure success.

> Interviewee B: "…one longer-term perspective that most businesses do once a year is top-level budgeting… also approving or reviewing a marketing strategy… it could be said that marketing data is used on a daily basis especially to support sales, while longer-term decisions (1-5 years) are often related to investments."

> Interviewee C: "…how to use the available budget as efficiently as possible, which actions should be done, where to focus, which channels should be used, what target groups and markets should be used etc."

> Interviewee E: "Data guides what kind of things you want to invest in and what kind of things to do. I would see that there are very few things that data is not related to today."

> Interviewee I: "Investment allocation between different medias so which medias work best for certain activities and product categories etc."

Other decision-making types that can be considered strategic are product development, and predictive and real-time decision-making. Analyzed data supports product development and customer insights are used to create better products and services for customers. Analyzing large data sets with traditional analytics takes time and companies that are advanced in exploiting data are using predictive analytics to analyze historical data and anticipate future events. Machine learning techniques such as regression, classification and clustering are often used in predictive modeling. In practice, predictive decision-making can be automation of customer service and developing solutions to challenges before they arise. Companies are pursuing towards ROMI modeling and scenario building which evaluates the potential impact of future investments. Velocity of data also enable companies to do real-time decision-making and different data sources such as weather conditions or location information can be used in advertising.

> Interviewee C: "Towards the ROMI way of thinking so what is the real impact."

> Interviewee I: "We built attribution and ROMI models, and all kinds of dashboard development to present the data in a form that it is easier to interpret and make conclusions based on that."

> Interviewee D: "Predictive decision-making is partly used. We can see the business impact but making a prediction model is very difficult and laborious and it is a work in progress."

> Interviewee H: "Predictive modeling data is also available in Google ads, so, it tells you that if you raise your bids by x, it may generate x number of clicks. But mostly historical data is used when analyzing data."

At operational level, there are a number of different possibilities to make decisions based on analyzed data. When the role of marketing department is mostly to create sales, then decision-making is often short-term. Operative decision-making is often related to different actions at the campaign level. Analyzed data is used to see which activities has the most impact and based on that companies optimize and streamline performance. Data allows quick reactions and modifications at the campaign level and is constantly used to find opportunities in advertising effectiveness whether it is related to targeting, personalization, content, main message or campaign timings. Data also determines what kind of content companies should create and these insights can also be used in communication with the customers. At operative level, data is also used for testing in different channels and adjusting prices. Survey studies help to understand what kind of things are important for employees which guides internal decision-making.

> Interviewee B: "In some companies, the role of marketing decision-making is mostly to support sales and the data is used in sales promotion, which is often short-term data usage and decision making. This applies for example e-commerce companies."

> Interviewee E: "…we look at how the campaigns work."

> Interviewee: "…if we think about the content of advertising, we can make insights for example main message has not been understood…and then we can think about how to crystallize the message…print texts, slogans or messages in specific ads etc."

> Interviewee E: "Decisions based on data are made everywhere, starting with the survey studies on what kind of corporate culture companies want to create.

During the last years, companies such as Google and Facebook have made the decision-making more data-driven. A lot of companies use their platforms and bidding systems which are based on algorithms that are automatically data-driven and make decisions independently according to the given goals.

> Interviewee H: "Google and Facebook systems make independent bidding decisions based on the data and our job is to fetch the program with the right data and goals... Before these algorithm-based bidding systems, the data-driven decision-making was mostly looking at the sales, market and trend data, and making decisions based on them."

4.2.5 Contextual factors of data-driven decision-making

This chapter provides some additional insights that were discovered during the study. While marketing communication departments perceive the role of data-driven decision-making as central, interviewees emphasized that it depends on the size, maturity level and industry of the company. Most of the interviewees had worked in several data-driven positions in different companies and they stated that data-driven decision-making also varies across business units and teams within the company. Some teams are advanced at data utilization while some teams are at the early stage of development. The importance of data varies between companies and business units because data is different for different companies. The role and responsibilities of marketing communication departments also varies across companies and measurement is more challenging for some companies than another depending on the available data sources. It is easier to collect data through applications because everything happens through logged in users. Similarly, it is easier to measure e-commerce and tactical campaigns than brand equity in the long-term. Therefore, companies also need different types of data.

> Interviewee B: "Data-driven decision-making in marketing has taken big leaps forward during the last 10 years, however, the differences among companies are significant depending on the company's capabilities to invest in it financially and competence wise."

> Interviewee C: "The intention of the company is that data-driven decision-making plays a big role throughout the organization, however, it is not business as usual yet even though some teams appear as pioneers."

> Interviewee E: "I would say that data is different for different companies. Data is very important fuel for everything in platform and application businesses while for certain companies it is very difficult to get direct data about how the various activities have affected."

B2B vs B2C

Both B2B and B2C sectors collect and combine data from different sources in order to create insights for decision-making, however, utilizing big data is more common in B2C compared to B2B. The main reasons for this are summarized in Table 7. Major factor is that the number of customers is significantly lower in B2B than B2C, therefore, the amount of available data points differs. The same goes for predictive modeling of future events and machine learning, which are more often utilized in B2C than B2B because training these models requires a lot of data sets in specific formats. Another perspective difference is the length of the sales process, which is longer for B2B customers, therefore, results can be seen faster in B2C, which motivates the use of data. In addition, B2C often focus on short-term goals and has often larger resources compared to B2B businesses. Typical use case of big data is lead generation which is often the responsibility of B2B sector.

> Interviewee G: "In B2B, we have focused on the data during the last three years. We have created different dashboards with the help of analysts on everything we want to follow, however, we feel that we should do more continuous analysis. So, even if we try to interpret the data through our dashboards, we have limited resources and less time for continuous analysis in order to create insights."

> Interviewee G: "Lead generation has a big role for us in B2B business."

Table 7 Perspective differences of big data in B2B and B2C

Perspective	B2B	B2C
Number of customers	Lower	Higher
Amount of data and available data points	Less	More
Length of sales process	Longer	Shorter
Available resources	Smaller	Higher
Time period	Long-term	Short-term

Marketing vs communication

Both marketing and communication departments collect and combine different data sources in order to create insights for decision-making, however, the verification of results is more difficult for communication departments especially from a commercial perspective. The main reason for this is that marketing and communication departments have different roles, goals and responsibilities. Communication usually focuses on building reputation capital in the long-term while marketing often has sales-oriented short-term goals. Therefore, the message is very different in communication compared to marketing. Marketing departments also have access to a wider range of data sources and they monitor data on a daily or weekly basis while communication has less data sources and the data is monitored usually once a quarter or less frequently. Long-term impact is more difficult to measure accurately due to external factors. The differences of marketing and communication departments that affect big data utilization are summarized in Table 8.

> Interviewee D: "Communications focus on building reputation capital for all stakeholders in the long term, while marketing is usually and especially today focusing more on the short-term actions such as lead generation."

> Interviewee H: "Of course the purpose of marketing is purely to generate more sales while communication focus on image and brand work for example through corporate communication."

> Interviewee B: "On the other hand, it can be said that communication is more authentic and it can be interpreted as more credible. However, I find measuring communication more challenging from a commercial perspective."

Table 8 Big data utilization differences among marketing and communication

Differences	**Marketing**	**Communication**
Role, goals and responsibilities	Sales, branding	Reputation capital, image
Access to data sources	Wide range	Limited
Frequency of looking data	Daily - weekly	Once a quarter or less
Media	Paid	Non-paid
Message	Highlight products	Storytelling

According to the interviewees, marketing and communication departments co-operate a lot and information sharing is important. Marketing and communication need to have a common line for example in terms of tone of voice. Interviewees also stated that the departments have clear boundaries, however, there are some grey areas regarding organic social media and website traffic to some extent. Ultimately, the relationship between marketing and communication depends on the organization structure.

> Interviewee D: "We need to accept that different things are measured with different metrics but when they are viewed together, then they can tell more than just a one metric. For example, communication departments are hardly interested in click through rates at all. On the other hand, if the communication tells the marketing that the reputation capital has increased by x% then again it may not be relevant for the marketing."

> Interviewee I: "There can be some small channel-specific overlapping e.g., related to social media but basically the boundaries are quite clear. This depends on the organization and how it is organized."

4.3 The role of big data

Big data is an integral part of the data-driven decision-making process. Big data enrich the process by creating opportunities for data collection, analysis and decision-making. On the other hand, the data-driven decision-making process also strengthens the big data capabilities of a company.

4.3.1 Benefits and opportunities of big data utilization

The interviewees shared several benefits and opportunities of utilizing big data in decision-making, which are divided into strategic, operative and process-related benefits and summarized in Table 9.

TABLE 9 Benefits and opportunities of big data utilization

Strategic	Operative	Process-related
• Guides resource allocation • Holistic understanding • Predictive decision-making • Real-time decision-making • Product development • Business impact and customer value	• Justifies decision-making • Gives certainty • Optimize and streamline actions • Improve efficiency • Confirm and demonstrate results • Personalization • Hidden patterns	• Automation of processes • Data democratization • KPI discussions • Promote data-driven decision-making

The most evident operative benefit and opportunity of using big data is justifying decision-making and giving certainty. The use of data helps to optimize and streamline actions, improve efficiency and confirm results. Data guides operative work and dashboards has made it easier to follow changes and alerts in the market. Big data also creates targeting opportunities through look-a-like audiences and may reveal hidden patterns of customer behavior.

> Interviewee A: "Data gives me confidence that I'm doing the right things. As long as you have used the data and interpreted it correctly, and if something goes wrong or doesn't work, then you can always look at the data and justify why you made that decision."
>
> Interviewee B: "The benefit is definitely that marketing has traditionally been a matter on which everyone has an opinion… data brings a certain kind of common sense in order to be able to better justify the decision-making."
>
> Interviewee G: "In my team, it has been easier to justify for business units why something should be done in a certain way."

At strategic level, data helps to make strategic guidelines on resource utilization and allocation on where to focus, how to spend the budget effectively and which activities should be done. One of the main benefits of big data is real-time and predictive decision-making. Real-time data enables immediate and informative decisions for example in pricing. The growing amount and variety of data with advanced analytics enable predictive and proactive decision-making and companies can assess the potential impact of investments. Predictive analytics can also help to identify the most profitable customer segments and markets.

> Interviewee D: "If we exclude the verification of results which is quite obvious benefit and focus on the insight perspective, data helps to make strategic guidelines."

> Interviewee E: "Data helps us to optimize everyday life at a very precise level. Based on data, we can do targeted marketing activities in real-time."

> Interviewee C: "Data can be used to model what really has the biggest impact on, for example, brand awareness. I think that's the biggest benefit… Since we have more and more historical data in use, we can build different scenarios based on the existing data."

Most of the interviewees mentioned automation as a key benefit of big data utilization. Automation reduces manual work and enhance company's internal processes. Big data also helps to see how customers are using the products and services which guides product development and market communication. This information can be used to improve the user experience, motivate customers and create more value. Based on big data, companies can develop holistic understanding of customers and based on that offer them relevant products and services.

> Interviewee F: "...automation of our customer service has helped us tremendously and it has also helped our customers. Previously, we had traditional call center where customers called and our customer service representatives responded, however, based on data we were able automate it."

> Interviewee G: "If we think about data from a wider perspective, it enables us to utilize automation and robotics which allow us to implement tasks that were previously done manually."

> Interviewee F: "…helps greatly our product development but it also helps our marketing communication. Based on the analytics we are able to communicate much better."

One of the benefits that big data and automation brings to decision-making is data democratization. Besides of increasing access to data, data democratization is about educating employees, implementing tools and creating data-driven culture.

> Interviewee C: "…data visualization through PowerBI democratizes the data because everyone has access to it and there is no need to specific request access to GA, Twitter, etc."

4.3.2 Challenges of big data utilization

When it comes to applying big data in decision-making, interviewees mentioned several challenges related to data dimensions, company's capabilities and privacy. These challenges are summarized in Table 10.

TABLE 10 Challenges of applying big data in decision-making

Data dimensions	Company-related	Privacy
• Veracity • Variety • Volume • Value • Velocity • Attribution modeling and conversions	• Data interpretation and utilization • Quality of processes and analysis • Reporting and visualization • Goal- and KPI-setting	• Recent cookie changes (e.g. iOS) • GDPR • Data storage • Customer permissions

From different big data dimensions, especially the veracity and variety of data were emphasized. It is difficult to turn data into insights when the available data is poor quality or it is not versatile enough. Recent privacy and cookie changes has brought additional challenges to data availability and quality. Apple has made iOS changes of how they collect and hand over data to third parties. This has created challenges for companies who do Facebook advertising making it more difficult to obtain comparable data. Some data sources have become less accurate and reliable which poses challenges to decision-making. It is also more difficult to understand the big picture when each platform has their own way of handling data. Browsers not supporting third party cookies concern especially the field of digital marketing.

> Company I: "The biggest challenge is data quality. You can always find errors in the data and fixing those may take time."

> Interviewee B: "What has happened over the past year is that previously open and important data sources in the field of digital marketing such as data provided by Apple, as well as cookie data, which is central to the functioning of digital marketing, has become more difficult to access. This has hampered decision-making, which has played a key role in the past."

> Interviewee E: "iOS changes of how Apple collects data and hand it over to third parties. The good things here are consumer focus and privacy, but this leads to data silos, where each platform has its own way of handling the data… Now due to iOS and GDPR changes, data is much more uncertain and can no longer be linked in the same way e.g., cookies and pixels to humans."

> Interviewee A: "It is difficult to trust the data coming from certain sources, for example advertising platforms. We have to run it through our own attribution model to make it more reliable."

Variety of data is a major challenge in most of the interviewed companies. Companies collect and combine different data sources, which produce integration challenges because different data formats are in different places, and they are not often automatically linked. Interviewees emphasized that ideally all the data is in one place. When combining different data sources, the privacy and anonymity of the data needs to be considered. Therefore, even if there is data, it may not always be used. There can also be conflicting data in different data sources, and it is important to understand how the data is collected. Data collection depends on the available data sources and companies face challenges when integrating offline and online data. Digital and online data collection can be mostly automated, however, it is difficult to integrate offline data that is not in digital form, into data pool or warehouse. Combination of different data sources requires experts from multiple fields.

> Interviewee A: "Combining all of these data sources is something that I was not prepared for and have learned by doing."

> Interviewee C: "…utilization of offline data and how to integrate this into automated data warehouse."

> Interviewee D: "…context awareness and understanding of the business and data…when social media data is combined with marketing automation data or CRM data, it requires experts from different fields in order to know which data should be included in the analysis and how to interpret it."

The volume of data was also perceived as a challenge. Data can be collected almost from anywhere and it may be difficult to understand which data is relevant and where companies should focus and invest resources. Also, velocity of streaming data from IOT devices produce large data sets which can be difficult to collect and process. Some interviewees also emphasized the challenges related to attribution modelling and conversion calculation. Different companies have different attribution systems and conversions are calculated in different ways. This creates challenges when measuring customer path and for example Google and Facebook approach the attribution systems differently and they are not synced. This becomes visibly when companies model returns of marketing investments. ROMI modelling and scenario building also require a lot of data sets in the right format and new technologies that can be applied to create models.

> Company F: "…there is so much data so how can you recognize what is relevant and turn that into relevant insight and understanding."

> Interviewee E: "Currently, several companies are focusing and trying to solve attribute modeling challenges and how to combine different individual data silos

into a form that could be used to draw holistic conclusions, but it is very difficult. I don't think any company has fully solved it yet."

Besides of challenges related to data dimensions, interviewees mentioned several company-related challenges. The main company-related challenge was data interpretation and utilization. Interviewees told that they have been many times in situations where they have seen interesting data, but the usability remained a question mark. Data without context is difficult to interpret and utilize in decision-making. Collecting and measuring data is one thing while utilizing data is another, therefore, data interpretation and utilization are fundamental challenges in decision-making.

> Interviewee B: "...there is so much data available and companies can measure basically everything, but then it is different thing how the data can be utilized."

> Interviewee A: "There is so much data available that it can be difficult to interpret. One key thing is that you don't try to prove your own opinion with the data but try to refute it."

The quality of processes, analysis and methods produce challenges in data interpretation and utilization. The process of incorporating data into systems and for analysis affects the quality of data usage. Systematicity has a key role in data collection, analysis and decision-making. In general, one of the challenges related to data analysis is that it is difficult to exclude all the external factors when analyzing data set. This becomes evident when the purpose of analysis is to give recommendations based on the data. Reporting and data visualization are key tools in data analysis, however, interviewees identified challenges of how to present results in an understandable and interesting form.

> Interviewee I: "I believe that I speak on behalf of every advertiser when I say that today there are a lot of information, and when you work at big company, you have resources to build those tools, but the hardest parts are the processes and how to be as systematic as possible."

> Interviewee D: "…how to create a report that all different stakeholders understand… and present key insights in an interesting format."

One major challenge that the interviewees reported was goal- and KPI-setting. There are a lot of different metrics and sources available that companies can follow, hence, they need to identify and decide what are the most relevant KPIs regarding their goals and objectives. This requires an understanding of which questions you want to answer with the data. It also became evident that it is very important to have the right KPIs especially when companies are using Google or Facebook algorithms-based platforms. Few interviewees also identified that in goal-setting, one of the issues is that data-driven activities are often driven by short-term goals, and it is more difficult to measure brand development than digital performance campaigns.

> Interviewee E: "I would say that if you want to use data, you usually need to know in advance what you want to get from the data. It's not usually like warehouse data where you can just go to and grab whatever you want for yourself."

> Interviewee I: "…there is so much data and it may be difficult to think what are the most important and relevant KPIs that should be used".

> Interviewee C: "KPI conversations are endless…what we want to achieve, how it should be measured, and which indicators should be chosen."

> Interviewee B: "...the problem is that rationalization based on the data can often be short-term. Data-driven often means measuring short-term marketing...marketing also has significant effects on long-term especially concerning brand building."

Interviewees also stated that companies have faced challenges regarding resources and capabilities. Data investments can be expensive especially for small companies and data utilization usually require specific skills. There is a growing need for data-driven roles in marketing communication. In large companies, big data implementation and educating employees in companywide may take some time.

> Interviewee F: "…I don't think we are very good at this (combining data sources) or at least we could be better."

> Interviewee B: "This (data-driven marketing roles) is something that has taken leaps in recent years, but it still needs to be a pretty big company to have its own analysts for marketing at the Finnish level."

> Interviewee I: "…one of the challenges is to educate the whole company, and one should choose the words wisely in order to avoid wrong conclusions."

While companies have faced data-related challenges regarding privacy and cookie changes, companies have also faced company-level data privacy challenges related to GDPR. Companies need customer permissions to gather data, which requires certain checks from a data privacy perspective. The data also needs to be accredited before data integration is done. Companies need to decide how they store data and what and how much data they are willing to hand over to partners and agencies. This may pose challenges when outsourcing analysis.

> Interviewee C: "Data privacy is a challenge that needs to be taken care of even before the data is collected and this is also related to capabilities and knowledge."

> Interviewee H: "…privacy issues and consent modes. How much we can gather data from customers…permissions to gather data."

> Interviewee D: "...how far customers are willing to hand over their data to third parties in order to do these kinds of things? And then there is also contextual

awareness. So, who to give CRM data? I would not give CRM data to advertising or communication agencies."

4.4 Capabilities in data-driven decision-making

While big data is an integral part of the data-driven decision-making process, capabilities are prerequisites for its success. Organizations need certain capabilities for data collection, data analysis and decision-making. On the other hand, the data-driven decision-making process also strengthens the company's capabilities and dynamic capabilities emphasize when companies are utilizing big data in data-driven decision-making.

4.4.1 Organizational capabilities

Organizational capabilities needed for data utilization depends on the company and the role and responsibilities of marketing communication departments. Different stages of data utilization require different types of capabilities, which are summarized in Table 11. Capabilities are different for born online companies compared to traditional industries. All interviewees emphasized the importance of capabilities in data-driven decision-making process. Partnerships can be useful throughout the different phases for example by collecting survey data, creating attribution models or following the latest analytics tools. Data privacy also emphasizes throughout the process and companies need systematic ways to collect and handle data.

TABLE 11 Organizational capabilities required to collect, analyze and apply data in decision-making

Data collection	Data analysis	Applying data in decision-making
• Data infrastructure • Data sources and integrations • Data warehouses and cloud platforms • Automation • Mar-tech • Programming (e.g. SQL or Python) • Creating pixels and tags • Attribution logic	• Understanding of different data sources • Analytics tools • Business/context understanding • Data visualization and reporting • Analytical competence • Testing • Advanced analytics • ROMI modeling	• Goal-setting • Systematic processes • Decision execution • Actionable insights and recommendations • Management support • Teamwork and communication • Understanding of the data analysis process

Data collection

Data collection is dependent on the available data sources that companies can collect. It requires capabilities to build the infrastructure, systems and data integrations through API interfaces. This also requires understanding of different data sources, data warehouse types and cloud platform services. Data collection are IT projects and the profiles needed are often data analysts, scientists or engineers. Data collection is mostly automated these days and companies need capabilities to combine different data sources. Technical knowledge is needed to manipulate data from different sources and ensure the data quality, which requires certain mar-tech understanding. Data warehouse should be built logically in order to retrieve the data into dashboards. Data querying for example in BigQuery requires programming skills such as SQL or Python. Data collection from certain sources require knowledge of how to create pixels and place the tags on the website. Statistical knowledge and mathematical capabilities are useful in predictive modeling. When creating attribution models, there needs to be understanding of the logic behind the model. Most of the interviewees emphasized that business understanding is also needed when determining what kind of data should be collected.

> Interviewee I: "…data collection requires building API interfaces and data integrations…when we start doing dashboards or we need to collect certain data set for modeling, then we need SQL knowledge."

> Interviewee C: "Regarding data collection, I look this from recruitment perspective, it is important to understand different types of data warehouse and cloud platforms and services e.g., knowing BigQuery. Data querying is also important, which often needs SQL and/or Python skills."

> Interviewee E: "Data collection in modern world requires above all technical skills if we are talking about for example how to measure web analytics or data from advertising platforms or how to create pixels… Basic IT skills can get you somewhere but usually there are specific agencies and people who are able to build the system in a way that it collects data automatically."

Data analysis

The common perception among interviewees was that all marketing communication people should have basic understanding of data, analytics, data interpretation and insights. When it comes to more in-depth insights, these are usually done by dedicated analysts which can be in-house or outsourced. Overall, the interviewees highlighted that the role of analysts in marketing communication departments has been increasing and will continue to increase in the future.

> Interviewee F: "Every marketing person should have a basic knowledge of data, analytics and insights."

> Interviewee A: "When it comes to producing and analyzing the data, I think our analysts are the most important people in our team... analytical skills are essential especially in digital businesses."

> Interviewee E: "When it comes to analyzing the data, this requires a certain kind of curiosity in each person in the organization and a desire to understand things as well as becoming familiar with the tools and see what can be found in there."

Data analysis requires understanding of different data sources and how they are collected. Analytics tools are essential in order to analyze the data while business and context understanding is needed to give recommendations based on the data. Insights arise through substance knowledge and experts from different fields should be involved in the data interpretation process. Data analysis requires capabilities to process the data and present it in an understandable form, therefore, data visualization and reporting skills are essential in order to crystallize conclusions. Data analysis also requires people who can build and maintain the dashboards and reports.

> Interviewee D: "…knowledge of data and business, reporting and visualizing, and crystallization of conclusions in order to create insights."

Data analysis and testing requires analytical knowledge in order to determine whether something is statistically significant. In some companies, data analysis requires strong data knowledge for example integrating different data sources, maintaining data warehouse and developing marketing technologies. For big data sets, companies need more advanced analytics capabilities who can manipulate, combine different data sources and ensure data quality. Some interviewees emphasized that they need to be able to evaluate what is the impact of new ideas and actions on business before they are executed. Therefore, understanding of marketing dimensions and the whole customer funnel are needed for ROMI modeling.

> Interviewee F: "…companies should have a person who has more specific analytics knowledge, and who is capable to crunch the data, combine different data points, produce relevant insight and ensure data quality."

> Interviewee I: "…when it comes to analyzing, you need to understand marketing data in order to make correct recommendations. So, understanding of how the data is collected, how the conversions are calculated, which metrics are used in ROMI modeling and understanding the logic behind it. Also, a general understanding of marketing dimensions and the whole customer funnel."

Applying data in decision-making

Utilizing data in decision-making is heavily dependent on the quality of data collection and analysis processes. Besides of goal-setting and systematic processes, companies need to be able to execute decisions which requires project management capabilities. Most of the interviewees emphasized that decision execution is dependent on the actionable insights and recommendations that are produced in data analysis phase, however, actionable insights cannot be created without knowing where the data comes from, how it is collected and what is the context of the data. Utilizing data in decision-making also requires teamwork and open communication. It is a process and continuous work, which requires experts from different fields, therefore, active information sharing is required inside and across teams. Channel specific knowledge is useful and companies must reach over data silos in order to gain access to different data sources and then create an understanding of what the data means. Not all information is in digital format which also emphasizes the need for communication. Besides of curiosity and willingness to understand the different data dimensions as well as analytic tools, data-driven decision-making requires organizational encouragement, therefore, company's culture is a key factor. There needs to be motivation to run data-driven initiatives.

> Interviewee F: "…I would emphasize the insight aspect. We have loads of data and analytics tools but what it means? Turning data to actionable insights is the important and interesting thing in my opinion. And this cannot be done without understanding of the data and analytics."
>
> Interviewee D: "Relevant business units should be involved in data interpretation in order to determine the actionable insights."
>
> Interviewee I: "Of course, working in a big company, this requires team effort."

4.4.2 The role of dynamic capabilities

Dynamic capabilities play a key role when dealing with data-driven decision-making and big data. Table 12 summarizes how marketing communication departments scan the environment, react to identified opportunities and transform company's capabilities.

TABLE 12 The role of dynamic capabilities in practice

Sensing opportunities and threats	**Seizing opportunities**	**Transforming company's capabilities**
• Market information and trends • Consumer and customer behavior • Competitor's actions • New technologies • International examples	• Additional information search • Product development • Investments • Change of tactics	• Streamline internal and external processes • Acquire new resources • Shift the focus of strategy or business model

Companies are making decisions all the time based on the current market situation. In rapidly changing conditions, companies need to be able to scan the environment in order to recognize potential possibilities and threats. Data has a major role in scanning the environment and it helps companies to evaluate what works and what does not. Marketing communication departments scan the environment by following market developments, new technologies, trends, customers and consumers, competitors, new arrivals and international case examples.

> Interviewee H: "…we follow quite a lot of what is happening in the market, what competitors are doing, what kind of market shares we have etc."

> Interviewee I: "We have business and services units that follow market changes, competitors and international examples of similar companies. Then customer understanding has a big role."

> Interviewee B: "Companies do this by monitoring and following market development, consumers purchase power and competitors."

Most of the interviewees stated that it is important to conduct customer surveys regularly in order to stay informed of customer needs. Partners can also be used to monitor possible opportunities and threats. Sensing opportunities and threats also depends on the size and maturity of the company as well as resources and availability of the data sources. Some companies consider market monitoring as nice-to-know information and not at the top of priority list. Scanning the market changes is not always necessarily marketing communication related task and some companies have dedicated business units that are responsible for doing this. Interviewees also emphasized that scanning environment is a continuous work and active information sharing inside and across teams is important in order to disseminate information effectively. Silent knowledge that employees and customers have may be vital.

> Interviewee B: "I would say this is related to the company's degree of maturity and willingness to invest. For many companies, this is considered as nice-to-know information and may not be seen as the first thing to allocate resources."

> Interviewee E: "…if we think about marketing and data utilization, then you can follow start-ups who are able to provide something new. So, either you have to monitor what is happening in the market yourself or have a good network of partners who can do it for you."

> Interviewee G: "One of the goals is to share information actively inside the team…This starts from the company's strategy and is continuous work."

When companies identify new opportunities and threats, they need to find out if and how it should be reacted. This can mean for example searching additional information of the topic through customer surveys, creating new products or services, implementing new tools, investments, changes in tone of voice, marketing tactics or adjusting budget or prices. Sometimes the focus of actions needs to be shifted for example from sales to branding or vice versa. Potential business and publicity threats should be eliminated before they become issues. Many industries are currently faced by a dynamic environment circumstances and rapid changes, therefore, companies can benefit from agile and flexible decision-making. By sensing and seizing opportunities, companies can make better and faster decisions.

> Interviewee I: "...if we see that something needs to be reacted, then we usually start by doing customer surveys and validation, or prototypes planning with customers, in order to understand what should be done."

> Interviewee H: "In general, our industry is quite turbulent…and we need to be able to react quickly... The focus of more sales-oriented advertising can be shifted to branding etc."

> Interviewee D: "Data is a key when monitoring what is happening in the market... Traditionally, communication teams need to follow threats and try to eliminate them as well as utilize opportunities and take advantage of them."

When companies seize opportunities by product development, investments or changing the current tactics, they aim to modify their current capabilities and maintain or improve company's competitive advantage. This can be done by streamlining company's internal and external processes or acquiring new type of resources. Companies streamline their processes especially through automation and by making processes more efficient. In dynamic industries, there are constant need to find a competitive advantage over competitors and sometimes the focus of the strategy or business model needs to be shifted. Data has a big role in managing companies and interviewees emphasized that customer satisfaction is a big source of competitive advantage. Companies are also seizing opportunities and transforming company's assets by predictive and proactive decision-making. ROMI modeling and scenario building are used to evaluate the potential impact of investments and actions. Companies who are able to use the data most efficiently has the chance to invest in other things, which in turn enables gaining competitive advantage.

> Interviewee E: "Data has a big role in many ways from how the business is managed and how to streamline operations…the one who can manage data the best, is able to invest in other things. If we would not follow these, then the competitor does and make better and faster decisions based on the data."

> Interviewee A: "We work in a way that if you want to get bigger ideas through you always need to have data that support your idea. We need to be able to evaluate for example what is the impact of new ideas and actions on sales."

5 DISCUSSION AND CONCLUSIONS

This chapter discusses the theoretical and practical contributions of the study. The results of the study are considered from the perspective of the research questions and previous studies. This is followed by a discussion of managerial implications. Finally, limitations of the study are discussed and future research suggestions proposed.

5.1 Theoretical contributions

The objective of this research was to examine what kind of role big data have in marketing communication decision-making and what kind of organizational capabilities data utilization requires. Dynamic capabilities, which are part of the organizational capabilities, were chosen for the theoretical framework because previous research has emphasized its role in big data implementation (Cao et al., 2021; Erevelles et al., 2016; Johnson et al., 2019; Mikalef et al., 2020; van Rijmenam et al., 2019). The focus of the study was on managerial perspectives of B2B and B2C marketing communication departments. Empirical data was collected by conducting nine semi-structured interviews of managers, leaders and entrepreneurs who worked closely with data-driven initiatives.

Previous research strongly justifies the research gap between big data, decision-making and organizational capabilities. Hence, the following research questions were created:

- How marketing communication departments use big data in data-driven decision-making?
- What kind of organizational capabilities are required in order to utilize data in decision-making?

The study results provide three main theoretical contributions. First, the framework created from the findings extend the framework of data-driven decision-making created by Tabesh et al. (2019) by adding big data perspective and dynamic capabilities into the process. The framework created from the main results clarifies the data-driven decision-making process by explaining what data sources marketing communications departments collect, how they analyze data with different analytical tools and how they apply insights in strategic and operative decision-making. This study confirms the findings of Johnson et al. (2019) and Sleep et al. (2019) who stated that marketing communication departments have access to large volumes of data from different sources, however, what the existing research has not highlighted is that marketing communication departments are building their own data warehouses where they collect and combine data from different sources in order to create insights for decision-making. This study concretizes that marketing communication collect data from websites, advertising platforms, brand surveys, media monitoring, internal sources and customer data sources. Then, these data sources are analyzed by analytical tools such as BigQuery, visualized in tools such as Tableau or PowerBI and used in strategic and operative decision-making.

Secondly, this study identified benefits and challenges of big data utilization. While the previous research has linked big data with competitive advantage (Fosso Wamba et al., 2015; Mikalef et al., 2020), firm performance (Ferraris et al., 2019), differentiation (Barton & Court, 2012) and cost reduction (Benoit et al., 2020), this study identified that big data utilization has strategic, operative and process-related benefits and opportunities. The study also found out that big data enables predictive and real-time decision-making which can be used to identify future customer needs, streamline company's processes and enhance product development, which is in line with the previous research (Cao et al., 2019; Erevelles et al., 2016; Fosso Wamba et al., 2015; Sleep et al., 2019).

The study findings identified similar big data utilization challenges with the existing research. Big data dimensions bring additional challenges when turning data into insights (Bumblauskas et al., 2017; Jabbar et al., 2020; Troisi et al., 2020) and especially data veracity (Fosso Wamba et al., 2015; Janssen et al., 2017; van Rijmenam et al., 2019) and data variety (Sleep et al., 2019; Van Auken, 2015) produce challenges for companies. Variety and veracity are also the most important data dimensions from analytics perspective, which was also identified by Wedel & Kannan (2016). The findings also identified company-related challenges such as quality of processes (Intezari & Gressel, 2016), data analysis (Sheth & Kellstadt, 2021), company's capabilities (Mikalef et al., 2020) and privacy concerns (Benoit et al., 2020). In addition, the study results elaborate the findings of Benoit et al. (2020) by identifying that companies have faced recent iOS and cookie challenges, which has made data combination and decision-making more difficult especially in the field of digital marketing.

Thirdly, the study complements and reinforce the existing research by indicating what kind of organizational capabilities are required in each step of the data-driven decision-making process. Data collection requires developing relevant data sources (Tabesh et al., 2019) and building data integrations (Jeble et al., 2018), which requires technical knowledge and automation (Gandomi & Haider, 2015). Data analysis requires understanding of the context of the data (Bumblauskas et al., 2017), understanding of analytical tools (Tabesh et al., 2019), ability to interpret the data (Eletter et al., 2019) and advanced analytics skills for big data processing (Barton & Court, 2012). Applying insights in decision-making requires goal-setting (Barton & Court, 2012), clear processes (Janssen et al., 2018), communication (Sleep et al., 2019), management support and organizational encouragement (Troisi et al., 2020) and capabilities to produce meaningful insights and recommendations from the data (Bumblauskas et al., 2017; Davenport, 2014).

The study findings also confirm that dynamic capabilities emphasize in big data utilization (Cao et al., 2021; Erevelles et al., 2016; Mikalef et al., 2020; van Rijmenam et al., 2019) and the results contribute to existing knowledge by identifying what dynamic capabilities are in practice from marketing communication perspective. The study shows that companies sense opportunities and threats by following markets, trends, developments of technologies, customers and competitors. Identified opportunities are then seized by product development (van Rijmenam et al., 2019), investments and change of tactics. Finally, companies aim to maintain and improve their competitiveness by transforming processes, resources, strategy or business model, which confirmed the study results of Cao et al. (2021).

5.2 Managerial implications

The main results of the study provide four main implications for managers. The study focused on managerial perspectives and the implications are relevant especially for marketing communication departments but can also be useful for marketing-, media- and communication agencies who provide data-driven marketing communication services to other companies. First, the study results clarify the role of marketing communication departments in data-driven decision-making. Findings advice managers and decision-makers on what kind of data sources marketing communication departments can collect, what kind of analytical tools can be used, how data can be analyzed and what kind of decisions can be made based on analyzed data. When marketing communication departments aim to foster the level of data-driven decision-making in their organization, this research help them to understand how to develop relevant data sources, create analysis capabilities and establish processes for decision-making. Marketing communication departments should strive to combine different external and internal data sources and build prediction models in order to achieve actionable insights for decision-making.

Secondly, this study clarifies why companies should care about big data by identifying strategic, operative and process-related benefits and opportunities. Big data does not only enhance processes and activities, but it can also reveal hidden insights and even completely new business opportunities. Utilization of big data lift the credibility of marketing communication departments and it improves the company's capability to demonstrate the impact of investments. Companies who understand the potential of big data in decision-making can generate more value for both the customer and the company. By ignoring these opportunities, companies may face challenges in terms of competitiveness.

The study also identified that the most common challenge of big data utilization is to combine scattered data from different sources behind a single platform in order to build a holistic understanding of customers and company's actions. In order to tackle this challenge, companies should build processes around key performance indicators and invest in tools and capabilities that enable data manipulation and aggregation. Instead of looking data as a separate part of the business, data should be integrated into company's processes and decision-making. The role of data in companies will continue to grow and it is indeed suggested that marketing communication departments should embrace new technologies and investigate what kind of data sources they could utilize and how. The study indicates that marketing communication departments should invest in data and analytics expertise who can enable and guide with data-driven initiatives.

Thirdly, the study results help managers to understand what kind of organizational capabilities are required in order to collect data, analyze data and apply insights in decision-making. Marketing communication departments should invest capabilities and resources of big data utilization because it democratizes the data analysis and decision-making process and increase the level of data-driven decision-making. Companies need technical knowledge and data integrations to collect the data, tools, analytical skills and business understanding to analyze the data, and goal-setting, systematic processes and management support to apply data in decision-making. The study also shows that big data fosters dynamic capabilities and companies can sense opportunities and threats by following market information, trends, customer behavior, competitors' actions and technological development. Sensed opportunities can then be seized by product development, investments or change of tactics. Finally, with the use of big data, companies can transform their capabilities by streamlining internal and external processes, acquire new resources or shifting the focus of strategy or business model.

Additionally, the study results show differences of big data utilization among business units and functions. The findings indicate that both B2B and B2C sectors collect and combine data from different sources in order to create insights for decision-making, however, it is more common in B2C because they have more customers and therefore, the amount of available data points is bigger. In addition, B2C has often more resources and the length of the sales process is shorter, which motivates the use of data.

5.3 Limitations of the study

The study results should be approached in the light of its limitations. Trustworthiness of the qualitative research can be evaluated by reliability and validity (Rose & Johnson, 2020). Reliability refers to the transparency, consistency and justification of research methods and it usually answers the question of can the study be reproduced (Rose & Johnson, 2020). This study aims to describe and conduct data collection, analysis and reporting of results as transparently and systematic as possible, however, company names and title of interviewees were not disclosed due to confidentiality reasons, which limits the transparency of the findings. The results of the study are also limited by data analysis and the choices made by the researcher during the research process (Hair et al., 2015, p. 295). Qualitative research is strongly subjective and context-sensitive and there are no general guidelines for qualitative data analysis which also reduce generalizability. Thus, the study results are limited to one data collection method (Braun &

Clarke, 2006) and the quality of the study depends on the researcher's ability to understand and examine the topic.

Validity refers to accuracy of the findings related to theoretical framework and research questions while focusing on whether the research measure what it is supposed to measure (Rose & Johnson, 2020). The study aimed to improve the validity of the study by creating a coherent theoretical framework, using a wide range of peer-reviewed journal references and conducting insightful interviews with respect to the research questions. However, similar to most qualitative studies, the sample size of nine interviews limits the credibility, accuracy and generalizability of the findings (Adams et al., 2014, p. 97). In addition, data was gathered from one geographical location although most of the interviewees operated in an international environment.

All the interviewees were experienced professionals and worked in large companies who had invested in data and analytics, which may create the impression that marketing communication departments are more advanced in data utilization than in reality. Therefore, results obtained from purposeful sampling tactic may not reflect the greater group of marketing communication departments. By investigating smaller companies, the study could have revealed different kind of results. In addition, the study results are not able to prove causal evidence between the findings.

5.4 Future research suggestions

Although the findings were largely consistent with the existing research and the importance of big data and data-driven decision-making has been proven, there is room for further research on the topic. Since the data collection of the study consisted of large companies, future research could investigate the role of big data and dynamic capabilities among mid-size and smaller companies. The same theoretical framework could be utilized in order to explore what kind of data sources smaller companies collect, how they turn data into insights and apply analyzed data in decision-making. In addition, the role of big data could be examined more specifically in marketing strategies.

While one the main challenges of big data utilization concern combining data from different sources, further understanding of how to combine structured and unstructured data sources behind a single platform should be conducted. Additionally, predictive analytics and decision-making was identified as a clear benefit of big data, therefore, both scientific and practice community could benefit from case studies that document how this can be done and what kind of tools, technologies, data sources and capabilities it requires.

When companies want to foster data-driven decision-making across business units and teams, it is important that all employees understand what is being discussed. Therefore, a useful topic for future research is building a taxonomy of different terms related to data sources, data combination, data utilization and KPI measures. This was also mentioned by one interviewee who emphasized the need for certain type of taxonomy, which would allow everyone in the company to use and understand the same terms.

Geographical location of the study was limited, therefore, similar studies could be conducted elsewhere in order to understand cultural factors and differences in big data utilization and data-driven decision-making. One evident finding of the study was that big data is democratizing the analysis and decision-making. Based on this, future research of how companies can scale data-driven initiatives into a company-wide capability could be valuable. In addition, since the role of data in decision-making will continue to increase, the business value of big data will remain an important research topic in the future.

REFERENCES

Adams, J., Khan, H.T.A. & Raeside, R. 2014. Research Methods for Business and Social Science Students (2rd ed). Sage Publications.

Agrawal, D. 2014. Analytics based decision making. Journal of Indian Business Research, 6(4), 332-340. https://doi.org/10.1108/JIBR-09-2014-0062

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R. & Childe, S.J. 2016. How to improve firm performance using big data analytics capability and business strategy alignment? International Journal of Production Economics, 182, 113-131. http://dx.doi.org/10.1016/j.ijpe.2016.08.018

Barton, D. & Court, D. 2012. Making Advanced Analytics Work for You. A practical guide to capitalizing on big data. Harvard Business Review, 90 (10), 78-83.

Bean, R. & Davenport, T. H. 2019. Companies Are Failing in Their Efforts to Become Data-Driven. Harvard Business Review. [Referred 26.1.2022]. Available at: <URL: https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven>

Belk, R.W., Fischer, E. & Kozinets, R.V. 2013. Qualitative consumer & marketing research. Approaches to data analysis, interpretation and theory building for scholarly research. London: Sage.

Benoit, D. F., Lessmann, S. & Verbeke, W. 2020. On realizing the utopian potential of big data analytics for maximizing return on marketing investments. Journal of Marketing Management, 36(3-4), 233-247. https://doi.org/10.1080/0267257X.2020.1739446

Boldosova, V. 2020. Telling stories that sell: The role of storytelling and big data analytics in smart service sales. Industrial Marketing Management, 86, 122-134. https://doi.org/10.1016/j.indmarman.2019.12.004

Boyd, D. & Crawford. K. 2012. Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon. Information, Communication, & Society, 15(5), 662-679.

Branda, A. F., Lala, V. & Gopalakrishna, P. 2018. The marketing analytics orientation (MAO) of firms: Identifying factors that create highly analytical marketing practices. Journal of Marketing Analytics, 6(3), 84-94. DOI:10.1057/s41270-018-0036-8

Braun, V. & Clarke, V. 2006. Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101.

Brynjolfsson, E., Hitt, L. & Kim, H. 2011. Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance? Social Science Research Network, Electronic Journal 1. http://dx.doi.org/10.2139/ssrn.1819486

Bumblauskas, D., Nold, H., Bumblauskas, P. & Igou, A. 2017. Big data analytics: transforming data to action. Business Process Management Journal, 23(3), 703-720. DOI 10.1108/BPMJ-03-2016-0056

Cao, G., Tian, N. & Blankson, C. 2021. Big data, Marketing Analytics, and Firm Marketing Capabilities. Journal of Computer Information Systems, 62(3), 442-451. DOI: 10.1080/08874417.2020.1842270

Cao, G., Duan, Y. & Banna, A.E. 2019. A dynamic capability view of marketing analytics: Evidence from UK firms. Industrial Marketing Management, 76, 72-83. https://doi.org/10.1016/j.indmarman.2018.08.002

Carillo, K.D.A, Galy, N., Guthrie, C. & Vanhems, A. 2019. How to turn managers into data-driven decision makers: Measuring attitudes towards business analytics. Business Process Management Journal, 25(3), 553-578. https://doi.org/10.1108/BPMJ-11-2017-0331

Chen, H., Chiang, R. H. L., & Storey, V. C. 2012. Business Intelligence and Analytics: From Big Data to Big Impact. MIS Quarterly, 36(4), 1165–1188.

Court, D., Perrey, J., McGuire, T., Gordon, J. & Spillecke, D. 2015. Big Data, Analytics and the Future of Marketing & Sales. Putting Big data and advanced analytics to work. McKinsey and Company. [Referred 16.9.2021]. Available at: <URL: https://www.mckinsey.com/business-functions/growth-marketing-and-sales/our-insights/ebook-big-data-analytics-and-the-future-of-marketing--sales>

Day, G.S. 2011. Closing the Marketing Capabilities Gap. Journal of Marketing, 75 (4), 183-195.

Davenport, T. 2014. How strategists use "big data" to support internal business decisions, discovery and production. Strategy & Leadership, 42(4), 45-50. https://doi.org/10.1108/SL-05-2014-0034

Davenport, T. 2013. Analytics 3.0. Harvard Business Review, 91(12), 64-72.

De Luca, L.M., Herhasen, D., Troilo, G. & Rossi, A. 2020. How and when do big data investments pay off? The role of marketing affordances and service innovation. Journal of the Academy of Marketing Science, 49(4), 790-810. https://doi.org/10.1007/s11747-020-00739-x

Eletter, S.F., Yasmin, T. & El Refae, G.A. 2019. Marketing Intelligence in the Era of Big Data. TEM Journal, 8(3), 938-944. DOI: 10.18421/TEM83-35

Erevelles, S., Fukawa, N. & Swayne, L. 2016. Big data consumer analytics and the transformation of marketing. Journal of Business Research, 69(2), 897-904. https://doi.org/10.1016/j.jbusres.2015.07.001

Eriksson, P. & Kovalainen, A. 2008. Qualitative Methods in Business Research. Sage Publications.

Fan, S., Lau, R.Y.K. & Zhao, J.L. 2015. Demystifying Big Data Analytics for Business Intelligence Through the Lens of Marketing Mix. Big Data Research, 2(1), 28-32.

Ferraris, A., Mazzoleni, A. Devalle, A. & Couturier, J. 2019. Big data analytics capabilities and knowledge management: impact on firm performance. Management Decision, 57(8), 1923-1936.

Fitzgerald, M. 2015. How to Hire Data-Driven Leaders. MIT Sloan Management Review, 56(3), 63-68.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G. & Gnanzou, D. 2015. How 'big data' can make big impact: findings from a systematic review and a longitudinal case study. International Journal of Production Economics, 165, 234-246.

Forrester, 2012. The Big Deal About Big Data for Customer Engagement Business: Leaders Must Lead Big Data Initiatives to Derive Value. [Referred 11.9.2021]. Available at: <URL: http://www.iab.fi/media/tutkimus-matskut/130822_forrester_the_big_deal_about_big_data.pdf>

Frisk, J.E. & Bannister, F. 2017. Improving the use of analytics and big data by changing the decision-making culture. A design approach. Management Decision, 55(10), 2074-2088. DOI 10.1108/MD-07-2016-0460

Gandomi, A. & Haider, M. 2015. Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), 137-144. http://dx.doi.org/10.1016/j.ijinfomgt.2014.10.007

Germann, F., Lilien, G.L. & Rangaswamy, A. 2013. Performance implications of deploying marketing analytics. International Journal of Research in Marketing, 30(2), 114-128. DOI: 10.1016/j.ijresmar.2012.10.001

Gnizy, I. 2020. Applying big data to guide firms' future industrial marketing strategies. Journal of Business & Industrial Marketing, 35(7), 1221-1235. https://doi.org/10.1108/JBIM-06-2019-0318

Grandhi, B., Patwa, N. & Saleem, K. 2020. Data-driven marketing for growth and profitability. EuroMed Journal of Business, 16(4), 381-398. https://doi.org/10.1108/EMJB-09-2018-0054

Grix, J. 2002. Introducing Students to the Generic Terminology of Social Research. Politics, 22(3), 175-186. https://doi.org/10.1111/1467-9256.00173

Hair, J.F., Money, A.H., Samouel, P. & Page, M. 2015. The essentials of business research methods (3rd ed.). London: Routledge.

Hallikainen, H., Savimäki, E. & Laukkanen, T. 2020. Fostering B2B sales with customer big data analytics. Industrial Marketing Management, 86, 90-98. https://doi.org/10.1016/j.indmarman.2019.12.005

Helfat, C.E. & Winter, S.G. 2011. Untangling dynamic and operational capabilities: strategy for the (n)ever-changing world. Strategic Management Journal, 32, 1243-1250. DOI: 10.1002/smj.955

IBM. 2017. Making Sense of Big Data. A Day in the Life of an Enterprise Architect. An Enterprise Management Associates (EMA) White Paper.

Intezari, A. & Gressel, S. 2016. Information and reformation in KM systems: big data and strategic decision-making. Journal of Knowledge Management, 21(1), 71-91. DOI 10.1108/JKM-07-2015-0293

Jabbar, A., Akhtar, P. & Dani, S. 2020. Real-time big data processing for instantaneous marketing decisions: A problematization approach. Industrial Marketing Management, 90, 558-569. https://doi.org/10.1016/j.indmarman.2019.09.001

Janssen, M., vander Voort, H. & Wahyuidi, A. 2017. Factors influencing big data decision-making quality. Journal of Business Research, 70, 338-345. DOI: 10.1016/j.jbusres.2016.08.007

Jeble, S., Kumari, S. & Patil, Y. 2018. Role of Big Data in Decision Making. Operations and Supply Chain Management, 11(1), 36-44.

Jobs, C.G., Gilfoil, D.M. & Aukers, S.M. 2016. How marketing organizations can benefit from big data advertising analytics. Academy of Marketing Studies Journal, 20, 18-35.

Johnson, D.S., Muzellec, L., Sihi, D. & Zahay, D. 2019. The marketing organization's journey to become data-driven. Journal of Research in Interactive Marketing, 13(2), 162-178. DOI 10.1108/JRIM-12-2018-0157

Kachouie, R., Mavondo, F. & Sands, S. 2018. Dynamic marketing capabilities view on creating market change. European Journal of Marketing, 52(5-6), 1007-1036. DOI 10.1108/EJM-10-2016-0588

Kahneman, D., Lovallo, D. & Sibony, O. 2011. Before You Make That Big Decision. Harvard Business Review, 89(6), 50-60.

Laney, D. 2001. 3D data management: Controlling data volume, velocity and variety. META Group Research Note, 6(70), 1.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. and Byers, A.H. 2011. Big data: the next frontier for innovation, competition, and productivity, McKinsey and Company. [Referred 10.9.2021]. Available at: <URL: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/big-data-the-next-frontier-for-innovation>

McAfee, A. & Brynjolfsson, E. 2012. Big data: The Management Revolution. Harvard Business Review, 90 (10), 60-68.

Mikalef, P., Krogstie, J., Pappas, I.O. & Pavlou, P. 2020. Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & Management, 57(2), 1-15. https://doi.org/10.1016/j.im.2019.05.004

Mikalef, P., Pappas, I. O., Krogstie, J. & Giannakos, M. 2018. Big data analytics capabilities: a systematic literature review and research agenda. Information Systems and e-Business Management, 16, 547-578. https://doi.org/10.1007/s10257-017-0362-y

Power, D. J. 2014. Using 'Big data' for analytics and decision support. Journal of Decision Systems, 23(2), 222-228. http://dx.doi.org/10.1080/12460125.2014.888848

Provost, F. & Fawcett, T. 2013. Data Science and its Relationship to Big Data and Data-Driven Decision Making. Big data, 1(1), 51-59. DOI: 10.1089/big.2013.1508

Rejeb, A., Rejeb, K. & Keogh, J. G. 2020. Potential of Big Data for Marketing: A Literature Review. Management Research and Practice, 13(3), 60+.

Rose, J. & Johnson, C. W. 2020. Contextualizing reliability and validity in qualitative research: toward more rigorous and trustworthy qualitative social science in leisure research. Journal of leisure research, 51(4), 432-451. https://doi.org/10.1080/00222216.2020.1722042

Shah, S., Horne, A. & Capellá, J. 2012. Good Data Won't Guarantee Good Decisions. Harvard Business Review, 90(4), 23-25.

Shah, D. & Murthi, B.P.S. 2021. Marketing in a data-driven digital world: Implications for the role and scope of marketing. Journal of Business Research, 125, 772-779. https://doi.org/10.1016/j.jbusres.2020.06.062

Sheth, J. & Kellstadt, C. H. 2021. Next frontiers of research in data driven marketing: Will techniques keep up with data tsunami? Journal of Business Research, 125, 780-784. https://doi.org/10.1016/j.jbusres.2020.04.050

Sleep, S., Hulland, J. & Gooner, R.A. 2019. The Data Hierarchy: factors influencing the adoption and implementation of data-driven decision making. Academy of Marketing Science Review, 9, 230-248. https://doi.org/10.1007/s13162-019-00146-8

Smallwood, N. & Ulrich, D. 2004. Capitalizing on Capabilities. Harvard Business Review. [Referred 12.11.2021]. Available at: <URL: https://hbr.org/2004/06/capitalizing-on-capabilities>

Song, I. Y. & Zhu, Y. 2016. Big data and data science: What should we teach? Expert Systems, 33(4), 364–373.

Suoniemi, S., Meyer-Waarden, L., Munzel, A., Zablah, A. R. & Straub, D. 2020. Big data and firm performance: The role of market-directed capabilities and business strategy. Information & Management, 57(7), 103365. DOI:10.1016/j.im.2020.103365

Suri, H. 2011. Purposeful Sampling in Qualitative Research Synthesis. Qualitative research journal, 11(2), 64-75.

Tabesh, P., Mousavidin, E. & Hasani, S. 2019. Implementing big data strategies: A managerial perspective. Business Horizons, 62(3), 347-358. https://doi.org/10.1016/j.bushor.2019.02.001

Teece, D.J. 2014. The foundations of enterprise performance: dynamic and ordinary capabilities in an (economic) theory of firms. The Academy of Management Perspectives, 28(4), 328-352. http://dx.doi.org/10.5465 /amp.2013.0116

Teece, D.J. 2007. Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. Strategic Management Journal, 28(13), 1319-1350.

Troisi, O., Maione, G., Grimaldi, M. & Loia, F. 2020. Growth hacking: Insights on data-driven decision-making from three firms. Industrial Marketing Management, 90, 538-557. https://doi.org/10.1016/j.indmarman.2019.08.005

Van Auken, S. 2015. From consumer panels to big data: An overview on marketing data development. Journal of Marketing Analytics, 3, 38-45. DOI:10.1057/jma.2015.2

van Rijmenam, M., Erekhinskaya, T., Schweitzer, J. & Williams, M.A. 2019. Avoid being the Turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty. Long Range Planning, 52(5), 101841. https://doi.org/10.1016/j.lrp.2018.05.007

Wang, W. & Wang, Y. 2020. Analytics in the era of big data: The digital transformations and value creation in industrial marketing. Industrial Marketing Management, 86, 12-15. DOI:10.1016/j.indmarman.2020.01.005

Wedel, M. & Kannan, P.K. 2016. Marketing Analytics for Data-Rich Environments. Journal of Marketing: AMA/MSI Special Issue, 80, 97-121 DOI: 10.1509/jm.15.0413

Weinberg, B.D., Davis, L. & Berger, P.D. 2013. Perspectives on Big Data. Journal of Marketing Analytics 1, 187-201. DOI:10.1057/jma.2013.20

Westermann, A. & Forthmann, J. 2020. Social listening: a potential game changer in reputation management – How big data analysis can contribute to understanding stakeholders' views on organizations. Corporate Communications: An International Journal, 26(1), 2-22. DOI 10.1108/CCIJ-01-2020-0028

Winter, S.G. 2003. Understanding dynamic capabilities. Strategic Management Journal, 24(10), 991-995. https://doi.org/10.1002/smj.318

APPENDICES

APPENDIX 1 The structure of the interview

Warm up questions

1. What is your current role and main tasks?
2. How long have you worked in your current position? What about similar positions?
3. What kind of expertise do you have in your team related to marketing or communication?

Data-driven decision-making (making decisions based on the analysis of data rather than purely on intuition or expertise)

4. How do you perceive the role of data-driven decision-making in your current position? What is the role of it in your organization?
5. What is the role of management/executives in data-driven decision-making?
6. What do you think are the possibilities of using data in decision-making? Can you elaborate how data has been useful in decision-making related to your tasks?
7. Have you faced any challenges when applying data in decision-making? If yes, what kind of challenges?

(Big) data (refers to volume, variety, velocity, veracity and value of the data)

8. What type/kind of data do you collect and use in your current position?
9. How do you collect the data? Who is responsible for collecting the data?
10. How is the collected data analyzed? What kind of analytics tools do you use? Who is responsible for analyzing the data?
11. Is the analyzed data used in decision-making?
    a. If yes, in what kind of decisions?
    b. If no, why the analyzed data is not used in decision-making?

Organizational capabilities (refer to collective skills and intangible assets of an organization, not so much about the competence of individual employees)

12. What kind of organizational capabilities do you think is required in order to …?
    a) collect the data
    b) analyze the data in order to create insights
    c) apply data/insights in decision-making
13. How do you / your organization scan the environment in order to identify and discover new market opportunities or threats?
14. How do you / your organization react to identified market opportunities or threats?
15. Are those recognized opportunities or threats used to improve the company's competitive advantage? If yes, how?

Ending question

16. Is there anything else that you would like to emphasize that has not been clarified yet regarding the use of (big) data or organizational capabilities in decision-making?