THE USE OF BIG DATA ANALYTICS IN THE STRATEGIC MARKETING DECISION-MAKING

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ABSTRACT

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Big Data has emerged as an impactful technology across industries, including marketing. Big Data Analytics refers to the technologies and analytical methods used to process Big Data, and it is considered as an innovative tool for data-driven decision-making. The use of Big Data Analytics creates an opportunity for insights that will positively support strategies and marketing actions in data-driven marketing and is still yet to reach its full potential. Despite the recognized potential that Big Data Analytics offer for decision-making, it remains unclear how Big Data Analytics are used in the strategic marketing decision-making.

This study aims to offer knowledge how Big Data Analytics is utilized in the strategic marketing decision-making and how Big Data Analytics provide firms with knowledge for strategic marketing decision-making through knowledge management processes and dynamic capabilities. The study conducted in this thesis is a qualitative study that uses exploratory research design. The data was collected with five semi-structured interviews of experts in marketing organizations.

The findings of this thesis are in accordance with the existing literature, but also provides an original data-driven marketing model for the use of Big Data Analytics in strategic marketing decision-making through knowledge management processes and creation of dynamic capabilities. The veracity and validity of the data used in Big Data Analytics emerged as an important factor, and the use of Big Data Analytics in strategic decision-making must be guided by a good understanding of the organisation's marketing operations. The findings draw connections between Big Data Analytics and strategic marketing decision-making phases, emphasizing dynamic capabilities provided by Big Data Analytics in improved reactivity and adaptiveness. In addition, the findings provide new insights on the utilization of Big Data Analytics in strategic decision-making and on data-driven marketing.

Key words
Big Data Analytics, data-driven marketing, strategic decision-making, dynamic capabilities, knowledge management

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Massadata (engl. Big Data) on noussut esiin merkittävänä teknologiana useilla eri toimialoilla, markkinointi mukaan lukien. Massadata-analytiikka viittaa massadatan käsittelyssä käytettäviin teknologioihin ja analyyttisiin menetelmiin. Massadata-analytiikkaa pidetään innovatiivisena työkaluna tietopohjaisessa päätöksenteossa. Vaikka massadata-analytiikan käyttö luo mahdollisuuden näkemyksiin, jotka tukevat positiivisesti strategioita ja markkinointitoimia tietopohjaisessa markkinoinnissa, sen täyttä potentiaalia ei ole vielä saavutettu. Massadata-analytiikan päätöksentekoon tarjoaman potentiaalin tunnistamisesta huolimatta, ymmärrys massadata-analytiikan käytöstä markkinoinnin strategisessa päätöksenteossa on toistaiseksi vajavaista.

Tämän tutkimuksen tavoitteena oli tutkia, kuinka massadata-analytiikkaa hyödynnetään markkinoinnin strategisessa päätöksenteossa ja kuinka massadata-analytiikka tarjoaa yrityksille tietoa strategista päätöksentekoa varten hyödyntäen tietämyksenhallinnan prosesseja ja dynaamisia kyvykkyyksiä. Tutkielmassa käytettävä tutkimusmuoto oli kartoittava ja kvalitatiivinen tutkimus. Tutkimuksen aineisto muodostui viidestä puolistrukturoidusta haastattelusta, joissa haastateltiin asiantuntijoita markkinointiorganisaatioista.

Tulokset olivat pääosin linjassa aiempien tutkimustulosten kanssa, mutta tutkimus syvensi aiempia tuloksia esittelemällä alkuperäisen tietopohjaisen markkinoinnin mallin massadata-analytiikasta markkinoinnin strategisessa päätöksenteossa, hyödyntäen tietämyksenhallinnan prosesseja, sekä luoden dynaamisia kyvykkyyksiä. Massadata-analytiikassa käytettävän datan oikeellisuus ja validiteetti nousivat esiin merkittävinä tekijöinä, ja massadata-analytiikan käyttöä markkinoinnin strategisessa päätöksenteossa ohjaa hyvä ymmärrys organisaation markkinoinnin toiminnoista. Tulokset yhdistävät massadata-analytiikan ja strategisen päätöksenteon vaiheet korostaen massadata-analytiikan tarjoamia dynaamisia kyvykkyyksiä reaktiivisuuden ja sopeutumiskyvyn kautta. Lisäksi tutkimuksen tulokset antavat uusia näkemyksiä massadata-analytiikan hyödyntämisestä strategisessa päätöksenteossa ja tietopohjaisessa markkinoinnissa.

Asiasanat
massadata-analytiikka, tietopohjainen markkinointi, strateginen päätöksenteko, dynaamiset kyvykkyydet, tietämyksenhallinta

Säilytyspaikka
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1 INTRODUCTION

This master's thesis aims to discover how Big Data Analytics is used in strategic marketing decision-making. The introduction of the thesis starts with the background of the study and then we move on to the research gap and research questions that support the objective of the study. In the last part of the introduction the structure of the research is presented.

1.1 Background of the study

Data has become central and essential asset to any business, and it can be seen as a form of capital which has an important role in business decisions, and the amount of data and data-based products is exponentially increasing (Sadowski, 2019). A good example of this is the fact that four of the five biggest companies in the world based on market capitalization are technology companies, whose main asset is data (Statista, 2021).

According to Xu et al. (2016), most of marketing decisions is based on analytics that deals with small data sets such as megabytes or gigabytes. The problem concerning the small data sets and the methods to analyse those is that the analyses are hard to replicate as small datasets do not represent all relevant information about the setting at hand (Xu et al., 2016). Thus, leading to limitations for implementation of analytics into decision-making (Xu et al., 2016). Recent innovations in information technology and marketing have given versatile solutions for applying Big Data into firm's data-driven decision-making.

Big data is a term to describe data sets that presents challenges to conventional database, software, and analysis tools, which has been created by the firms' access to large quantities of internal and external data (Johnson et al., 2019). Big Data as a concept was formed by a rapid growth in digital data flows and in information technology innovation (Johnson et al., 2019). The growth of data flows that has created Big Data is the result of new developments in communication technology, such as smart devices, Internet of Things, web 2.0, and social media (Gökalp et al., 2022; Rust & Huang, 2014). These technological advancements have brought customers closer to firms, together with the implementation of ERP, CRM software, and other IT technologies (Rust & Huang, 2014; Shah, 2022). This has further led to generating huge amounts of complex data to be collected, developments in data storage capabilities, and developments in computational speed to process the data (Gökalp et al., 2022; Shah, 2022). Hence, all the vast amounts of data must be stored in an organizational knowledge repository, such as data server or cloud (Shah, 2022).

Big Data has become a disruptive technology that has a big impact across industries, including marketing, and is still yet to reach its full potential (Cao et al., 2019; Gnizy, 2020). Big Data is considered as a tool for innovation, optimizing processes and predictive analysis for future decision-making (Gnizy, 2020; Shah, 2022). In turn, Big Data marketing analytics, which refers to the technologies and statistical techniques used by marketers to process Big Data, creates an opportunity for insights that will positively support strategies and marketing actions (Gnizy, 2020; Johnson et al., 2019). On the organizational level Big Data Analytics give opportunities in business intelligence, cognitive computing, business innovation, customer churn prevention, knowledge co-creation and organization agility (Fosso Wamba et al., 2015). This is supported by recent research that states that marketing analytics have potential to efficiently drive and improve firm's competitiveness and performance (Cao et al., 2019). Big Data analytics differ from traditional marketing analytics by offering real time analysis of enormous volumes of data to generate a flow of information, whereas traditional marketing analytics focus on key performance indicators' performance in the past (Xu et al., 2016).

Big Data Analytics have given firms a real-time access to information that help firms to achieve significant results in sales revenues, retention rates, and in market capitalization (Fosso Wamba et al., 2015). According to Fosso Wamba et al. 2015, in the current highly competitive markets analytics have become a vital part of decision-making and those decisions must be informed, timely, and accurate. They also state that has led to Big Data Analytics transforming into a necessity in order to compete successfully in the competitive markets (Fosso Wamba et al., 2015).

As firms have adopted Big Data Analytics into their marketing operations and incorporate data and automation to highly complex decisions that have traditionally been led by human intuition, they have been able to establish data-driven marketing in their organization (Chen et al., 2015; Johnson et al., 2019). Data-driven marketing is the combination of traditional strategic and tactical marketing actions and the utilization of analysis based on organizational customer and cost data to gain better insights from the data that create business value (Johnson et al., 2021; Sheth & Kellstadt, 2021). Data-driven marketing supports marketing professionals' creativity and strategic decision-making with data analytics for better tactical and strategic actions (Johnson et al., 2021; Shah & Murthi, 2021). Data-driven marketing organizations understand better their customers, costs, sales potential, and possible market opportunities and apply data more efficiently in decision-making on all levels of the firm (Johnson et al., 2019).

However, much of the potential in analytics is still yet to be utilized, especially in marketing since many firms still lack a comprehensive understanding of the reasons and benefits behind Big Data marketing analytics (Cao et al., 2019; C. Zhang et al., 2020). After all, Big Data itself does not offer value because it is purely a raw material and therefore marketers need to harness the Big Data to create big impact, so that it is effectively used to its full potential (Amado et al., 2018; Xu et al., 2016). Firms become data-driven by creating Big Data segments based on the data from social networks, business meters and monitors, Internet of Things, clickstream data, integrated transactions, and third-party data (Erevelles et al., 2016; Johnson et al., 2019; Sivarajah et al., 2017). Big Data analytics has gained an increasingly important role in business and marketing decisions and management because Big Data Analytics gives managers an opportunity to make real-time decisions based on evidence rather than intuition (Erevelles et al., 2016; Ferraris et al., 2019).

Big Data is still a developing subject and the definition of Big Data itself is constantly reinvented to keep up with the technological advancements of Big Data. This makes it a highly dynamic subject and combined with the proven but still underused potential in marketing, it needs further research (Amado et al., 2018; Ducange et al., 2018; Fan et al., 2015; Fosso Wamba et al., 2015).

1.2 Study objectives and research questions

As Big Data has emerged as a disruptive technology, it has been studied in multiple contexts. A lot of research has been done from the technical/computer science point-of-view, but the number of relevant Big Data research focusing on marketing is still low. However, in the recent years marketing has become a field for experiments with Big Data, which has accelerated the number of research in the context of marketing (Amado et al., 2018).

Many factors can be used to divide Big Data and Big Data analytics research based on the context or theoretical backgrounds. Big Data gathered from social media has been in the focus of the research. For example, Ducange et al. (2018) studied the competitive advantages that can be discovered in social Big Data, whereas Zhang et al. (2022) studied how social Data can be used for business decisions.

In the industrial or B2B marketing context, Big Data has been studied a lot from multiple viewpoints. Wang & Wang (2020) identified how Big Data analytics can be used for value creation in the B2B markets. Wright et al. (2019) studied utilizing Big Data for business innovations in B2B markets. Whereas the focus for Jabbar et al. (2020) was on how Big Data analytics could be used in programmatic marketing to make better real-time decisions in B2B markets. Gnizy (2020) studied how Big Data analytics can be leveraged in strategic decision-making in marketing through selecting between generic strategies of differentiation, focus, and cost leadership strategies. The study by Gnizy (2020) differs from this one by being done in B2B context and how to use Big Data Analytics to choose a generic strategy, whereas this study focuses on how Big Data Analytics is used in the strategic decision-making process. Big Data from the viewpoint of strategic decision-making has also been studied by Kumar et al. (2013) but in B2C context.

Different theoretical viewpoints have been applied to Big Data research as well. Marketing mix has been used as the theoretical background in some studies. Fan et al. (2015) approached Big Data analytics through the lens of marketing mix in their research and Kumar et al. (2020) studied how to use Big Data to optimize marketing activities based on the marketing mix. Gupta et al. (2021) studied utilization of Big Data analytics on firm performance based on the knowledge-based view, whereas Xu et al (2016) applied knowledge-based view on their study where they studied the impact of Big Data on new product success. Côrte-Real et al. (2017) used knowledge-based view on their study to gain understanding how Big Data Analytics offer firms dynamic capabilities in the form of organizational agility. Erevelles et al. (2016), Ferraris et al. (2019) and Zhang et al. (2020) have applied resource-based theory to their research on Big Data. Erevelles et al. (2016) studied how Big Data can impact marketing activities to better exploit firms' resources. Zhang et al. (2020) investigated the driving forces behind assimilation of Big Data analytical intelligence and its impact on customer relationship management performance.

Data-driven marketing has been a focal viewpoint in other studies as well. Johnson et al. (2019) studied how organizations can improve data-driven marketing better by implementing Big Data analytics into marketing functions. Troisi et al. (2020) studied the use of Big Data marketing analytics as a function for data-driven decision. Kumar et al. (2020) applied data-driven marketing to investigate the use of Big Data analytics in different marketing activities and to refine a framework for customer demands. Akter et al. (2021) studied Big Data through the lens of data-driven marketing to build a holistic framework for strategic orientations in international markets.

Big Data has also been studied from the following perspectives. Buhalis & Volchek (2021) and Hofacker et al. (2016) studied from the perspective of consumer decision-making. Buhalis & Volchek (2021) combined consumer decision-making with marketing attribution methods in their study. Hofacker et al. (2016) studied how Big Data be used to give further understanding of different stages in consumer decision process. In addition to Zhang et al. (2020) and Amado et al. (2018) studied Big Data analytics in marketing in the context of customer relationship management performance. Whereas Kunz et al. (2017) studied how Big Data can be used to create customer engagement.

Ferraris et al. (2019) state that the information that is generated from Big Data can be transformed into efficient decisions that improve firm's performance as well as its whole decision-making processes. They also add that a research gap exists in the knowledge on how the implementation of Big Data is connected to the strategic management of a firm. This is also supported by Gupta et al. (2021) and Johnson et al. (2021) who state that, even though Big Data analytics have been implemented in marketing organizations, the use of it is superficial and a gap exists in the implementation of Big Data analytics for the strategic decision-making in marketing, to the extent that some marketing organizations are unaware of the benefits of using Big Data to improve decision-making. Gupta et al. (2021) add that further research is needed on how knowledge management can be utilized in the use of Big Data Analytics for superior decision-making in marketing strategy. To conclude, the key research gap that this thesis aims to fill is presented by Ferraris et al. (2019), Gupta et al. (2021), and Johnson et al. (2021), who state that there is a gap in research on how Big Data Analytics is utilized in strategic marketing decision-making.

As stated earlier, Big Data has been studied from multiple perspectives. Organizational theories and knowledge management have been applied in Big Data research to provide a theoretical foundation for the studies. De Camargo Fiorini et al. (2018) present that the application of organizational theories in Big Data research is important, because they give a better and deeper understanding of the implications of Big Data in the organizational context. Knowledge-based view, as an organizational theory, offers a thorough understanding of how information and knowledge can be applied at the organizational level for effective strategic decision-making (Grant, 1996). Big Data Analytics as a dynamic capability has been studied and found to support knowledge creation that improves capability in strategic decision-making (Chen et al., 2015). Knowledge-based view combined with dynamic capabilities provide a theoretical lens on to understand the use of Big Data Analytics in strategic decision-making in marketing through knowledge management (Côrte-Real et al., 2017; de Camargo Fiorini et al., 2018). Based on the theoretical support that organizational theories and knowledge management offer for Big Data research, presented by de Camargo Fiorini et al. (2018), this thesis uses knowledge management and knowledge-based view as theoretical basis. To gain a stronger theoretical foundation for the use of Big Data analytics in knowledge creation, this thesis utilizes dynamic capabilities with knowledge-based view as presented by Côrte-Real et al. (2017) and de Camargo Fiorini et al. (2018).

The implementation and use of Big Data analytics does not only concern academics but practical questions from the managerial point-of-view have risen as well. Managerial challenges that concern the practice of Big Data analytics in marketing have been discussed in the past year in managerial literature. Bean (2021) presented that many firms have invested heavily in Big Data solutions during the past ten years but few of them have had significant success, whereas many of the investments have not turned into profit. Therefore, Bean (2021) states that the challenge still continues to be that firms need better understanding as to how to utilize Big Data and Big Data analytics, and how to create a culture that supports it. Knowledge@Wharton (2020) discussed how data analytics will change marketing in the future and they presented upcoming challenges such as how the removal of third-party data makes firms shift to their own first-party data and how generates a challenge of how firms can create a culture that supports the utilization of data to predict the future instead of looking at the past. Based on these, there clearly is a practical gap on the organizational understanding of big data and the culture to leverage it to support the decision-making.

The study objectives of this master’s thesis are to fill the research gap and give deeper insight in the Big Data based strategic decision-making in marketing by employing a suitable framework based on knowledge management, knowledge-based view, and dynamic capabilities.

Therefore, in this master's thesis the main research question is:

How can Big Data Analytics be utilized in the strategic decision-making in marketing organizations?

To support the practical challenges and the overall study the additional research question is:

How Big Data Analytics support knowledge creation that generates dynamic capabilities useful for strategic decision-making?

The study conducted in this thesis is an exploratory study. The method for the study is qualitative and data is collected with semi-structured interviews of experts in marketing organizations relevant for this thesis. Qualitative study is justified for this research because the aim of this thesis is to gain a deeper understanding of a novel phenomenon of how Big Data Analytics are utilized in strategic decision-making in marketing (Hirsjärvi et al., 2009). The methodology and collection of data is further discussed later in the thesis.

1.3 Big Data and other key concepts

Big Data is usually presented through its characteristics or Vs. Most commonly Big Data is described by using three Vs; Volume, Velocity, and Variety (Ducange et al., 2018; Gnizy, 2020; Hofacker et al., 2016). The volume of Big Data refers to the massive quantity of data available to organizations and firms, that are so large, complex, and unstructured that it requires unique skills and technology to acquire, store, manage and analyse the data to a usable form (Ducange et al., 2018; Xu et al., 2016). The volume of Big Data is measured in terabytes, petabytes, exabytes or zettabytes and the volume of Big Data is estimated to double in every two years (Erevelles et al., 2016). To put this into perspective, one petabyte is equivalent to 20 million filing cabinets of text and Walmart alone creates 2.5 petabytes of consumer data every hour (Erevelles et al., 2016). However, Big Data is not ultimately about the pure size of the data, but it is about the insights from the data, and therefore the methods to analyse and process the massive datasets has become more vital for firms to gain competitive advantage (Erevelles et al., 2016; Xu et al., 2016).

The velocity of Big Data refers to the high speed of the data that is gathered and created, and to the frequency the data changes and when the old data becomes inaccurate (Erevelles et al., 2016; Kunz et al., 2017). Jabbar et al. (2020) add that the velocity in which the data is gathered, is in direct influence on how quickly it can be analysed. The velocity of the data calls for real-time processing and analysis of the data for it to be useful when used in decision-making

(Ducange et al., 2018; Kunz et al., 2017). Erevelles et al. (2016) state Big Data differs from other large datasets by giving access to current, real-time data at any given time, which gives the opportunity for marketing executives make better decisions based on insightful, relevant, and current data.

The variety of Big Data refers to how Big Data is gathered from multiple sources, which leads to the data being stored in numerous different formats (Xu et al., 2016). Generally, the formats of Big Data are heterogenous and can be structured or unstructured. Structured data is in a pre-defined tabular format and are therefore analytics ready without any processing, such as dates or addresses (Jabbar et al., 2020). Whereas unstructured data has no predefined data model and can be in a text, image, audio, or data format, such as clickstreams or social media (Jabbar et al., 2020). Unstructured data covers 95% of all data, hence it provides undiscovered valuable insights (Jabbar et al., 2020). The variety also covers how the different formats can be converted efficiently into cohesive information (Ducange et al., 2018). According to Johnson et al. (2019) the variety in marketing context refers to flows of data from transactions, social media and website and clickstream data. In addition to the data itself, the variety refers to the subjects that the Big Data covers, such as customers, markets, transactions and interactions, resources, and industry changes (Grover et al., 2018; Wright et al., 2019).

Big Data is a big construct and the definition of it changes with the technological developments. In addition to the three Vs, more Vs have been presented to further describe the characteristics of Big Data. These additional five Vs are based on the development of Big Data to give Big Data a more up-to-date description (Akter et al., 2019; Ducange et al., 2018; Sivarajah et al., 2017). The five additional Vs are: Veracity, Value, Variability, Visualization and Volatility.

The first three Vs focus more on the properties of Big Data from the processing standpoint but give little information about the nature of the data. The complexity and inconsistency of the gathered data can create unreliability in some datasets (Akter et al., 2019; Sivarajah et al., 2017).

Veracity refers to the underlying trustworthiness, authenticity, quality, consistency, uncertainty, and biases in the data that add up to the dependability and overall quality and further to the value of the data (Akter et al., 2019; Ducange et al., 2018; Gupta et al., 2021; Wright et al., 2019). Veracity covers how credible a data source is to validate the data correctness and accuracy (Intezari & Gressel, 2017). As the Big Data constantly increase their volume, velocity and variety, veracity becomes more important so that firm's and marketers can be sure about their data quality (Erevelles et al., 2016). Ducange et al. (2018) present validity as and additional V to complement veracity. Validity adds to the veracity in the integrity of the data through the correct usage of verified data (Ducange et al., 2018).

Value refers to the improvements that Big Data has on businesses through the insights and processes that Big Data offers to firms and what can be used to make or improve strategies (Gupta et al., 2021; Jabbar et al., 2020). The value in Big Data is in the knowledge, competitive advantage and return on investments that is gained from the information by analysing and investigating Big Data (Ducange et al., 2018). Erevelles et al. (2016) further add an important aspect to the value of Big Data that it also refers to the data itself to be valuable and relevant so that the insights and information generated from the data is valuable.

Variability of the data is often confused with variety of the data, but it offers more insight into the analysis of the data. Variety refers to the formats of the data, but variability refers to the different meanings that Big Data offers depending on the timeframe and context it is analysed in (Sivarajah et al., 2017). Additionally, this relates to the velocity of the data, because the variability of the data is linked to the velocity the data flow rates in which the new data is gathered and the old data becomes irrelevant (Akter et al., 2019; Sivarajah et al., 2017). Therefore, the insights based on the data should be tied to a certain situation to get an exact analysis from the data so that the changes over time do not invalidate the analysis (Ducange et al., 2018).

Visualization of Big Data is important for the big datasets to be understandable and available for interpretation and decision-making (Ducange et al., 2018; Gupta et al., 2021). Visualization also covers the user experience and services for the utilization of data so that it is easy to consume (Ducange et al., 2018). Visualization is a process to share the data and its resources for better efficiency and scalability of the services (Jabbar et al., 2020). At the core of data visualization is representing key-information in visual formats, for example with graphics (Sivarajah et al., 2017). Due to the velocity of Big Data, the visualization also must have a limited processing time to keep up with the constantly and rapidly changing data to offer real-time information (Amado et al., 2018).

Volatility of data refers to how long the data is relevant and usable for processing and how long the data should be stored for future use (Ducange et al., 2018). The value of the data is relevant to time, as stated with the variability of Big Data, and therefore the value of the data may vanish even in minutes (Hofacker et al., 2016). Other relevant concepts of this master's thesis are defined as follows.

Big Data Analytics refer to the analytical methods to manage and process Big Data and the systematic architecture to enable the mining and software analysis of Big Data (Gupta et al., 2021). Data for Big Data Analytics is collected from social networks, business meters and monitors, Internet of Things, clickstream data, integrated transactions, and third-party data (Erevelles et al., 2016; Johnson et al., 2019; Sivarajah et al., 2017). Big Data Analytics is used to discover the underlying patterns and relationships from the data by exploring it and to find information and knowledge that can be used as valuable insights from the data for strategic decisions, marketing actions, business intelligence, customer churn prevention, knowledge co-creation and organization agility (Erevelles et al., 2016; Ferraris et al., 2019; Fosso Wamba et al., 2015; Gnizy, 2020).

Data-driven marketing is the combination of traditional strategic and tactical marketing actions with the implementation of data analytics to gain better insights from the data that create business value and competitive advantage (Johnson et al., 2021; Sheth & Kellstadt, 2021). Data-driven marketing views creativity as an important aspect in marketing for effective strategic decision-making with data analytics for better tactical and strategic actions (Johnson et al., 2021; Shah & Murthi, 2021).

Knowledge management is a managerial process of systematically and actively managing the organizational knowledge assets, as well as the organizational design, structure, and technologies, to improve organizational learning capabilities that enhances the leveraging of knowledge to create value that generates a competitive advantage and supports business processes (Alavi & Leidner, 2001; Côrte-Real et al., 2017; de Camargo Fiorini et al., 2018; Gold et al., 2001). Knowledge management consists of five processes: knowledge creation, knowledge storage and retrieval, knowledge transfer, knowledge application, and knowledge protection (Alavi & Leidner, 2001; Gasik, 2011; Gold et al., 2001). Big Data Analytics can be seen as a tool for knowledge management, that provides competitive advantage through knowledge (Côrte-Real et al., 2017). Therefore, the design of Big Data database and analytics systems should be guided by understanding of the organizational knowledge (Alavi & Leidner, 2001; de Camargo Fiorini et al., 2018).

Knowledge-based view is an organizational theory that views that knowledge is at the core of the firm's competitiveness (Grant, 1996). According to knowledge-based view, knowledge and related intangibles are seen valuable, rare, inimitable, and non-substitutable resources, and that the way that firms create, acquire, and utilize knowledge leads to competitive advantage and better performance over competing firms (de Camargo Fiorini et al., 2018; Grant, 1996; Varadarajan, 2020). In Big Data research, knowledge-based view offers a theoretical background behind the knowledge required to manage Big Data as well as the knowledge to create value and competitive advantage from Big Data (de Camargo Fiorini et al., 2018).

Dynamic capabilities refer to firm's capabilities to reconfigure, renew, and modify its competencies to adapt to rapidly changing conditions to maintain its competitive advantages (Teece et al., 1997). Dynamic capabilities have been applied in Big Data research to describe how Big Data and Big Data Analytics as a capability offers a competitive advantage in dynamic markets (Chen et al., 2015; de Camargo Fiorini et al., 2018).

Strategic decision-making has three phases: the identification, development, and selection of decision (Mintzberg et al., 1976). Strategic decisions are important commitments to activities that determine the actions taken and the resources used, which affect the organizational health (Intezari & Gressel, 2017; Mintzberg et al., 1976). Strategic decisions reflect the interaction between an organization and its environment, and they cover novel, complex, and open-ended issues (Elbanna, 2006).

1.4 Structure of the research

This master's thesis is structured into five chapters. In this introduction chapter the background of the study, the research gap with the research questions and objectives of the study, the chosen methodology, and definitions of Big Data and other relevant concepts are presented. The second chapter of the thesis presents the theoretical framework of the thesis with the theoretical concepts in which it is based on. The chapter covers academic literature on knowledge-based view, Big Data Analytics, knowledge management, dynamic capabilities, and strategic decision-making, as well as how those relate to Big Data Analytics.

In the third chapter the research of this thesis is presented. The chapter introduces the qualitative research design and methodology. The chosen data and its criteria and the validity reliability is discussed in this chapter. The fourth chapter goes through the analysis of the data collected from the study and the results of the study are presented based on the theoretical framework. The last chapter of the thesis is conclusions, which provides theoretical and practical conclusions reflected on the research questions and implications for future research.

2 THEORETICAL FRAMEWORK

This theory chapter introduces Big Data Analytics and the theoretical foundation of this thesis and how the theories relate to Big Data in the context of this thesis. Knowledge-based view provides the theoretical lens to view the utilization of organizational knowledge in strategic decision-making, and therefore it is presented first to give a basis for the theoretical framework. Knowledge-based view is followed by the introduction of Big Data Analytics, and from there this theory chapter moves on to knowledge management, dynamic capabilities, and lastly to strategic decision-making. At the end of the chapter the theoretical framework is presented in Figure 5.

2.1 Knowledge-based view

To understand knowledge-based view and knowledge management, we first have to establish what knowledge is. The definition of knowledge has been debated since the ancient Greek era (Alavi & Leidner, 2001), but for the purpose of this thesis, knowledge is only defined in the context of firm. Nonaka (1994) defines knowledge as a set justified true beliefs. Knowledge also requires the condition of understanding gained through experience or study (Alavi & Leidner, 2001). Ferraris et al. (2019) add that knowledge can be organized and managed to improve organization's performance through competent actions. So, for firms to compete effectively, they must utilize their existing knowledge and create new knowledge that gives them an advantage to their rivals (Gold et al., 2001). Knowledge is seen as an intangible asset, which are characterized as something that is not physical and cannot be seen and they can provide a competitive advantage to firms (de Camargo Fiorini et al., 2018).

Knowledge can be either tacit or explicit (Alavi & Leidner, 2001; Grant, 1996; Nonaka, 1994). Grant (1996) identifies tacit knowledge as knowing how and explicit knowledge as knowing about. Tacit knowledge combines both cognitive and technical elements, whereas explicit knowledge consists of articulated and communicated elements (Alavi & Leidner, 2001; Nonaka, 1994). Cognitive refers to mental models held by individuals and technical refers to concrete skills and know-how (Alavi & Leidner, 2001; Nonaka, 1994). The crucial difference in the tacit and explicit knowledge is their transferability and absorptive capacity, which refers to the ability to utilize existing knowledge to recognize the value of new information and to use it to create new knowledge (Gold et al., 2001; Shah, 2022). Tacit knowledge is exposed through its application and attained in practice making its transfer slow, irregular, and uncertain, whereas explicit knowledge is exposed through its communication making its transfer fast and easy to attain to whom it is available (Grant, 1996). Knowledge that is analysed from Big Data by using Big Data Analytics is explicit knowledge because, it provides articulate and communicated knowledge (Alavi & Leidner, 2001). However, knowledge to use and understand Big Data Analytics and to make effective strategic decisions by utilizing Big Data Analytics is tacit knowledge, because it requires cognitive and technical elements (Alavi & Leidner, 2001). In addition, knowledge has more dimensions to describe the characteristics of certain knowledge. Knowledge can also be declarative: know-about, causal: know-why, conditional: know-when, and relational: know-with (Alavi & Leidner, 2001). An important term related to knowledge is information, which are often used to describe the same phenomenon. However, there is a distinctive difference between the two. Information is a flow of data, such as numbers or facts without context, that add to, restructure, or change knowledge and therefore, knowledge is authenticated flow of information based on the beliefs of the individual who holds it (Alavi & Leidner, 2001; Nonaka, 1994).

Even though all tacit knowledge and most explicit knowledge is attained by individuals, it is created within the firm and therefore is specific to that firm (Grant, 1996). This creates the basis of organizational knowledge. Organizational knowledge in the context of knowledge-based view is the knowledge acquired by its individuals about the organization and the processes through which the organization can reach and use the knowledge its individuals possess (Grant, 1996). Organizational knowledge is a key source of competitiveness for the organization (Côrte-Real et al., 2017; Grant, 1996). Therefore, the aggregation of tacit and explicit knowledge within the firm is crucial for creating organizational knowledge that can be utilized in strategic decision-making (Nonaka, 1994). Organizational knowledge and other intangible assets have become important sources of value for firms in high-tech markets (Alavi & Leidner, 2001; Martín-de Castro, 2015). Big Data Analytics provide additional value in organizational knowledge by improving an organization's capacity to discover new knowledge and insights (Chen et al., 2015). Big Data has transformed data to be more available, as well as lowered the costs of analytics, which has evolved the nature and importance of knowledge (Xu et al., 2016).

As we have established knowledge in the context of this thesis, we can move on to knowledge-based view. Knowledge-based view is a theory of the firm that aims at explaining and predicting the structure and behaviour of the firm in its market (Grant, 1996). Knowledge-based view builds on the resource-based view, which sees a firm as a combination of resources and that the efficient utilization of those resources is the foundation for the firm's competitive position (Kearns & Sabherwal, 2007). Knowledge-based view places knowledge at the core of the firm's competitiveness and emphasizes the strategic role of knowledge as the primary source of value and the most important, and only sustainable, resource for creative competitive advantage (Grant, 1996). However, as firms seek to acquire, create, and protect knowledge so they can integrate it in their processes, they also combine it and create new knowledge (Cormican & O'Sullivan, 2003; Grant, 1996; Gupta et al., 2021; Kearns & Sabherwal, 2007). According to knowledge-based view, knowledge and related intangibles are seen valuable, rare, inimitable, and non-substitutable resources, and that the way that firms create, acquire, and utilize knowledge leads to competitive advantage and better performance over competing firms (Côrte-Real et al., 2017; de Camargo Fiorini et al., 2018; Grant, 1996; Varadarajan, 2020).

Knowledge-based view sees the primary role of firms is to create multiple streams of knowledge for the application of knowledge to the production of goods and services (Grant, 1996; Kearns & Sabherwal, 2007). Gold et al. (2001) state that the novel competence in the organizing of firm's processes is the key to effectively utilize knowledge and to gain knowledge-based competitive advantages, which lead to organizational success. The knowledge that a firm has created gives the firm an ability to renew and reorganize its resources and build dynamic capabilities (Côrte-Real et al., 2017).

As knowledge-based view emphasises the importance of knowledge it views the competitive advantage is established with directives, sequences, organizational routines, and self-organizing teams, which structure the mechanisms that facilitate the application of knowledge in the organization's processes (Alavi & Leidner, 2001; Grant, 1996). Directives are an exact set of instructions, rules, standards, policies, and procedures developed to integrate experts' knowledge to non-experts and to regulate the communication of knowledge with the goal to guide the organization to the efficient use of knowledge (Alavi & Leidner, 2001; Grant, 1996).

Sequencing is a very simple way to apply and integrate specific knowledge in processes with as little communication as possible (Grant, 1996). Sequencing is performed by organizing activities in time-based sequences where individuals or teams with specific knowledge perform their input to the process independently and then the process is moved to the next sequence (Grant, 1996).

Organizational routines refer to a pattern of behaviour and interaction protocols that is initiated by the organization's desire to function efficiently and automatedly (Grant, 1996). Organizational routines exists so that individuals and teams can apply and integrate their knowledge without the inconvenience of having to communicate their knowledge to others in situations where it is unnecessary (Alavi & Leidner, 2001). Not all routines have to be complex, and routines can be assessed to simple tasks as well if it makes them more efficient (Alavi & Leidner, 2001). Routines can be used to support simultaneous performances that result in a bigger and more complex processes in the organization (Grant, 1996). Routines can also be used to support sequential performances that are interdependent of each other in the process (Grant, 1996).

The fourth knowledge application mechanism is self-organizing teams. This mechanism is used in dynamic processes of high uncertainty and complexity where directives and organizational routines do not support the knowledge application and teams of individuals with specific knowledge are formed to solve the task (Alavi & Leidner, 2001). Self-organized teams rely on personal, high-interaction, and communication-intensive forms of knowledge application, which is efficient decision-making (Grant, 1996). However, this tends to stall the processes and therefore self-organizing teams should be reserved for task that are complex and important (Grant, 1996).

While knowledge required for decision-making exists in multiple levels within the firm, to increase the speed of decision-making and the quality of strategic decisions, firms should not establish hierarchies within the organization, because they generally stall the movement of knowledge (Grant, 1996). Rules and directives within the firm should only be put in place to facilitate and ensure the integration of knowledge in firms (Grant, 1996). Firms that have a high level of knowledge and involvement implemented in their routines are more capable to make decisions about necessary actions to improve the firm's performance (Côrte-Real et al., 2017). This is also supported in knowledge-based view, where firms utilize their knowledge reserves to make decisions, which provides a basis for the use of the theory in strategic decision-making (Gupta et al., 2021).

Knowledge-based view has been combined with knowledge management to facilitate the integration of organizational knowledge in IT processes to gain insights on the integration of knowledge from IT processes to business processes (Kearns & Sabherwal, 2007) and the performance of IT investments (Côrte-Real et al., 2017), as well as the role of knowledge management in the creation of dynamic capabilities (Cormican & O'Sullivan, 2003). Advanced IT-systems provide firms an ability to systemize and enhance large scale knowledge within the firm (Alavi & Leidner, 2001). Therefore, the development of an IT-based knowledge infrastructure is necessary for staying competitive in today's dynamic markets (Cormican & O'Sullivan, 2003).

In Big Data research, knowledge-based view offers a theoretical background behind the knowledge required to manage Big Data as well as the knowledge to create value and competitive advantage from Big Data (Alavi & Leidner, 2001; de Camargo Fiorini et al., 2018; Gupta et al., 2021). Knowledge-based view states that a part of firm's knowledge is its ability to combine and apply its tangible resources, such as Big Data Analytics, in its strategic actions (Alavi & Leidner, 2001; Shah, 2022). An example of that is that Big Data Analytics itself do not offer any improvement to decision-making, and it is often underutilized in decision-making (Erevelles et al., 2016; Gupta et al., 2021). Therefore, knowledge-based view offers firms a basis for the application of Big Data Analytics to create knowledge, so that firms can have the ability and knowledge to creatively use Big Data Analytics as a knowledge point for improved decision-making and to find insights from Big Data (Erevelles et al., 2016; Gupta et al., 2021). The knowledge gained from the insights can be applied into the strategy and marketing activities, which generates competitive advantage, which is hard for their competitors to imitate (Erevelles et al., 2016; Gupta et al., 2021). This is further supported by Shah (2022) who used knowledge-based view to present that Big Data Analytics offer firms competitive advantage through the authenticity, real time access and applicability of the data, which is further developed into knowledge.

2.2 Big Data Analytics

Big Data analytics refer to the analytical methods that combines mathematics, statistics, and computer science, to process Big Data and the systematic architecture to enable the mining and software analysis of Big Data (Gökalp et al., 2022; Gupta et al., 2021). Big Data Analytics offer the business-centric practices and methodologies that provide capabilities to sense, acquire, process, store, and analyse the data simultaneously, which leads to the creation of knowledge from Big Data and provide competitive advantage and business value to the firm (Chen et al., 2015; Côrte-Real et al., 2017; Wright et al., 2019). For analytics to be considered Big Data, the analysis must have the ability to take place in real-time or near real-time, and therefore in Big Data Analytics the data is not analysed in hindsight but in constant flows and processes (Intezari & Gressel, 2017). Big Data analytics is used to discover the underlying patterns and relationships from the data in high velocity by exploring it (Erevelles et al., 2016).

The goal in Big Data Analytics is to find valuable consumer, market, competitor, and product insights from the data that offer information and knowledge for strategic decisions, marketing actions, business intelligence, customer churn prevention, knowledge co-creation and organization agility (Erevelles et al., 2016; Ferraris et al., 2019; Fosso Wamba et al., 2015; Gnizy, 2020; Gupta et al., 2021). Therefore, Big Data Analytics does not only cover the technology but the skills and understanding to exploit the technology for generating insights from several petabytes of data (Shah, 2022). This process cannot be done by the technology itself but by the skilful human components which are responsible of the technology (Shah, 2022).

Marketing professionals have been criticized for not being capable of demonstrating the effectiveness of marketing actions through ROI, and using soft goals, such as brand equity, as evidence of efficient performance (Johnson et al., 2019; Shah & Murthi, 2021). One benefit of establishing data-driven marketing in firms is that improvements in the utilization of data and analytics increase marketing accountability by accurate attribution of marketing spend (Johnson et al., 2019; Shah & Murthi, 2021). Therefore, analytics is seen as the solution to the abiding problem of justifying marketing actions (Johnson et al., 2019; Shah & Murthi, 2021). However, firms have to ensure that short term ROI targets are not achieved at the expense of the firm's brand and values (Johnson et al., 2019). Big Data-driven marketing utilizes predictive modeling, data visualization, prospecting, sales cost reduction, advertising optimization, and other marketing metrics for better insights to make strategic decisions to maximize customer lifetime value and return on investment (Johnson et al., 2019, 2021).

Big Data Analytics are built on established technologies, such as data warehouses and database management systems, so it is not completely new product, but more of a new step in the evolution of data (Intezari & Gressel, 2017). Big Data Analytics are associated to business intelligence and analytics technologies that mostly cover data warehousing, regression analysis, database querying, data mining and statistical analysis (Côrte-Real et al., 2017; Gupta et al., 2021). However, in business intelligence technologies the data is structured, and it is stored in relational database management systems, but in Big Data Analytics the data is both structured and unstructured and stored in distributed cloud-based database management systems (Intezari & Gressel, 2017; Jabbar et al., 2020). Big Data Analytics differ from traditional marketing analytics by capturing, processing, analysing, and managing massive and complex amounts of data in real-time, whereas traditional marketing analytics focuses on improving key performance indicators in certain context (Chen et al., 2015; Xu et al., 2016). This provides Big Data Analytics with the advantage of not only offering business reporting functions but accurate models and analysis of customers, market, and products (Intezari & Gressel, 2017). An important part of Big Data Analytics is the visualization of the data, which refers to the analytical techniques and tools that offer coherent and relevant information in visual form from the data to be presented for decision-making and reporting (Gupta et al., 2021). With the development of Big Data Analytics, another technologies, such as artificial intelligence and machine learning, have been integrated to Big Data Analytics for improved analytical performance in the form of automated decision-making (Gupta et al., 2021).

Since traditional programming and database technologies cannot be used to handle Big Data, there have been developed new analytic technologies to efficiently explore and exploit Big Data (Ducange et al., 2018; Jabbar et al., 2020). Traditional programming languages, such as Python and R, have been developed with new models and packages that are highly effective and capable of processing, managing, and analysing Big Data (Álvarez Cid-Fuentes et al., 2020; Sedlmayr et al., 2016).

In addition, one of the key programming models for the processing of Big Data is MapReduce programming model, which is based on three elements: mapper, combiner, and reducer functions (Ducange et al., 2018). In MapReduce the input data is mapped to key values, which are further combined and grouped together based on their similarities and then the data is reduced to a set of output values (Ducange et al., 2018; Jabbar et al., 2020). Apache Hadoop is the most important and widely used programming framework where MapReduce paradigm can be implemented (Ducange et al., 2018; Jabbar et al., 2020). Hadoop offers a storage repository known as Hadoop Distributed File Systems (HDFS), which spreads the data in clusters across multiple nodes, and processing capabilities with parallel processing built on a MapReduce programming model (Ducange et al., 2018). Another programming frameworks can be combined with Hadoop to improve the performance, such as Apache Spark, which is efficient in iterative processes (Ducange et al., 2018).

Also, another data storage systems can be combined with the framework, for example cloud-based and distributed NoSQL databases, such as MongoDB and graph-based databases (Ducange et al., 2018; Jabbar et al., 2020). Cloud-based computing provides processing power, scalability, and visualization for Big Data Analytics that support real-time analysis of the data (Jabbar et al., 2020).

Distributed stream processing computation frameworks, such as Apache Storm, can be used for handling big streams of data and making real-time analysis of the data, such as rapidly changing social media and ecommerce data (Ducange et al., 2018). For example, by utilizing Big Data Analytics Amazon continuously tracks the searches and transactions of its customers and simultaneously provides product recommendations based on that data (Shah, 2022). The process of real-time data streams to cloud-based processing that offers the ability to both store the data and to process it in real-time, provides real-time decision-making and generates a feedback loop that further refines the analytics (Jabbar et al., 2020).

Big Data Analytics processes have various frameworks, which have been established both in practice and in research but all of those share a common perspective of data analytics lifecycle and are based on six dimensions, that are illustrated in Figure 1. These dimensions are: business understanding, data understanding, data preparation, investigation/model building, evaluation, and deployment and use (Gökalp et al., 2022; Gupta et al., 2021).

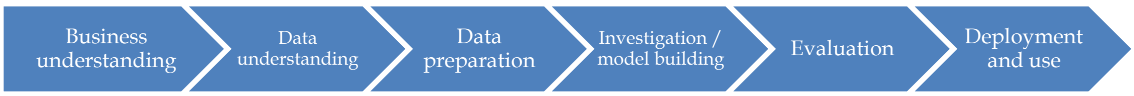

Figure 1: Six dimensions of Big Data Analytics process

The investigation of data is the most important process in Big Data analytics to gain valuable insights from Big Data for future suggestions that guide decisions (Gupta et al., 2021). According to Gnizy (2020) and Gökalp et al. (2022) Big Data opens opportunities for four different investigative analytic categories. As illustrated in Figure 2, these categories are descriptive, diagnostic, predictive, and prescriptive (Gnizy, 2020; Shah, 2022). Descriptive displays what has happened, diagnostic tells why it has happened, predictive gives insight on what could happen and prescriptive gives recommendations for future actions based on the probabilities (Gnizy, 2020; Shah, 2022).

Big Data analytics is used predictively to analyse business trend on revenues by observing data flows and assessing customer data (Gnizy, 2020). Big Data Analytics utilize data that is gathered and used by many departments of the firm, such as marketing, accounting, and logistics, simultaneously and therefore utilized throughout the organization, which unifies the firm's activities toward organizational goals (Johnson et al., 2019). The ability to make predictions from multiple models is made possible by the Big Data Analytics' capability to give insight on the most detailed phenomena (Shah, 2022). The predictions will provide scenarios with anticipated consequences and outcomes for strategic decisions (Shah, 2022). Good example of predictive analysis is Apple and their use of Big Data Analytics to recognize patterns and needs in the current markets, to discover opportunities and to develop new business and marketing models (Gnizy, 2020).

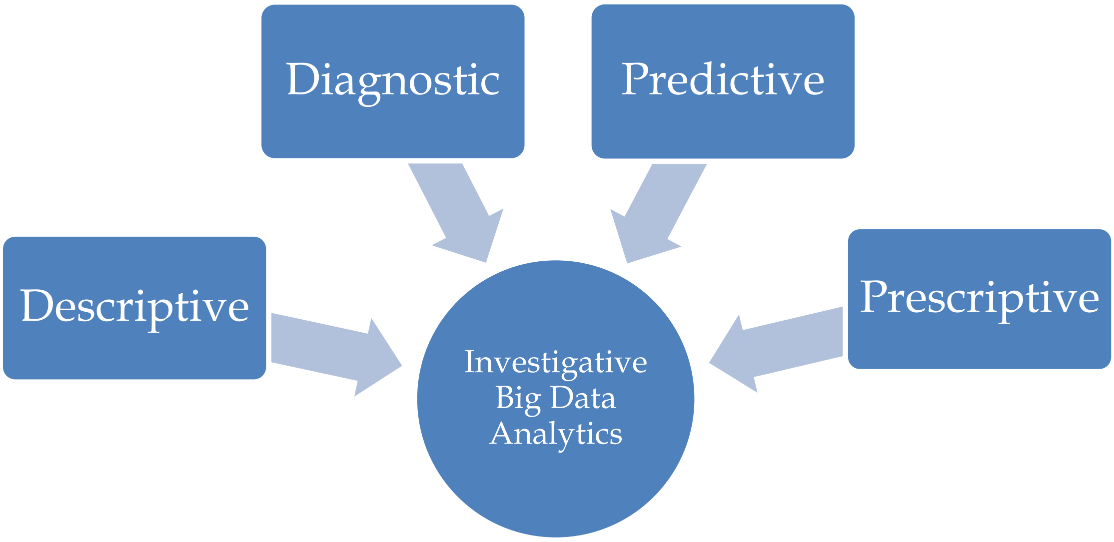

Figure 2: Investigative Big Data Analytics

2.3 Knowledge management

As stated in the previous chapter, Big Data Analytics provides the marketing organization with knowledge and insights generated from Big Data. Therefore, knowledge management should be applied in the management and the use of Big Data in the organization (Alavi & Leidner, 2001; Toro et al., 2015). Knowledge management offers theoretical foundation and understanding to what data is required for the organization's operations and how that data could be analysed to provide useful information (Alavi & Leidner, 2001; Gupta et al., 2021). The information can be implemented in the processes of the organization and in the decision-making to create knowledge base feedback loops that further enhance the utilization of data in the organizational level (Alavi & Leidner, 2001; Gupta et al., 2021).

Knowledge management is a process of systematically and actively managing and leveraging the organizational knowledge assets to improve organizational learning capabilities, which ultimately creates value that generates a competitive advantage and supports business processes (Alavi & Leidner, 2001; Côrte-Real et al., 2017; Gold et al., 2001). Knowledge management has also been described as the organizational design and structures, processes and technologies that help the organization and its individuals to leverage knowledge to deliver business value (de Camargo Fiorini et al., 2018).

To achieve competitive advantage through knowledge that stems from Big Data Analytics, the design of Big Data database and analytics systems should be guided by understanding of the organizational knowledge (Alavi & Leidner, 2001; de Camargo Fiorini et al., 2018). Big Data Analytics can also be seen as a tool for knowledge management, because Big Data Analytics allows firms to add value to the information chain and helping knowledge to flow to attain business goals (Côrte-Real et al., 2017).

Knowledge is important in decision-making, because the possession of knowledge results in an ability to interpret information and to understand what information is vital and useful in decision-making (Alavi & Leidner, 2001). Therefore, Big Data is a strategic knowledge asset and Big Data Analytics have potential to improve decision-making in rapidly changing markets by providing more accurate and transparent information (Côrte-Real et al., 2017; Intezari & Gressel, 2017). The knowledge provided by Big Data gives an ability to make better strategic decisions cheaper and faster (Intezari & Gressel, 2017), and firms that are efficient in managing a variety of knowledge are often more innovative (Ferraris et al., 2019). However, Intezari & Gressel (2017) add that Big Data databases and Big Data Analytics alone do not result in successful strategic decision-making, but individual and organizational learning is required for the expertise to utilize Big Data successfully in strategic decision-making.

As presented in Table 1, knowledge management has five major processes: knowledge creation, knowledge storage and retrieval, knowledge transfer, knowledge application, and knowledge protection (Alavi & Leidner, 2001; Ferraris et al., 2019; Gasik, 2011; Gold et al., 2001). These processes are very similar to the capabilities required for Big Data Analytics according to Côrte-Real et al. (2017), which supports the use of knowledge management in this thesis.

Table 1: Five knowledge management processes

Knowledge management process	**Description of the process** **Role of Big Data Analytics in the process**	**Associated literature**
Knowledge creation	Creating, acquiring, and converting new content or replacing old content within the organization's knowledge with new content through social and collaborative processes.	Alavi & Leidner, 2001; Gasik, 2011; Gold et al., 2001; Nonaka, 1994
	Big Data Analytics offer a strategic ability for firms through efficient tools to create knowledge by utilizing their information analysis capabilities to process information assets.	Chen et al., 2015; Ferraris et al., 2019; Shah, 2022; Varadarajan, 2020
Knowledge storage and retrieval	The tools and processes that are used to store and retrieve organizational data, information, and knowledge. For efficient knowledge retrieval the knowledge must be, not only accessed, but found efficiently for quick utilization of that knowledge.	Alavi & Leidner, 2001; Cormican & O'Sullivan, 2003; Gasik, 2011; Huber, 1991; Inkpen & Dinur, 1998
	Big Data technologies improve the organizational memory by providing a centralized and quickly accessible unit to store, share, and retrieve real-time knowledge.	Côrte-Real et al., 2017; Erevelles et al., 2016; Intezari & Gressel, 2017; Shah, 2022
Knowledge transfer	The purpose of knowledge transfer is to share knowledge within the organizational context to support the creation and application of organizational knowledge.	Alavi & Leidner, 2001; Andersson et al., 2015; Cormican & O'Sullivan, 2003; Gasik, 2011; Gold et al., 2001; Inkpen & Dinur, 1998
	Big Data technologies enhances knowledge transfer by offering a capability to customize specific real-time information that is needed for insights and knowledge.	Chen et al., 2015; Côrte-Real et al., 2017; de Camargo Fiorini et al., 2018; Ferraris et al., 2019; Gupta et al., 2021; Shah, 2022
Knowledge application	The process where the created knowledge is used and applied to the performed task or used in decision-making. Knowledge application is established with directives, sequencing, organizational routines, and self-organizing teams.	Alavi & Leidner, 2001; Gasik, 2011; Gold et al., 2001; Grant, 1996
	Big Data Analytics are used for application of the data and organizational knowledge that is used in multiple levels and functions of the organization.	Chen et al., 2015; Ferraris et al., 2019; Intezari & Gressel, 2017; Shah, 2022
Knowledge protection	Process to protect the organizational knowledge to sustain its competitive advantage so that rare and inimitable knowledge does not leak out and lose its important qualities.	Gold et al., 2011; Ha et al., 2021
	Big Data technologies are used to protect organizational knowledge by restricting and tracking the shared and processed data.	Zeiringer & Thalmann, 2021

2.3.1 Knowledge creation

Organizational knowledge creation and acquisition considers creating new content or replacing old content within the organization's knowledge with new content (Alavi & Leidner, 2001; Gasik, 2011; Gold et al., 2001). Important dimension in knowledge creation is the use of existing knowledge and the effective acquisition of new knowledge that is implemented in the existing knowledge (Gold et al., 2001). The acquisition of knowledge refers to getting knowledge from outside of the unit that is going to process it (Gasik, 2011). The source of the acquired knowledge can be the organization's own knowledge repository, a team or individual from the organization that possesses the knowledge, or the knowledge may be collected from outside of the organization (Gasik, 2011). Therefore, organizations should provide itself with a strategic ability to acquire, create and exploit knowledge (Nonaka, 1994). Big Data Analytics provides organizations with strategic ability to require knowledge by offering an efficient tool to process data acquired and possessed by the organization into knowledge (Shah, 2022). Additionally, Big Data Analytics provide tools to sense opportunities to find new knowledge (Shah, 2022).

Knowledge is created in social and collaborative processes along with an individual's cognitive processes (Alavi & Leidner, 2001), and those processes are amplified and developed within organizational settings (Nonaka, 1994). Another process to create new knowledge is by benchmarking best practices within their own organization or from an outside organization (Gold et al., 2001). In the creation of knowledge, the accumulation of knowledge is always present (Gold et al., 2001). Technology, such as Big Data Analytics, serves as a vital element of structural, as well as infrastructural, dimension necessary for knowledge creation (Gold et al., 2001).

Knowledge conversion is a crucial part of knowledge management, and it is incremented in knowledge creation. Knowledge conversion refers to creating new knowledge and making existing knowledge useful by transforming and combining tacit knowledge and explicit knowledge (Ferraris et al., 2019; Gold et al., 2001; Nonaka, 1994). This continuous dialogue between tacit and explicit knowledge accelerates the creation of new ideas and concepts (Nonaka, 1994). The benefits of knowledge conversion include consistent representation of knowledge, enhanced flow of knowledge in the organization, and the ability to replace outdated knowledge (Gold et al., 2001).

As illustrated in Figure 3, knowledge creation has four modes: socialization, combination, externalization, and internalization (Alavi & Leidner, 2001; Nonaka, 1994). The socialization mode refers to the conversion from tacit-to-tacit knowledge (Nonaka, 1994). Socialization is created through social interactions and shared experiences between organizational members (Alavi & Leidner, 2001). Emphasis on acquiring tacit knowledge is on the experience, and therefore socialization can be achieved without language through observation, imitation, and practice (Nonaka, 1994). The combination mode covers the creation of new explicit knowledge from existing explicit knowledge (Nonaka, 1994). The combination mode involves reconfiguring existing knowledge through merging, adding, recategorizing, synthesizing, and recontextualizing into new knowledge (Alavi & Leidner, 2001; Nonaka, 1994). Due to the articulated and communicated elements of explicit knowledge through language, text and symbols, the combination mode takes place in meetings, conversations, presentations and so forth (Nonaka, 1994). Externalization and internalization present the creation of new knowledge through the exchange of tacit knowledge and explicit knowledge, and they provide an explanation to the idea that tacit and explicit knowledge are interdependent and complementary and can expand over time in a process of mutual interaction (Nonaka, 1994). Conversion from tacit knowledge to new explicit knowledge is the externalization mode, which is visible in, for example, the articulation of best practices or in the use of metaphors to explain a phenomenon (Alavi & Leidner, 2001; Nonaka, 1994). The internalization mode refers creating new tacit knowledge form existing explicit knowledge (Nonaka, 1994). Internalization can be described with the classical term of learning, which happens by drawing understating from sources of explicit knowledge (Alavi & Leidner, 2001; Nonaka, 1994). If knowledge is acquired from outside of the organization, it must be internalized before it can be exploited (Gasik, 2011). Therefore, the organization's ability to acquire and internalize knowledge partly dependent on its absorptive capacity (Gold et al., 2001). In many cases organizational knowledge creation is dependent on the dynamic interaction of different conversion modes (Alavi & Leidner, 2001). Therefore, the modes overlap, because the modes are highly interdependent and intertwined, and they all benefit, rely, add, and contribute to each other in knowledge creation (Alavi & Leidner, 2001; Nonaka, 1994). Nonaka (1994) presents that this interactive nature of the modes creates a spiral model of knowledge creation, where knowledge spirals through all modes from individuals to the organizational level and leads to creation of new organizational knowledge.

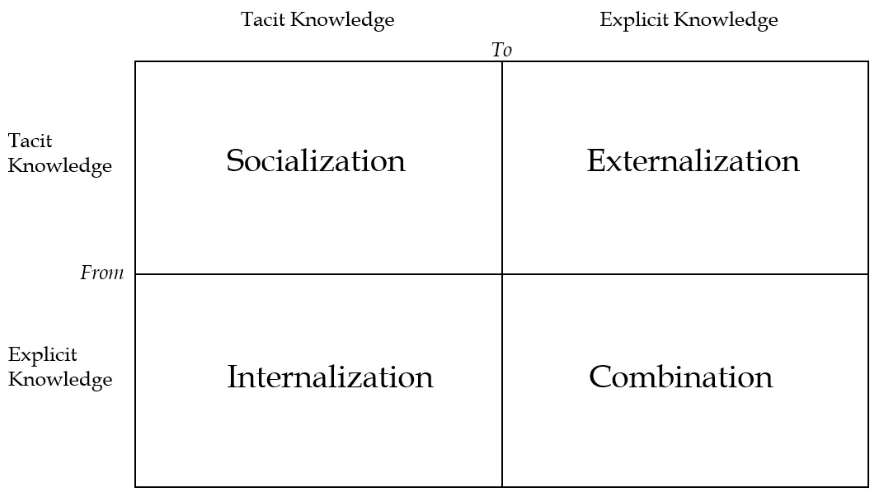

Figure 3: Four modes of knowledge creation (Nonaka, 1994)

By utilizing Big Data Analytics, Big Data is transformed from data to information to knowledge and knowledge is a key strategic resource for the firm (Shah, 2022).

Big Data Analytics support organizations in establishing knowledge creation processes, especially in a highly dynamic markets due to the velocity of the data in Big Data Analytics (Chen et al., 2015). Big Data Analytics offer a way for firms to create knowledge by utilizing their information analysis capabilities to process information assets (Ferraris et al., 2019; Varadarajan, 2020). Big Data Analytics also increase the absorptive capacity of the organization by improving the capabilities to acquire, process and store information, which improves the knowledge creation (Shah, 2022).

2.3.2 Knowledge storage and retrieval

While organizations continuously create new knowledge, they also forget the created knowledge by either not remembering it or losing the track of it (Alavi & Leidner, 2001).Making the storage and the processes to retrieve the organizational knowledge an important factor in knowledge management (Alavi & Leidner, 2001). Knowledge storage refers to the tools and processes that are used to store and retrieve organizational data, information, and knowledge (Cormican & O'Sullivan, 2003). Therefore, the organizing of the organization's knowledge storages and repositories is crucial so that the knowledge can be, not only accessed, but found efficiently for quick utilization of that knowledge (Gasik, 2011). Knowledge storage is also important because the ability and capacity to store data and knowledge in the organization is related to corresponding increase in firm performance (Shah, 2022).

Organizational knowledge can be stored in multiple locations, such as in written documents, organizational procedures, in the individuals of the organizations, and in databases (Alavi & Leidner, 2001; Huber, 1991; Inkpen & Dinur, 1998). Explicit knowledge is easily stored in databases, and although tacit knowledge is harder to document, it can go through the processes of externalization so it can be codified and stored in a database (Gasik, 2011; Inkpen & Dinur, 1998). Databases offer the ability to quickly and precisely to retrieve the organization's knowledge (Huber, 1991). In Big Data technologies the knowledge is stored and retrieved from the Big Data database of the organization so it can be easily accessible and used by other members of the organization (Cormican & O'Sullivan, 2003; Côrte-Real et al., 2017). Knowledge storage includes knowledge verification and the rating of its usefulness, as well as updating knowledge and deleting knowledge that is no longer useful for the organization (Gasik, 2011).

Organizational memory refers to the means of how the existing knowledge and experiences are stored for later use and how it is taken into consideration in the organizational activities (Alavi & Leidner, 2001; Huber, 1991). Organizational memory covers the memory of the individuals in the organization, as well as the organizational culture, processes and procedures, structure of the organization, ecology, and information systems (Alavi & Leidner, 2001). The individuals of the organization constantly gain new knowledge and share it with other individuals in the organization and therefore increase the collective store of knowledge in the organization (Inkpen & Dinur, 1998). Organizational memory benefits firms by offering chances to reflect future actions to those made in the past, so that the decision-making is efficient (Alavi & Leidner, 2001). Organizational memory also facilitates the storing of effective solutions and procedures to enhance organizational processes, and the use of organizational resources, so that the organizational knowledge is stored in those processes (Alavi & Leidner, 2001; Grant, 1996).

Big Data technologies are efficient instruments to improve the organizational memory by providing a centralized and quickly accessible unit to store, share, and retrieve knowledge (Alavi & Leidner, 2001; Côrte-Real et al., 2017). This has been made possible by the effective utilization of cloud-based database solutions in Big Data databases that increases the capacity to store data and information (Intezari & Gressel, 2017; Shah, 2022). If Big Data Analytics is used to create knowledge, the organization must provide a platform that is suitable for efficient storage of Big Data in real time from multiple sources, so it can be utilized effectively for decision-making (Erevelles et al., 2016). With the massive amounts of data that organizations possess today, all of their data, information and knowledge should be stored in the organizational knowledge repository, which could be in the form of a database (Shah, 2022).

2.3.3 Knowledge transfer

The organization's ability to move, share and utilize knowledge inside the organization for different purposes and processes is vital to the creation of organizational capabilities that builds the foundation for organization's success (Andersson et al., 2015). Knowledge transfer is an important process in knowledge management and the purpose of knowledge transfer is to share knowledge within the organizational context to support the creation and application of organizational knowledge (Alavi & Leidner, 2001; Cormican & O'Sullivan, 2003; Gold et al., 2001). In the center of knowledge transfer is the communication of knowledge and it involves two parties, the sender and the receiver (Andersson et al., 2015; Gasik, 2011). The sender and receiver can be individuals or teams in the organization and knowledge transfer happens in various levels of the organization between individuals and teams or across them, and from individuals and teams to explicit sources of knowledge (Alavi & Leidner, 2001; Gasik, 2011). More frequent communication between the sender and receiver increases the amount of knowledge that is shared (Cormican & O'Sullivan, 2003). Knowledge must be transferred into various forms so that it can be accessed and leveraged to benefit the organization (Cormican & O'Sullivan, 2003).

An important aspect in the process of knowledge transfer is to transfer the knowledge to the locations of the organization where it is needed and can be applied (Inkpen & Dinur, 1998). This involves the storing of useful created knowledge that benefits the organization in the organization's knowledge repository (Gasik, 2011). The knowledge is shared from the repository to other individuals or teams of the organization, and they can access it when necessary (Gasik, 2011). Huber (1991) points out that many organizations struggle to know what they know and that even though knowledge is stored, the processes do not support the use of it. He also adds that it can be overcome by transferring and distributing knowledge so that multiple sources of knowledge exist within the organization which ensures the efficient use and understanding of organization's knowledge (Huber, 1991).

According to Alavi & Leidner (2001), knowledge transfer has five elements: perceived value of the source's knowledge, source's willingness to share knowledge, existence and richness of the transmission channels, the receiver's willingness to acquire knowledge from the source, and the absorptive capacity of the receiving unit. Nonaka (1994) states that in knowledge transfer, the perceived value of source's knowledge is dependent of the quality of the knowledge. As stated earlier, in Big Data Analytics the competitive advantage is gained through data quality, which is ensured with verified sources of data (de Camargo Fiorini et al., 2018).

Knowledge transfer is dependent on personal networks and those play an important role in the willingness of individuals to share their knowledge and receive new knowledge due to the fact that knowledge is created and shared in interaction between individuals and teams (Cormican & O'Sullivan, 2003). Therefore, the managers should encourage the individuals to proactively transfer their knowledge (de Camargo Fiorini et al., 2018).

The knowledge transfer channels can be both formal or informal and personal or impersonal (Alavi & Leidner, 2001). Informal channels, such as conversations outside of meetings, support socialization but there is no guarantee that all the exchanged knowledge is stored by the receiver (Alavi & Leidner, 2001). Formal channels, such as scheduled meetings, provide a better platform for an effective transfer of knowledge, especially for knowledge that is tied to a certain context, but it may prevent creative application of the knowledge (Alavi & Leidner, 2001). Personal channels, such as apprenticeships, are better suited for knowledge that is highly context specific, whereas impersonal channels, such as databases or other knowledge repositories, are efficient for knowledge that is not so context specific and easier to generalize in various situations (Alavi & Leidner, 2001). The selection of knowledge transfer channel is highly tied to the types of knowledge that is transferred (Inkpen & Dinur, 1998). The last element is the least controllable since the absorptive capacity is dependent entirely on the receiver and their ability to process the incoming stimuli and information and to understand it, so it becomes knowledge (Alavi & Leidner, 2001). The transferring and sharing of knowledge are required for its application (Gasik, 2011).

Technology, such as databases, is an efficient tool to transfer knowledge within an organization and helps to extend the reach for gaining knowledge beyond the formal communication channels, and therefore to improve organizational knowledge (Alavi & Leidner, 2001; Côrte-Real et al., 2017). Big Data technologies enhance knowledge transfer by offering a faster solution than traditional data analytics, with the capability to customize specific real-time information that is needed for insights and knowledge (Gupta et al., 2021). Shah (2022) presents that speed is an important aspect in the transfer of knowledge, and as the processing of information can be brought to real-time with Big Data Analytics, which provides a competitive advantage for organizations that use Big Data Analytics. Big Data Analytics is a highly efficient tool for knowledge transfer in dynamic and volatile markets because the leveraging of organizational knowledge is important for making efficient and timely decisions through knowledge sharing (Chen et al., 2015). In the highly dynamic markets today, the knowledge is created and transferred throughout the organization and Big Data provides an efficient solution to support it (Ferraris et al., 2019). Therefore, the distribution of right data to the people in the organization who both understand the problems and have the techniques to solve them, is crucial for decision-making (Ferraris et al., 2019).

2.3.4 Knowledge application

Knowledge application is the process where the created knowledge is used and applied to the performed task or used in decision-making (Ferraris et al., 2019; Gasik, 2011; Gold et al., 2001). The efficient application of knowledge is important because it helps organizations to enhance their performance and reduce costs (Gold et al., 2001). Knowledge is an immaterial and intangible resource, which, as opposed to material resources, can be used and distributed to multiple processes within the organization without losing it (Gasik, 2011). Distribution of knowledge increases the organizational capabilities without taking away the ability to utilize that same knowledge in its original location (Gasik, 2011). Organization's benefits from knowledge, as well as the competitive advantage are embedded in the useful application of knowledge and not in the existence of knowledge (Alavi & Leidner, 2001; Ferraris et al., 2019; Gasik, 2011). Knowledge application is also necessary in strategic decision-making (Gold et al., 2001). In order to effectively apply and use the knowledge, the processes of knowledge creation, storage and retrieval, and transferring must be established with high quality (Gold et al., 2001).

As stated in the thesis, knowledge application is established with directives, sequencing, organizational routines, and self-organizing teams (Alavi & Leidner, 2001; Gasik, 2011; Grant, 1996). Additionally, Gasik (2011) introduces that knowledge application can be gained through elaboration, infusion, or thoroughness. Elaboration refers to a situation where the knowledge has to be interpretated to a new context, infusion refers to the process of combining sources of knowledge to be used in the performed task, and thoroughness refers to a situation where different individuals or teams create new understanding (Gasik, 2011).

Technology can enhance knowledge application in multiple ways. Technology can help the integration of knowledge in the existing routines, so that the technology itself becomes a part of organizational routines (Alavi & Leidner, 2001). Technology can also help advance the application of knowledge by providing a platform to capture, update, access, and to use the organizational knowledge and directives (Alavi & Leidner, 2001; Gold et al., 2001). As stated earlier, technology increases the speed that knowledge can be accessed and applied, which further speeds the creation of new knowledge and accumulation of organizational knowledge. Technology also supports the organizational knowledge application by offering the enhanced and faster ability to codify and automate organizational routines (Alavi & Leidner, 2001).

Big Data technologies can be used for all of the aforementioned processes, and it provides the organization with the ability to gain even deeper understanding from the data, which can be applied efficiently (Ferraris et al., 2019). The development of Big Data technologies and routines surrounding it, for example automated decisions, can improve the organization's efficiency by providing the organization's individuals with more time to focus on organizational activities that require human knowledge (Ferraris et al., 2019; Intezari & Gressel, 2017). Big Data Analytics has been utilized in marketing through operational versatility in real-time for application of the data and organizational knowledge that is used in multiple levels and functions of the organization (Shah, 2022). Big Data Analytics provides the organization with improved capabilities to process information and turn it into knowledge (Chen et al., 2015). That knowledge can be applied into the strategic decision-making, and therefore provide the organization with competitive advantages (Chen et al., 2015; Intezari & Gressel, 2017; Wright et al., 2019). Another benefit of Big Data Analytics in the application of knowledge is that if Big Data Analytics is utilized in the application of knowledge, it provides the ability to store the applied knowledge into the organization's knowledge storage where it can be accessed by others (Intezari & Gressel, 2017).

2.3.5 Knowledge protection

Knowledge protection processes are designed to protect the organizational knowledge from illegal or inappropriate use or theft (Gold et al., 2001; Ha et al., 2021). That is vital for the organization to sustain its competitive advantage so that their rare and inimitable knowledge does not leak out and lose its important qualities (Gold et al., 2001). Therefore, knowledge protection has a positive effect on business performance (Ha et al., 2021). Organizations can protect their knowledge with patents, trademarks, and copyrights, that prevent the copying of the ideas or inventions and give the ability to benefit from those with licensing (Ha et al., 2021). Although patents, trademarks, and copyrights are effective, those do not protect all knowledge (Gold et al., 2001).

Big Data technologies are an effective tool to protect organizational knowledge by restricting and tracking the shared and processed data (Gold et al., 2001; Zeiringer & Thalmann, 2021). However, since organizational databases contain huge amounts of data due to the technological advancements in the datasets and databases, it also has established new knowledge risk (Zeiringer & Thalmann, 2021). Therefore, knowledge protection should concentrate more on the protection of organization's databases because the sharing of the data is necessary for business processes (Zeiringer & Thalmann, 2021). Knowledge protection processes can be established throughout the knowledge management processes with structural and cultural dimensions, such as employee conduct rules and job design, that are reinforced with technical solutions (Gold et al., 2001).

Therefore, the knowledge protection through Big Data is achieved with technical skills and tools combined with organizational and individual policies that support the protection of organizational knowledge during its application (Zeiringer & Thalmann, 2021). If the processes for knowledge protection are inadequate, the inimitability and uniqueness of organizational knowledge are lost, and the organization loses its competitive advantages gained through its knowledge (Gold et al., 2001).

2.4 Dynamic capabilities

In today's hyper-competitive markets firms must respond to the rapidly and continuously changing business environment by updating and reconfiguring their competences and resources to create sustainable competitive advantages (Erevelles et al., 2016). Therefore, in knowledge-based and high-tech markets have knowledge, as a resource, and technological innovation, such as Big Data Analytics, as a dynamic capability, become key sources for firm's competitive advantage (Martín-de Castro, 2015). Dynamic capabilities refer to firm's ability to integrate, develop, and reconfigure their internal and external expertise and resources to react to rapidly changing and evolving business environments (Eisenhardt & Martin, 2000; Teece et al., 1997). Dynamic capabilities can also refer to describe the organizational processes that are used to react to the changing and evolving environment (Chen et al., 2015). The term dynamic refers to the ability response to the changing nature of the business environment due to technological developments and changes in market forces (Teece et al., 1997; Teece & Pisano, 1994). The term capability refers to the strategic management that is required for adapting, implementing, and reconfiguring organizational knowledge, resources, and competences to stay in pace with the changing business environment (Teece et al., 1997; Teece & Pisano, 1994).

The key for firms to renew and reconfigure their resources to build dynamic capabilities is embedded in the organizational knowledge (Côrte-Real et al., 2017). And the firms that have a high level of organizational knowledge, and are efficient in applying it, are more capable to recognize the need to reconfigure competences and resources, and to make decisions on how to achieve those changes (Côrte-Real et al., 2017). The value of the competitive advantage does not stem from the dynamic capabilities itself, but from the reconfiguration of the competences and resources that the dynamic capabilities provide (Karimi & Walter, 2015; Teece et al., 1997). Dynamic capabilities underline the timely responsiveness on changing environment with the coordination and redeployment of competences that are based on the development of management capabilities (Teece et al., 1997). Further, these timely capabilities are combined with organizational, practical, and technological skills that are hard to imitate (Teece et al., 1997), which gives a good foundation for this thesis for combining strategic decision-making, Big Data Analytics, and knowledge management.

To better understand what can be classified as a dynamic capability is to identify what is strategic. Strategic capabilities are refined to customer needs, unique so that the pricing of the goods or services can be done without a big regard to competition, and difficult for competitors to replicate (Teece & Pisano, 1994). Therefore, Big Data Analytics is a strategic capability because it is refined to customer needs, the analytics are unique because they are specific to the firm, and difficult to replicate due to the customer insights gained with Big Data Analytics (Erevelles et al., 2016).

According to Teece et al. (1997) dynamic capabilities and distinctive competences can be categorized in three categories: processes, positions, and paths, as illustrated in Table 2. Dynamic capabilities are implemented in the organizational processes but the core of the processes and the source for competitive advantage are related to firm's position of assets and to the paths that are available for the firm combined with the firm's relevant competences (Eisenhardt & Martin, 2000; Teece et al., 1997).

Table 2: Categories of dynamic capabilities

Category of dynamic capabilities	**Element of the category**	**Description**	**Associated literature**
Processes		The routines in the firm to support its practice and learning.	Eisenhardt & Martin, 2000; Karimi & Walter, 2015; Teece et al., 1997; Teece & Pisano, 1994
	Sensing	The capacity to identify and shape opportunities and threats outside of organization.	Teece, 2007
	Seizing	The ability to use resources to capture value from the opportunities and to effectively deal with the threats.	Teece, 2007
	Transformation	To continuously renew and reconfigure assets in a sustainable way to maintain and build competitiveness.	Teece, 2007
Positions		Positioning of firm's assets strategically. Organizational assets are divided into seven classes: technological assets, complimentary assets, financial assets, reputational assets, structural assets, institutional assets, and market assets.	Eisenhardt & Martin, 2000; Teece et al., 1997; Teece & Pisano, 1994
Paths		Available paths for the firm are determined by the increasing returns to the adoption of the markets. This encourages the firm to react to the business environment rapidly, so that the firm benefits from the change and has an advantage to their competitors.	Eisenhardt & Martin, 2000; Karimi & Walter, 2015; Teece et al., 1997; Teece & Pisano, 1994

2.4.1 Dynamic capabilities processes

Organizational processes refer to the routines and to the way things are done in the firm to support its practice and learning (Teece & Pisano, 1994). Organizational dynamic capabilities are in the firm's processes, which are built on three elements: 1) Sensing – the capacity to identify and shape opportunities and threats outside of organization, 2) Seizing – the ability to use resources to capture value from the opportunities and to effectively deal with the threats, 3) Transformation – to continuously renew and reconfigure assets in a sustainable way to maintain and build competitiveness (Teece, 2007).

Sensing and shaping new opportunities and threats requires research and analysis across technologies and market, so that the firm gains an understanding of customer needs and local and distant market possibilities (Teece, 2007). Sensing also offer understanding of latent demand, structural evolution of markets and the responses to the firm's actions (Teece, 2007). Sensing and shaping of opportunities depend on the access of information and efficient use of knowledge to sense opportunities from the information (Teece, 2007). Big Data Analytics has been found effective in sensing as Big Data Analytics enhances knowledge creation and stimulating insights from various sources (Chen et al., 2015; Shah, 2022).

To seize the market or technology opportunity, firms must utilize their technological and knowledge competences to effectively make the right strategic decisions (Teece, 2007). An important aspect in the seizing process is co-specialization of firm's assets, such as technology and the organizational knowledge, to generate a more sustainable competitive advantage (Teece, 2007). Big Data Analytics offer improved data resources and technological capacity to analyse and manage data provided by the ability to leverage organizational knowledge for enhanced decision-making (Chen et al., 2015; Gupta et al., 2021).

Transformation refers to the ability to identify the need to reconfigure the firm's asset structure and to implement the needed transformation, which is caused by the firm's growth or the evolution of the market (Teece, 2007; Teece et al., 1997). Therefore, firms must have the ability to scan and evaluate the business environment and to quickly and efficiently implement the process (Teece, 2007; Teece et al., 1997). Big Data technologies are used to manage firms' knowledge repositories and further used to reconfigure firms' resources and assets with improved knowledge (Côrte-Real et al., 2017; de Camargo Fiorini et al., 2018).

Dynamic capabilities highlight that the organizational knowledge is embedded in the processes and supported by learning (Eisenhardt & Martin, 2000; Teece & Pisano, 1994). Learning is similar to the whole organizational knowledge creation process in knowledge management. In dynamic capabilities learning refers to process of performing tasks better and faster, as well as finding new opportunities through repetition and experimentation (Eisenhardt & Martin, 2000; Karimi & Walter, 2015; Teece et al., 1997). Identifying the congruences in processes is critical to the understanding of organizational capabilities (Karimi & Walter, 2015; Teece et al., 1997). Big Data Analytics offer a competence to create an enhanced sensing, seizing, and transformation process through effective acquisition and analysis of information (Chen et al., 2015; Gupta et al., 2021). Table 3 summarizes how Big Data Analytics support dynamic capabilities processes.

Table 3: Big Data Analytics in dynamic capabilities processes

Dynamic capabilities process	Description	Associated literature
Sensing	Big Data Analytics reduce uncertainty in strategic decision-making through knowledge creation and stimulating insights from various sources to sense opportunities and threats.	Chen et al., 2015
	Big Data Analytics enhances dynamic capabilities by providing deeper and more accurate insights on the customers.	Erevelles et al., 2016
	Big Data Analytics offer real-time information to sense trends in the markets.	Shah, 2022
Seizing	Big Data Analytics offer improved capacity to leverage organizational knowledge for enhanced decision-making	Chen et al., 2015
	Big Data Analytics enhance the adaptiveness and reactivity to seize opportunities in the business environment through improved data resources and technological capacity to analyse and manage data.	Gupta et al., 2021
	Big Data Analytics provide predictive analyses to seize the business opportunities.	Shah, 2022
Transformation	Big Data technologies are used to reconfigure firms' resources and assets with improved knowledge.	Chen et al., 2015; Côrte-Real et al., 2017; de Camargo Fiorini et al., 2018

2.4.2 Dynamic capabilities positions

The organizational processes alone do not cover the strategic positioning of the firm, but it is also covered by the position of the firm's assets (Eisenhardt & Martin, 2000; Teece & Pisano, 1994). In dynamic capabilities, the assets of firm refer to tangible and intangible assets such as, the equipment of production or the knowledge assets (Teece et al., 1997). Organizational assets are divided in to seven classes: technological assets, complimentary assets, financial assets, reputational assets, structural assets, institutional assets, and market assets (Teece et al., 1997; Teece & Pisano, 1994).

Technological assets refer to the technological instruments that are used to utilize the firm's know-how (Teece & Pisano, 1994). Complimentary assets are related assets to technological assets that complement the new innovations and produces (Teece & Pisano, 1994). Financial assets are self-explanatory and refer to the financial state of the firm and how it supports the organizational processes (Teece & Pisano, 1994). Reputational assets refer to the intangible assets that help the firm to reach its goals in the market with effect the external information about the firm (Teece et al., 1997). Structural assets relate to the organization's structure and how it supports the processes and innovation within the firm (Teece et al., 1997). Institutional assets refer to the various institutions, such as public policies, regulatory systems, and different regional and geographical institutions, that affect the business environment, and how those can be utilized to support the organizational processes (Teece et al., 1997). Market assets describe the firm's position in the market that is built to support the firm's performance (Teece et al., 1997).

Organizational boundaries have a crucial impact on the organizational assets because the boundaries determine the degree of integration for the assets (Teece et al., 1997). Hence, firms must be aware of their organizational boundaries for the effective positioning of assets (Teece et al., 1997). Big Data Analytics is an organizational technological asset that affects the information integration process (Chen et al., 2015).

2.4.3 Dynamic capabilities paths

Available paths, as where a firm can go, are based on the current position of the firm, which is formed from the path that the firm has travelled and the state of the business environment it is in (Eisenhardt & Martin, 2000; Teece & Pisano, 1994). The path dependencies are determined by the increasing returns to the adoption of the markets, which provide the basis for dynamic capabilities as a capability (Teece et al., 1997). This encourages the firm to react to the business environment rapidly, so that the firm benefits from the change and has an advantage to their competitors (Teece et al., 1997; Teece & Pisano, 1994). The path dependencies explain the phenomenon that the best product does not always win in the markets, but the firm that has the best ability to adapt to the business environment in a way that the increasing returns work in favour of that firm (Teece et al., 1997). Technological opportunities of the firm's industry determine the possible paths in highly dynamic markets because the speed and size of the industry's expansion is related to the technological advancements available to be reached (Teece et al., 1997). Technological advancements are further developed and accelerated by the innovations in the market that support the technological opportunities (Karimi & Walter, 2015; Teece & Pisano, 1994). The innovations and technological advancements provide advantage to the firm but after some time supports the industry as well when other firms integrate those in their processes (Karimi & Walter, 2015; Teece et al., 1997). Big data technologies offer technological opportunities for firms that have an ability to develop the strategic opportunities, as well as the innovations that support the expansion of the industry (Erevelles et al., 2016; Gupta et al., 2021).

2.4.4 Dynamic capabilities and knowledge management through the lens of knowledge-based view

As knowledge-based view can be used to explain how firms can attain competitiveness in dynamic markets by the application of organizational knowledge, dynamic capabilities can be the key on how firms can create new and innovative ways to sustain the competitive advantage and flexibility on dynamic and unstable markets (Côrte-Real et al., 2017; Teece et al., 1997). To gain long-term sustainable competitive advantage, the key in dynamic capabilities is to use the capabilities sooner and more efficiently than the competition to find the right competence and resource configurations (Chen et al., 2015). Knowledge-based view combined with dynamic capabilities has been found to be efficient approach in high-tech markets where the unique innovations are not able to generate sustainable competitive advantage alone, but they need the support of competent knowledge management to effectively utilize organizational expertise that provides the firm with sustainable competitive advantage (Teece et al., 1997). This is also supported in the context of Big Data Analytics by Côrte-Real et al. (2017) and De Camargo Fiorini et al. (2018) who present that Big Data Analytics could provide dynamic capabilities through knowledge management, which further improves organizational processes and creates competitive advantage.

The extent of firm's competitive advantage depends on the inimitability of its capabilities that create the advantage (Grant, 1996). The more knowledge is integrated in the capability, the harder it is to imitate (Grant, 1996). Therefore, the more knowledge is integrated in the utilization of Big Data Analytics, as well as generated with Big Data Analytics, the harder it is to imitate by its competition, which gives a competitive advantage to the firm. If the dynamic capability of the firm can be replicated by the firm in its other processes, it provides even more strategic value to the firm (Teece et al., 1997). However, if firms are uncapable of establishing resources and capabilities to use and apply Big Data Analytics in their processes will have problems in creating sustainable competitive advantage (Côrte-Real et al., 2017; Erevelles et al., 2016).

As a knowledge-based resource Big Data Analytics is expected to create dynamic capabilities that improve strategic decision-making processes by enhancing the adaptiveness and reactivity to seize opportunities in the business environment through improved data resources and technological capacity to analyse and manage data (Gupta et al., 2021). This is supported by Chen et al. (2015) who discovered that the use of Big Data Analytics serves as a dynamic capability, which helps the firm to reduce uncertainty in strategic decision-making through knowledge creation and stimulating insights from various sources to sense opportunities and threats. Especially in rapidly changing and highly unstable and dynamic markets Big Data Analytics are more effective because the dynamic capabilities provided by Big Data Analytics are less dependent on existing knowledge and more dependent on creating new knowledge in real-time that is situation-specific (Chen et al., 2015), which offer valuable information to sense incoming opportunities and threats.

Shah (2022) states that in order to Big Data Analytics to serve as a dynamic capability, using it to look into the past is not enough but it must be used to make predictions about future trends. In addition, Big Data Analytics must offer real-time information to seize the business opportunities, so that strategic decision-making truly benefits from Big Data Analytics (Shah, 2022). This helps firms establish routines for knowledge creation with Big Data Analytics, which helps them in the highly dynamic markets (Chen et al., 2015). Big Data also enhances dynamic capabilities by providing deeper and more accurate insights on the customers that helps firms to understand unmet customer needs (Erevelles et al., 2016). Although, Big Data Analytics is available for competitors and there are many best practices and consulting services available for it, the application and implementation of Big Data Analytics for complex organizational processes ensures that the use of Big Data Analytics is unique to each firm (Chen et al., 2015). Therefore, it is hard for competitors to duplicate, which gives the theoretical basis for Big Data Analytics as a dynamic capability (Chen et al., 2015).

Earlier studies have proved that efficient use of Big Data Analytics through knowledge management are one dimension to successful dynamic capabilities by offering firms tools to continually renew their knowledge base and use that to reconfigure and transform their resources and competences with enhanced knowledge that leads to the improvement of their business performance (Chen et al., 2015; Côrte-Real et al., 2017; de Camargo Fiorini et al., 2018). At the same time, Big Data Analytics can support the organizational knowledge management (Côrte-Real et al., 2017).

2.5 Strategic decision-making

Making efficient strategic decisions is crucial for all firms in order to survive and thrive in competitive markets and the strategic decisions shape the course of the firm (Eisenhardt & Zbaracki, 1992; Intezari & Gressel, 2017). Mintzberg et al. (1976) define strategic decisions as important commitments to activities that determine the actions taken, as well as the resources that are committed for those actions, which affect the organizational health. Strategic decisions reflect the interaction between an organization and its environment, and they cover novel, complex, and open-ended issues and involve various departments of the firm, as well as multiple resources (Elbanna, 2006; Intezari & Gressel, 2017; Mintzberg et al., 1976). Strategic decisions often include trade-offs and risks, and are related to other decisions, which results in that there rarely is one best solution and once the decision is made, it is difficult to reverse (Elbanna, 2006).

In the decision-making model rational actors enter decision-making situations with known objectives and the objectives determine the value of the possible consequences of actions (Eisenhardt & Zbaracki, 1992). Then the actors acquire necessary information and make optimal actions based on the information they possess and objectives they have set (Eisenhardt & Zbaracki, 1992).

2.5.1 Decision-making phases

Strategic decision-making has been developed from the decision-making model and as illustrated in Figure 4, it has three phases: identification, development, and selection of decision (Mintzberg et al., 1976). The phases of the strategic decision-making do not have sequential relation to each other and are iterative (Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976). The identification phase consists of decision recognition and diagnosis (Mintzberg et al., 1976). In decision recognition, opportunities and problems are recognized and it initiates decision-making (Mintzberg et al., 1976). In diagnosis management the phase seeks to understand the decision situation and determine cause-effect relationships for the decision-making process (Mintzberg et al., 1976). At the core of strategic decision-making is the development phase, which refers to the activities that lead the organization to the development of one or more solutions for the decision situation from either already existing solutions or by designing a new solution (Mintzberg et al., 1976). Although, the selection phase is considered as the last phase of strategic decision-making, the development phase usually requires multiple solutions (Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976). This leads to a situation where usually is multiple selections of decisions and those selections are intertwined with the development phase (Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976). The selection phase consists of determination of criteria for choice, evaluation of consequences of alternatives, and the making of a choice (Mintzberg et al., 1976).

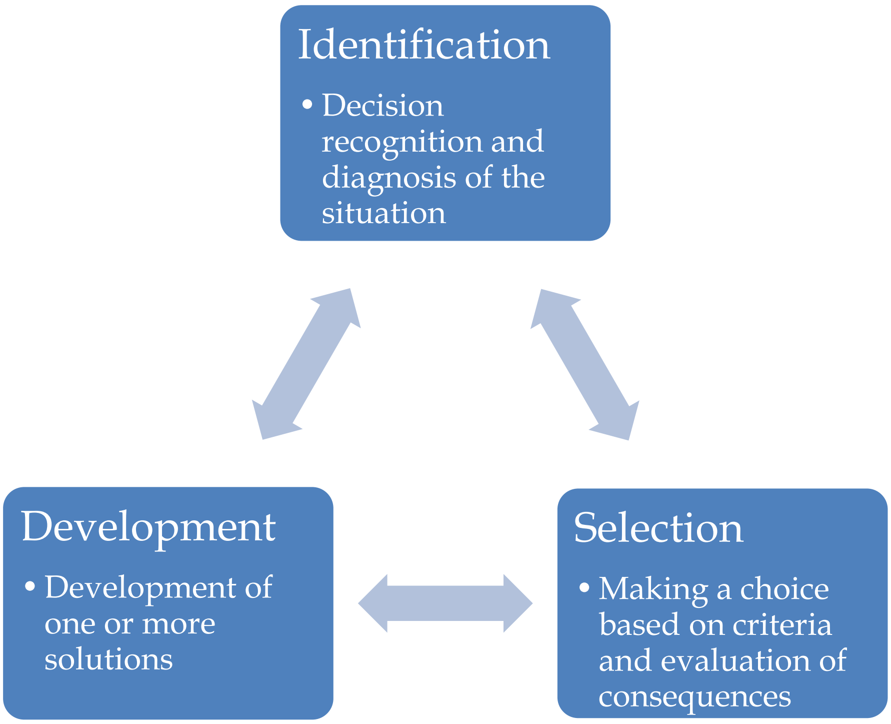

Figure 4: Strategic decision-making phases (Mintzberg et al., 1976)

Big Data Analytics provide improvements in all three phases of strategic decision-making as it offers the ability to recognize opportunities and problems in the identification phase, with a proactive and forward-looking approach to analytics (Ferraris et al., 2019). In the development phase Big Data Analytics offer the ability to model solutions based on data and with increased use of Big Data Analytics the decisions based on past experiences are more efficient as well (de Camargo Fiorini et al., 2018; Gupta et al., 2021; Toro et al., 2015). In the selection phase Big Data Analytics offer knowledge to make the decisions that are verified with the data (Chen et al., 2015; Erevelles et al., 2016).

2.5.2 Decision-making routines

To support the three phases of decision-making, Mintzberg et al. (1976) present three sets of routines: decision control routines, communication routines, and political routines. Decision control routines refer to the planning of the decision-making process and how that plan guides the process itself (Mintzberg et al., 1976). Communication routines cover the communication of the process to its actors, as well as input and output information required for the decision-making process (Mintzberg et al., 1976). The information required for the decision-making process includes the information to recognize decision situations, as well as the information needed to make the decisions (Mintzberg et al., 1976). Political routines refer to how individuals or teams can influence the decision-making and how the possible conflicts within the organization considering the decision-making can be solved (Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976). Political routines and behaviour have been stated as an important aspect in strategic decision-making because strategic decisions are made among people by people for people, and the human interaction creates influencing, alliances, and conflicts (Eisenhardt & Zbaracki, 1992; Elbanna, 2006). However, in this thesis the only set of support routines that is studied is the communication routines, because that is the only set of routines that is related to Big Data Analytics.

Strategic decision-making process also views the decision-makers as rational actors, but actually the decision-makers are boundedly rational and are limited by the information they have available (Chen et al., 2015; Eisenhardt & Zbaracki, 1992). Decision-makers are limited by their cognitive limitations, and by the restricted time that they have to make a decision (Chen et al., 2015; Eisenhardt & Zbaracki, 1992). As a result, many firms rely on heuristic decision-making models or managers' experience and knowledge for strategic decisions (Xu et al., 2016). Eisenhardt & Zbaracki (1992) and Papadakis et al. (1998) add that the size of the organization, firm's performance, corporate control on decisions, and volatile business environment decrease rationality in strategic decision-making. Strategic decisions involve increased uncertainty and risks (Intezari & Gressel, 2017), but with increased availability, quantity, timeliness, and accuracy of relevant information, the organization can make better and more accurate strategic decisions (Elbanna, 2006). Therefore, the acquisition and analysis of reliable data and information, which is refined into knowledge, is significant in strategic decision-making (Intezari & Gressel, 2017).

2.5.3 Big Data Analytics in strategic decision-making

Although many firms have established Big Data Analytics as a part of their decision-making processes and have implemented Big Data technologies in other business functions, Big Data Analytics is still under-utilized by many decision-makers in firms due to the lack of awareness on how to efficiently implement Big Data Analytics in the decision-making process, which leads to limited strategic decisions and further limits the firm's performance (Gupta et al., 2021; Intezari & Gressel, 2017; Xu et al., 2016). If Big Data Analytics is properly implemented in strategic decision-making processes, it improves the strategic decision-making with the enhanced ability to generate real-time insights and improved knowledge that gives the firm a competitive advantage (Chen et al., 2015; Erevelles et al., 2016; Gupta et al., 2021; Johnson et al., 2019; Shah, 2022). Especially, in highly dynamic and unstable business environments organizations must combine their strategic dimensions with their knowledge assets (Nonaka, 1994). The implementation of Big Data Analytics into strategic decision-making requires efficiently facilitated collaboration between the managers, and other individuals that are responsible for the strategic decisions, and data analysts, and other individuals who are responsible for Big Data Analytics, so the alignment of the utilization of Big Data Analytics and the strategic direction of the firm can be established (Intezari & Gressel, 2017).

Uncertainty in strategic decision-making comes from the lack of relevant knowledge to make the decision (de Camargo Fiorini et al., 2018). As a dynamic capability, Big Data Analytics offer improved information processing, which provides the firm with knowledge that decreases uncertainty in decision-making, and therefore increases managerial confidence, as well as organizational capability in strategic decision-making (Chen et al., 2015; de Camargo Fiorini et al., 2018). Chen et al. (2015) add that the managerial confidence in decision-making gradually grows as the understanding of different situations improves provided by Big Data Analytics. As organizations use Big Data Analytics to know more about themselves and their business environments, they transform the Big Data into organizational knowledge (Ferraris et al., 2019; Gupta et al., 2021).This organizational knowledge is then refined into better strategic decisions, improved performance, and further improved decision-making process (Ferraris et al., 2019; Gupta et al., 2021).

When compared to traditional marketing analytics, Big Data Analytics provide a crucial improvement on the real-time processing of the data due to the velocity of Big Data (Gupta et al., 2021). Hence, Big Data can be used to improve strategic decision-making with the better ability to deal with real-time uncertainties and making more rapid decisions (Gupta et al., 2021; Xu et al., 2016). As stated earlier, one of the limitations of strategic decision-making is the restricted time that managers have in decision situations. Therefore, Big Data Analytics help managers to evaluate situations rapidly and make decisions instantaneously and act efficiently (Chen et al., 2015; Shah, 2022). An improvement that Big Data Analytics offer in strategic decision-making is the ability to attain a proactive stance in the market with a forward-looking approach (Ferraris et al., 2019). Another benefit that Big Data Analytics offer is the potential to improve decision-making in rapidly changing markets by providing more information with increased accuracy, speed, and transparency (Côrte-Real et al., 2017; Fosso Wamba et al., 2015; Intezari & Gressel, 2017; Shah, 2022). Additionally, Big Data Analytics improve strategic decision-making by increasing the availability of the information, which enhances the accuracy of the decisions (Ducange et al., 2018; Xu et al., 2016).

The integration of Big Data Analytics in strategic decision-making helps firms and their marketing departments to become data driven as firms base their decisions on knowledge that is validated by data (Chen et al., 2015). As stated earlier, implementation of Big Data Analytics into marketing operations leads to significant improvement of marketing insights' quality, and hence enhances the data-driven decision-making in the firm (Akter et al., 2019; Johnson et al., 2021). Data-driven decision-making refers to implementing data and metrics in strategic decisions to support the organizational goals (Brynjolfsson & McElheran, 2016), and it has been found to further increase the level of data-driven marketing that improves the firm's performance and generates more data for better insights (Johnson et al., 2021). The firms that have efficiently established data-driven decision-making processes have better performances in financial and operational metrics, and they understand better their costs, sales potential, and marketplace opportunities (Ferraris et al., 2019; Johnson et al., 2019). Data-driven decision-making also means that firms must be aware of the areas of business that the data does not cover and to take those areas in to consideration in their marketing strategy (Johnson et al., 2019). Ferraris et al. (2019) present that Big Data Analytics improve data-driven decision-making and better management of firm's processes by facilitating organizational learning and innovations. Data-driven decision-making can be supported by including Big Data Analytics and increasing the influence of data analysts in decision-making, as well as teaching the marketing employees to utilize Big Data Analytics in their work (Johnson et al., 2021). Therefore, Big Data Analytics should be considered as a valuable strategic tool in marketing. Table 4 summarizes how Big Data Analytics support strategic decision-making.

Table 4: Big Data Analytics in strategic decision-making

Description	Associated literature
Big Data Analytics offer an improved ability to generate more accurate insights and knowledge with enhanced speed for strategic decision-making.	Akter et al., 2019; Chen et al., 2015; Erevelles et al., 2016; Gupta et al., 2021; Johnson et al., 2019; Shah, 2022
Big Data Analytics reduce uncertainty in strategic decision-making with improved information processing.	Chen et al., 2015
Big Data Analytics provides the firm with organizational knowledge of itself and its business environment that improves the decision-making processes.	Ferraris et al., 2019; Gupta et al., 2021
Big Data Analytics offer the ability for real-time analysis of data, which increases the speed of decision-making.	Chen et al., 2015; Gupta et al., 2021; Xu et al., 2016
Big Data Analytics increase the availability of information, which enhances the accuracy of strategic decisions.	Ducange et al., 2018; Xu et al., 2016

2.6 Theoretical framework of the study

Based on the literature review the theoretical framework is shown in Figure 5. The framework provides an illustration of how, based on the knowledge-based view, Big Data Analytics provides dynamic capabilities and increased knowledge management as an information processing capability. Knowledge-based view is used as a theoretical basis of the framework, as it places knowledge at the core of the firm's competitiveness and emphasizes the strategic role of knowledge (Grant, 1996). Knowledge-based view sees that a part of firm's knowledge is its ability to combine and apply its tangible resources, such as Big Data Analytics, in its strategic actions (Alavi & Leidner, 2001; Shah, 2022). Côrte-Real et al. (2017) and De Camargo Fiorini et al. (2018) support this by stating that as knowledge management improves organizational processes in the use Big Data Analytics, it provides dynamic capabilities. Knowledge management and dynamic capabilities support each other as dynamic capabilities enhance the knowledge management processes, especially knowledge creation (Teece et al., 1997). In turn, knowledge management processes enhance the use of knowledge, which offers dynamic capabilities (Chen et al., 2015). Increased dynamic capabilities and knowledge management provides firms with improved knowledge in strategic decision-making. Big Data Analytics offer knowledge to make the decisions that are verified with the data (Erevelles et al., 2016). Therefore, Big Data Analytics and strategic marketing decision-making are related to each other through data-driven marketing, as data is implemented into strategic decision-making (Johnson et al., 2021).

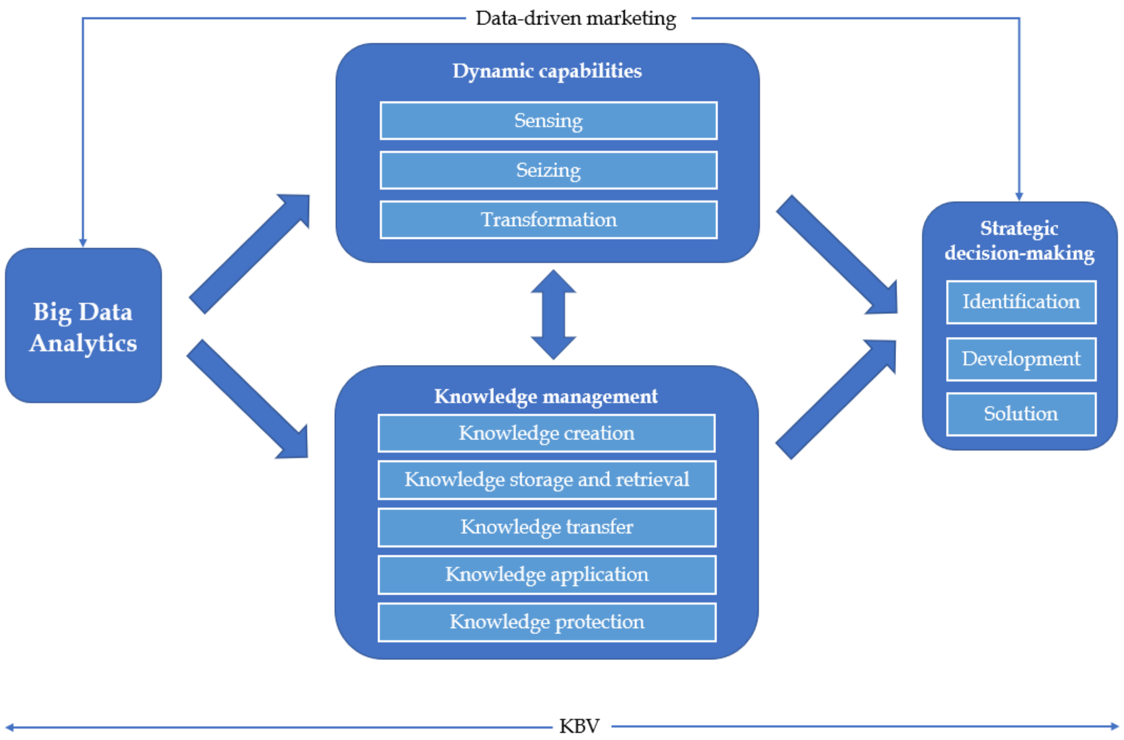

Figure 5: Theoretical framework

3 METHODOLOGY

This chapter covers the methodological approach of the thesis. First there is an introduction of the research design and chosen methods that are applied in the research, which is followed by the introduction of the data collection process and execution of the research. Further, we go through the data analysis methods.

3.1 Research design

The overall design of a research can be exploratory, descriptive, explanatory, evaluative or a combination of these (Malhotra, 2017; Saunders et al., 2019). Exploratory research fits situations where the goal of the research is to gain deeper understanding and insights of a subject, which has not been studied thoroughly yet (Hirsjärvi et al., 2009; Malhotra, 2017). The benefit of exploratory research is the flexibility of the research process, and therefore the process may evolve as new insights are found of the studied phenomena (Malhotra, 2017). The goal of this research is to learn more about a novel marketing phenomenon. Therefore, this thesis uses exploratory research design.

Research in this thesis is done with a qualitative method, since the research design is exploratory (Malhotra, 2017), and the aim of this thesis is to gain a deeper understanding of a novel phenomenon of how Big Data Analytics are utilized in strategic decision-making in marketing. Qualitative study is justified for this research because it is well-suited for exploring and thoroughly analysing complex real-life settings (Hirsjärvi et al., 2009). This is supported by the scarce and dispersed research on the phenomenon of Big Data Analytics in strategic decision-making in marketing (de Camargo Fiorini et al., 2018). Qualitative research studies meanings and relationships of a phenomenon expressed through words and images in a flexible way (Malhotra, 2017; Saunders et al., 2019). Qualitative research is interpretive as it is used to make detailed sense of subjective and socially constructed meanings of a phenomenon (Saunders et al., 2019).

Researchers can use inductive, deductive, or abductive approach to theory development (Saunders et al., 2019). Inductive approach starts the research by collecting data to study a phenomenon and builds the theory based on the data, while deductive approach starts with the theory and the data is used to test the existing theory that is based on literature (Saunders et al., 2019). The abductive approach was chosen for this master's thesis because it combines the inductive and deductive approach in the iteration of selected theory and collected data (Saunders et al., 2019). In abductive approach the theoretical framework is formed prior to the research, and the framework is used to present the identified preconceptions on the research subject (Dubois & Gadde, 2002). Abductive approach utilizes those assumptions in iteration with the empirical data to expand the existing theory instead of creating completely new theory (Dubois & Gadde, 2002). Therefore, abductive approach is suited well for combining the theory and data in research (Dubois & Gadde, 2002; Saunders et al., 2019).

3.2 Data collection

Qualitative research data is collected with observations, secondary data, or research interviews (O'Gorman & MacIntosh, 2015; Saunders et al., 2019). In this thesis the data is collected via interviews. Research interviews are well suited for research where the subject is complex and the goal is to find reasons to a phenomenon (Metsämuuronen, 2011). Research interviews are a conversation between the interviewer and interviewee to generate valid and reliable data (O'Gorman & MacIntosh, 2015; Saunders et al., 2019). Interviews provide rich information that offers understanding and insights of central themes of the research subject and research questions (O'Gorman & MacIntosh, 2015). Interviews for this thesis were one-to-one interviews instead of focus groups because one-to-one interviews provide a setting for the interviewees to be more comfortable to share their personal knowledge and experiences, which will lead to richer insights about the topic (Malhotra, 2017).

Research interviews can be classified into unstructured, semi-structured, or structured interviews (Saunders et al., 2019). When the subject of the research contains a scarcely studied complex phenomenon a semi-structured interview is suitable research interview method (Metsämuuronen, 2011). Semi-structured interviews are also well suited for research that applies exploratory research design, which is used in this thesis, as it gives the ability to gain deep insights about the context of the research (Saunders et al., 2019). Based on those reasons, the interview approach in this thesis is semi-structured. Semi-structured interviews apply predetermined themes and based on those the researcher arranges questions to ask for the interviewees (Saunders et al., 2019). It is a flexible interview approach as it gives the opportunity for the interviewees to explain and elaborate their own views, which can direct the conversation to areas that were not previously considered but that are important in addressing the research questions (O'Gorman & MacIntosh, 2015; Saunders et al., 2019). Therefore, the questions that the interviewer has prepared serve as a blueprint for discussion throughout the interview and the interviewer can freely alter the order of the questions and include or leave out other questions in accordance with the natural flow of the conversation (Eriksson & Kovalainen, 2008; Saunders et al., 2019).

The question list for the interviews in this thesis can be found in Appendix 1. Questions were divided into four themes: the use of Big Data, knowledge management processes, dynamic capabilities, and strategic decision-making. The interview questions were created in accordance with the framework of this thesis to assist in answering the research questions of this thesis. These questions served as blueprint throughout the discussion and the interviewees were solicited to share additional comments or statements after the interview questions and themes were covered in the interviews. Open conversation is encouraged in semi-structured interviews to generate rich information in the context of the subject by offering the interviewees the opportunity to present extensive reasoning behind their insights during the conversation (O'Gorman & MacIntosh, 2015).

The interviewees were selected using purposive sampling. Purposive sampling is a non-probability sampling technique where the sample is selected based on the researcher's own judgement to find the cases that will best answer the research questions and further reach the research goal (Saunders et al., 2019). Purposive sampling is widely used in case studies because it allows to select a sample that is highly informative on the subject (Saunders et al., 2019). The aim of the research is to find out the views of experts in the subject of the study in a rather limited and narrow field of marketing, which is a justified reason to use purposive sampling (Saunders et al., 2019). To fit the sample, the interviewee candidates had to meet the following criteria. The candidates must work for a company that utilizes Big Data and data analytics in their marketing, and the candidates must be familiar with using Big Data and data analytics in strategic marketing decision-making.

The data collection process began with finding suitable candidates for the interviews. The candidates were found by searching for companies in LinkedIn that have established data-driven marketing operations based on their LinkedIn sites. From those companies, the candidates were selected by looking for employees whose job title indicate that they are responsible for data-driven marketing, marketing data analytics, or marketing technologies. These experts that were contacted to take part in the study were from Finnish retail companies, software and management consulting companies, and marketing agencies. The companies were of different sizes, but the common factor was that all of them practiced data-driven marketing. Potential candidates were contacted in March and April 2022 via email or directly on LinkedIn. When they were contacted, they were delivered an overview of the topic, as well as the themes of the interview questions. To ensure that the candidates met the sampling criteria of the study, they were informed that they must be familiar with Big Data and data analytics in strategic marketing decision-making when asked if they wanted to participate in the interviews.

A total of twelve candidates were contacted, seven of whom responded. Five candidates from five firms agreed to be interviewed, and two candidates declined the interview request. The positions of the five candidates in their respective firms were similar and all their roles are related to marketing technologies and data-driven decision-making. Information about the interviewees is presented in Table 5.

The interviews were conducted during April 2022. Duration of the interviews lasted from 18 minutes to 56 minutes. The interviews were conducted online via Zoom instead of face-to-face interviews, due to the Covid-19 pandemic. All interviews were conducted in Finnish because it was each interviewees native language. The interviews were recorded with the permission of the interviewees to facilitate the analysis process of the research. The recordings were deleted after the completion of the analysis. Before each interview, the interviewee was given a written and oral briefing on the interview's confidentiality. Furthermore, all interview participants and their companies will remain anonymous to guarantee more honest and thorough answers, which is provided by the low risk of being associated to their employers and exposing confidential information presented in this study.

Table 5: Information on interviews and interviewees

Interviewee	Title of the interviewee	Industry experience	Industry	Firm size	Interview duration
Interviewee 1	Head of Digital Marketing	10-15 years	IT consultancy	Large	49 minutes
Interviewee 2	Customer Insight Manager	5-10 years	Retail	Large	56 minutes
Interviewee 3	Senior Manager, Marketing Technologies	5-10 years	Oil refining	Large	35 minutes
Interviewee 4	Marketing Technology Architect	5-10 years	Retail	Large	48 minutes
Interviewee 5	Chief Technology Officer	10-15 years	Marketing consultancy	Medium	18 minutes

3.3 Data analysis

Qualitative data sets are characterised by their richness and fullness, which offers possibilities for in-depth analysis of the data where the objective is to interpret, understand and explain a phenomenon in a context (Saunders et al., 2019). The process of analysing qualitative data is highly iterative as the dataset can be reviewed and analysed multiple times as new themes arise from the data (Saunders et al., 2019). Qualitative data analysis strives to make sense of the data and sort it in categories and themes, which create a basis for answering the research questions within the theoretical framework (Saunders et al., 2019).

Saunders et al. (2019) characterise qualitative data analysis as an interactive process, where the data is analysed both during the collection and after it. The analysis of the data during the collection is a great way for the researcher to shape the direction of the data collection to gain more relevant data and therefore a more precise answer to the research question (Saunders et al., 2019). Hence, it is recommended to choose a qualitative analysis technique before data collection (Saunders et al., 2019).

The analysis technique that was chosen for this thesis was thematic analysis. The goal in thematic analysis is to find themes or patterns within the datasets (Saunders et al., 2019). Thematic analysis provides a systematic as well as flexible way to analyse qualitative data (O'Gorman & MacIntosh, 2015; Saunders et al., 2019) It offers a logical way to analyse data, which provides in-depth explanations and theorising to answer the research questions (Saunders et al., 2019). In abductive theory development, thematic analysis is used to generate themes that add to or expand the theoretical framework of the study (Saunders et al., 2019). In this study, thematic analysis is based on the theoretical framework and aims to find themes to answer the research questions.

According to O'Gorman & MacIntosh (2015) thematic analysis has six phases: 1) familiarisation with the data, 2) generating initial codes, 3) searching for themes, 4) reviewing themes, 5) defining and naming themes, 6) producing the report. Thematic analysis starts with familiarisation with the data by reading the content multiple times and data transcription (O'Gorman & MacIntosh, 2015). During the first step, initial codes from the data should be generated, which are organized in the second phase of the process(O'Gorman & MacIntosh, 2015). After that, the initial codes are combined into patterns for potential themes (O'Gorman & MacIntosh, 2015). Potential themes are then checked against the codes and how the themes relate to each other (O'Gorman & MacIntosh, 2015). In the fifth phase, the themes are refined and identified to fit the argument of the research (O'Gorman & MacIntosh, 2015). The purpose of the themes is to highlight what is interesting in the data. The final phase in the process is to produce the results of the analysis to present the information from the data (O'Gorman & MacIntosh, 2015). The report should contain examples of data extracts to provide support for the results (O'Gorman & MacIntosh, 2015). This process was followed during the data analysis in this thesis. As the themes in the research interviews were based on the theoretical framework of the study, the analysis of the data also utilized the framework as the foundation for the thematic analysis. The research data was reflected on the framework in the coding phase. Also, the potential themes were checked against each other based on the theoretical framework, which helped checking how the refined themes relate to the theoretical framework.

The structure of themes and subthemes, which emerged from the data after thematic analysis, are illustrated in Tables 6 and 7. Specifically, Table 6 presents two themes: *data-driven decision-making* and *dynamic capabilities*, as well as their subthemes. In turn, Table 7 presents two remaining themes: *knowledge management processes* and *role of technologies in knowledge creation*, as well as their subthemes. In addition of the themes and subthemes, the tables present excerpts from the interviews experts to illustrate the subthemes. In total four themes emerged from the data.

Table 6: Data-driven decision-making and dynamic capabilities

INTERVIEW QUOTES	SUBTHEME	THEME
"The more we have high quality data […] the better it is for years to come." "We continually scan the acquired data to see where it comes from and if it meets the GDPR regulations."	Data veracity and validity	Data-driven decision-making
"Big Data and data analytics serve as a foundation for everything we do." "We make ROMI models through data science […] So, we can better understand what our value really is."	Big Data Analytics	
"Emotion and data must be close to each other. Because if you lead everything by only using data, then you can't see very far."	Implementation of analytics into marketing	
"Practically all strategic alignments we make are based on broader data analytics." "We have amount X of money to spend each year, so where we are going to strategically spend it next year .... And on these we have been doing more with data analyses."	Strategic decision-making	
"By using data analytics, sales and digital attribution models we continuously receive recommendations to recognize new opportunities."	Sensing	Dynamic capabilities
"We use it to improve our investments and if recognize that we can achieve better productivity, we are able to react to it."	Seizing	
"Resources have always been found if the cause is important enough and we are able to justify it with data analytics."	Transformation	

Table 7: Knowledge management processes and role of technologies in knowledge creation

INTERVIEW QUOTES	SUBTHEME	THEME
"Data is in data lakes and from there, the data can be utilized by data analysts, and they can make dashboards to create knowledge" "You also have to fix how people use the data and the processes and everything."	Knowledge creation	Knowledge management processes
"Reports live in applications or dashboards online […] the reports are stored as PDF or PowerPoint, and reports are saved in SharePoint or in other shared files"	Knowledge storage	
"If the knowledge is in reports, those go to general files or to the client files, where only the members of the client teams have access to" "We try to automize the user management in a way that if you are given a relevant role in the firm, you also gain access to the relevant knowledge."	Knowledge transfer	
"Client teams implement the insights into the client work through the [marketing] plans"	Knowledge application	
"Practically all information and knowledge are behind passwords and logins" "Of course, the reports and PowerPoints can be taken elsewhere but then those are protected by NDAs"	Knowledge protection	
"We try to combine those and build a relational model based on that, which has been helpful for the use of analytics."	Knowledge repositories and infrastructure	Role of technologies in knowledge creation
"Together with data scientists we create actionable insights through visualization."	Data visualization	
"Above all people interpret those [analyses] through some reports or tools." "The tools are just as good as their users."	Context of knowledge created with analytics	

4 RESULTS AND ANALYSIS

In this chapter, the results of the empirical study are presented and reviewed. The results of the study are based on the methods, which were presented in the previous chapter. In total, four themes were discovered from the data, consisting of fifteen subthemes. Results and further analysis are presented later in the chapter in separate subchapters.

Presentation of the results follows the same order as the theoretical framework with one exception. We start with Big Data Analytics, but after Big Data Analytics we move on to the strategic decision-making, since subthemes from Big Data Analytics and strategic decision-making form the theme of data-driven decision-making. This is in accordance with chapter 2.5, where it was presented that Big Data Analytics is combined with strategic decision-making in data-driven decision-making.

Strategic decision-making is followed by knowledge management, which includes two themes that emerged from the data: knowledge management processes and role of technologies in knowledge creation. The results of dynamic capabilities are presented after knowledge management. Lastly, the results are summarized at the end of this chapter with the data-driven marketing model of the use of Big Data Analytics in strategic marketing decision-making.

4.1 Big Data Analytics

In this subchapter the results of Big Data Analytics are presented. This covers the role of data, as well as the use of Big Data Analytics and the implementation of analytics into marketing. These are also the first four subthemes discovered from the research data: *data veracity and validity, Big Data Analytics, and implementation of analytics into marketing*.

4.1.1 Data veracity and validity

The basis for data-driven marketing is in the data itself. The results indicate that data is used for analysis, which provides the marketing organizations with knowledge. Interviewees brought up that data is collected from various internal and external sources and datapoints, such as data from CRM, cash register systems, media buying systems, Statistics Finland, websites, clickstream, applications, and different meters from differing business units. Data veracity and validity emerged as an important prerequisite to perform effective data-analysis in the interviews. It was highlighted that as data is used to create knowledge, which is subsequently used in multiple strategic functions, it is vital for the data to be of high quality. Interviewees described the importance of high-quality data for data analytics.

"You can't do those [data analyses] if you can't trust the information. As the saying goes if the input is trash, the output will also be trash. And that is especially true in marketing." (Interviewee 2 - Customer Insight Manager, Retail)

"We have all sorts of data, and it is reviewed from the viewpoint of technology through its quality and consistency and through the cycles in which, the data is updated and stored, so it is in the most utilizable form possible." (Interviewee 4 - Marketing Technology Architect, Retail)

The interviewees described data to be used to find answers to problems or questions revolving marketing. Data is also used to find new opportunities and prospects and to recognize customers. An interviewee described the benefit of having high quality data for recognizing customers.

"The more we have collected high-quality data, so it is verified information about people, and it has something concrete elements, which help us to connect the information to some person or company, the better it is for years to come." (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

Data validity came up in many interviews as a key factor in the data usage. Especially when recognizing new and existing customers, the data must be validated and abide by the General Data Protection Regulation - GDPR.

"We take regulations very seriously. [..] We scan the data to see if there is PII data, which is personally identifiable information, so that it follows the GDPR. We continuously scan the collected data to see where it is from and if it abides by the [GDPR] regulations." (Interviewee 4 - Marketing Technology Architect, Retail)

The data must be acquired in a way which guarantees the protection of the customer data and information legally, but it also guarantees the high quality of the data as it is collected under the permission of the customer. Thus, making the data validated and easy to connect to a specific customer. Interviewee 3 (Senior Manager, Marketing Technologies, Oil refining) brought up the importance of the trust between a firm and its customer. As customers trust the firms they are in business with, they are more comfortable in sharing more data with the firm and as the firms gain more customer data through the trust the customer has in the firm, the more high-quality information the firm gains. This information is used to improve the firm's marketing and to offer the customers a better customer experience, which further increases the trust between the customer and the firm.

4.1.2 Big Data Analytics

The data is utilized in Big Data Analytics, which was one of the subthemes discovered from the analysis of the research data. It includes how data analytics is used in marketing and what benefits the analytics offer for firms. The systems were described to collect, process, and analyse data, which can be connected to other business functions for broader analysis that in return support marketing. This is supported by Johnson et al. (2019) as data that is gathered and utilized throughout the organization unifies the firm's activities toward organizational goals. The results show that a variety of Big Data technologies are used in Big Data Analytics. Databases, data warehouses and data lakes are used to store and access data. R and Python came up as popular programming languages for the data-analyses.

The use of analytics to produce analysis of the results of differing marketing actions and the impact of the performance of marketing became clear. The findings support the view of Shah & Murthi (2021) of data analytics increasing marketing accountability by accurate attribution of marketing spend, instead of measuring the effectiveness of marketing actions through soft goals.

> *"We make ROMI models through data science and statistical methods, where we try to model wider cause and effect relationships from the results of marketing. So, we can better understand what our value really is. Like what the actions from our marketing bring to the business, and how much we get in return to the money we spend."* (Interviewee 4 - Marketing Technology Architect, Retail)

One of the benefits of Big Data Analytics is that it offers forward-looking analytics (Gnizy, 2020). The results indicate that Big Data Analytics is used to look forward with models and predictive analyses where knowledge for marketing can be created based on different variables. Many interviewees emphasized the gained knowledge from the predictive analyses and models. As one of the interviewees stated the role of forward-looking analytics in marketing:

> *"An ever-increasing number of recommendations and decisions are based on data analytics we do for our customers, and it serves as a foundation for where we start from."* (Interviewee 5 - Chief Technology Officer, Marketing consultancy)

4.1.3 Implementation of analytics into marketing

As the examples demonstrate, analytics are tied to a purpose and serve a function in data-driven marketing. Implementation of analytics into marketing was recognized as one of the subthemes in data-driven marketing. The results illustrate the importance of thoroughly understanding the organization's own marketing strategy, and its goals for the analytics to have a legitimate impact on the business results, and that data analytics is not done solely for the purpose of analytics. The understanding of organization's marketing enables the organization to use the right data in the right places, as one of the interviewees noted. Interviewee 2 (Customer Insight Manager, Retail) described this by pointing out that Big Data Analytics should support the marketing processes and not work in a silo. Interviewees described that the efficient use of Big Data Analytics also provide a better understanding of different marketing functions, which leads to a better understanding of the overall marketing.

The importance of understanding other aspects of marketing came up frequently and corresponds with the viewpoint of data-driven marketing. The results indicate that in addition to knowing in what functions to use Big Data Analytics, marketing organizations must also be aware of where the knowledge offered by data ends and other factors affect the marketing.

> *"Emotion and data must be close to each other. Because if you lead everything by only using data, then you can't see very far. And the data needs some sort of emotion behind it to interpret it, and not that there will only be some mere data. Especially if we talk about hygiene products and the sales of sensitive categories. If you only look at data there, and you start to make decisions on how to market products for men and women purely based on data. Then you are likely to go horribly wrong because it misses all the emotion behind it and everything else that relates to the purchases of those categories and what leads to the purchase decision in the store or online store."* (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

The results illustrate that a part of understanding marketing is combining the analytics with other dimensions of marketing, such as brand and customer experience. Big Data Analytics are used to create more personalized marketing and customer experience.

> *"Our vision is tied to offering a better, personalized customer experience. That we want to serve our end-clients as well as possible, and as personally as possible to produce a high-quality customer experience. And yeah, the marketing technologies and data have a big role in that."* (Interviewee 4 - Marketing Technology Architect, Retail)

4.2 Strategic decision-making

S*trategic decision-making* emerged as a subtheme from the data. And as stated earlier, strategic decision-making follows the Big Data Analytics chapter in the results because the subthemes from Big Data Analytics form a theme with strategic decision-making. The formed theme is data-driven decision-making, and it consists of four subthemes: *data veracity and validity, Big Data Analytics, implementation of analytics into marketing,* and *strategic decision-making.*

As the analytics are implemented into marketing it can be utilized efficiently in strategic decision-making. Therefore, strategic decision-making emerged as one of the subthemes in the theme of data-driven decision-making. The results illustrate that Big Data Analytics is used widely in strategic decision-making. The analyses are used to make strategic decisions that affect the business processes, allocation of budget, positioning, and segments.

"If we look from the viewpoint of marketing, that where we are going to focus our budget on the coming year based on how much of it, we have in use. Because we have amount X of money to spend each year, so where we are going to strategically spend it next year. What channels we choose to use and where we want to be seen, and that is a strategic decision, because we choose to commit to it for a long period of time. It also affects the organization models and how the money flows and the deals we make. And on these we have been doing more with data analyses." (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

The results show that Big Data Analytics is used to monitor and to predict how the evolution and changes in the business environment and markets affect the business and marketing. The use of Big Data Analytics requires the tools for the analyses and the data scientists to do them, and a good understanding of the business and the marketing as well. Four interviewees told that predictive analyses and scenario analyses are used to determine cause-effect relationships from the data for the strategic decision-making.

"It [Big Data Analytics] already has a big role but we also want to increase it, as it is involved in all decision-making. And the direction that it is already heading toward is that we are able to gain significantly better predictive capabilities by involving data science. And our goal is to increase our ability to predict and not only to show what has happened." (Interviewee 4 - Marketing Technology Architect, Retail)

Big Data Analytics is utilized in making and choosing the solutions for strategic decisions through different analyses and models. The information and knowledge that is acquired and created from the analyses are used to make the strategic decisions that improve the businesses of the firms. However, two interviewees pointed out that the analytics maturity of each firm affects the usage of data analytics to determine cause-effects relationships for strategic decision-making.

The results demonstrate that in essence the humans interpret the reports and analyses provided by Big Data Analytics and make better decisions based on the gained knowledge. Interviewee 4 (Marketing Technology Architect, Retail) also brought up the possibility of taking the human out of the decision-making process through an automated decision-making based on artificial intelligence and data analytics.

4.3 Knowledge management

The results of knowledge management are presented in this chapter. This covers the knowledge management processes, which was also recognized as one of the themes from the data. The theme consists of five subthemes: *knowledge creation, knowledge storage, knowledge transfer, knowledge application,* and *knowledge protection.*

In addition, the knowledge management includes the third theme of the research: role of technologies in knowledge creation. The theme consists of three subthemes: *knowledge repositories and infrastructure, data visualization,* and *context of knowledge created with analytics.*

4.3.1 Knowledge creation

Knowledge creation emerged as one of the subthemes from the research data. The results illustrate that Big Data Analytics is used to create knowledge from the data. When talking about knowledge creation by using data analytics, interviewees brought up the importance of high-quality data once more, as it is used to create knowledge. The benefit of data analytics in knowledge creation is in the capability to produce knowledge from all possible data that is collected from multiple sources. This knowledge is further utilized by many departments and individuals across the organization.

> *"We bring all of our data together, but we search for implications for what works now and what will bring us the best results with different scenario analyses. And if we make little adjustments with different variables, for example if we want to focus more to another channel or include the weather forecast into the analyses, we are more able to develop the analyses forward for others. And we can indicate that this is what is going to happen in the future, and we can see it from the data, so we should invest x amount of money into this media, for example."* (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

As interviewees agreed that data analytics are an efficient tool to create knowledge from Big Data, they also emphasized the importance of processes that support the knowledge creation. The processes concern how data analyses are done and utilized in marketing. Several interviewees emphasized the integrity of the processes enables the knowledge creation.

> *"That is the challenge. That you first have to get your own thoughts [about the use of data analytics] together, and after that you hit a wall. For example, that the CRM data is corrupt. And that opens a completely new path. That you have to fix the CRM and it is not just the data, but you also have to fix how people use the data and the processes and everything."*
> (Interviewee 1 - Head of Digital Marketing, IT consultancy)

4.3.2 Knowledge storage

As stated in chapter 2.3, Big Data technologies improve the organizational memory by providing a centralized and quickly accessible unit to store, and retrieve knowledge (Côrte-Real et al., 2017). The interviewees described that the data itself is stored in cloud, databases and data warehouses or data lakes, which enables the efficient use of information. However, all the interviewees agreed that the knowledge is stored in the reports and dashboards that are generated with data analytics. Reports are stored in cloud-based services, such as Microsoft Teams or SharePoint. Dashboards and applications utilize cloud as well. These cloud-based platforms provide an easily accessible and centralized knowledge repository from the point of knowledge management processes.

> *"Data itself is stored in a data lake and in the cloud, and it is crypted and backed up. Then different reports live in applications or dashboards online in the platforms. So, the data is in the databases. Otherwise, the reports are stored as PDF or PowerPoint, and reports are saved in SharePoint or in other shared files, where those can be retrieved"* (Interviewee 5 - Chief Technology Officer, Marketing consultancy)

Alavi & Leidner (2001) presented that knowledge is also stored in the organizational procedures. The results follow the findings of Alavi & Leidner as interviewees describe that knowledge is also stored in the procedures to share knowledge within and across teams. Therefore, the knowledge is stored in the teams and individuals as well.

> *"The knowledge is largely in the PowerPoints, reports, dashboards, and in meeting memos. Of course, the created knowledge that we process and what rests in the data warehouses in numerical format, is saved and reusable. But the conclusions what people make, those move with each team and each person wherever they go. [..] Each team has own customs in sharing and storing the knowledge within the team"* (Interviewee 4 - Marketing Technology Architect, Retail)

4.3.3 Knowledge transfer

As illustrated in the knowledge storage, the processes to store knowledge are also used to transfer knowledge within the organization. Interviewees pointed out that in addition to store knowledge, dashboards and other reports are efficient instruments to share knowledge to individuals or teams within the organization. Especially to the ones that are not responsible for the data analysis. Interviewees illustrated that each dashboard is personalized to fit the intended use, so that the knowledge is easily acquired by others.

The results indicate that for the knowledge to be available for the ones who need it and when they need it, the processes and structures must support to transfer knowledge from the reports. This includes the interpersonal communication between individuals of the organization. Interviewees demonstrated that the processes to share knowledge from the data analyses include best practices and demos to support the transfer of knowledge within the organization. Interviewees agreed on that the processes also include the technical access for the users to the platforms where the reports are, so they can access it when needed.

> *"As a big firm we have a good IT department that are taking care of the automatic user management and authorization. So that people have access to the right places and right channels. Since we have a lot of these ready, generated platforms Teams, SharePoint, OneDrive, or hard infrastructure, such as cloud or data warehouse or whatever. We try to automize the user management in a way that if you are given a relevant role in the firm, you also gain access to the relevant knowledge."* (Interviewee 4 - Marketing Technology Architect, Retail)

4.3.4 Knowledge application

Knowledge application covers the application of created knowledge into a task at hand or in decision-making (Ferraris et al., 2019; Gasik, 2011; Gold et al., 2001).

As stated in chapter 2.3, knowledge application includes the processes of knowledge storage and knowledge transfer. The results confirm this as organizations have processes in place to utilize the different dashboards, reports and applications that have been created to provide knowledge from the data. Two interviewees pointed out that the use of reports and dashboards are tracked, to ensure the use of them in their organizations. As presented by Alavi & Leidner (2001), this helps the integration of knowledge into the existing routines, which improves the application of knowledge.

> *"The team that builds the dashboards in our organization, they have it in their goal that the dashboards are used. We assume that when those are opened and we look at the unique users, that those are utilized in the work and the planning"* (Interviewee 2 - Customer Insight Manager, Retail)

Other interviewees did not mention the mandatory use of reports and dashboards, but all interviewees agreed that the insights that are gained from those are implemented into marketing actions and into decision-making. This demands for both efficient knowledge transfer and storage. Efficient knowledge transfer benefits the application of knowledge since the knowledge is also implemented into action and decision-making by internal teams. Interviewees agreed that the insights from the reports are applied through highly functioning processes among teams. The demand for efficient knowledge storage comes from the implementation of knowledge into the systems and platforms that are used by individuals and teams in the organization. Interviewee 4 (Marketing Technology Architect, Retail) stated that the implementation of knowledge into the systems benefits the use of knowledge in the future also. Therefore, the knowledge must be easily accessible for the application of it.

4.3.5 Knowledge protection

As stated in chapter 2.3, knowledge protection refers to the protection of organization's databases (Zeiringer & Thalmann, 2021), as well as the processes with structural and cultural dimensions, such as employee conduct rules and job design, that are reinforced with technical solutions (Gold et al., 2001). The results of the interviews line up well with the definition from the literature. The results indicate that the knowledge management process has two sides: the technical procedures to protect knowledge and who have access to it, and the guides and practices to protect the knowledge.

The technical aspect of knowledge protection is tied to the knowledge transfer processes, as firms share access to its individuals to the source of knowledge it also covers the protection of the knowledge. The results indicate that this is usually covered by only giving individuals the access to relevant and necessary knowledge and data. Interviewee 3 (Senior Manager, Marketing Technologies, Oil refining) states that the design of who has access and where is important.

> *"Practically all information and knowledge are behind passwords and logins, and rests there. As I said earlier, only restricted persons have access to the raw data from restricted IP addresses, and that is in crypted servers and cloud. The insights live in the dashboards, where the login is once again required or in the reports that are usually saved in the network drives that also require organization's login"* (Interviewee 5 - Chief Technology Officer, Marketing consultancy)

As the example illustrates, the systems are used to protect the organizational knowledge. This is enforced with other information security aspects, such as only using the organization's equipment and systems to process and handle the data and knowledge.

All interviewees emphasized that important phase in knowledge protection is the procedures put in place to handle knowledge in a secure way. This includes the practices of how the knowledge should be utilized, as well as the NDA's signed by the employees to protect the organizational knowledge. Interviewee 1 (Head of Digital Marketing, IT consultancy) noted that even though they have NDAs put in place, the employees must understand their responsibility in processing the data and information. One interviewee stressed that:

> *"We have a very, very strict process in place for this, and it starts with when anyone comes into the firm, they are taught in the introductions what is very sensitive information and what is less sensitive information. And everyone goes through the courses on what knowledge can be shared and in what ways it can be processed. We start all the way from where you can sit with your headphones on and where you can work, so for example you have to wear headphones on in the office so no one can hear what you are discussing."* (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

4.3.6 Knowledge repositories and infrastructure

As demonstrated in the knowledge management processes, the knowledge repositories and infrastructure have an important role in the use of Big Data Analytics to create organizational knowledge. The knowledge repositories and infrastructure emerged as one of the subthemes. The interviewees emphasized the role of databases, data warehouses, and data lakes in storing the Big Data. Especially cloud-based databases were described to having an important role in storing data.

The knowledge repositories offer a basis for the creation of knowledge. Multiple interviewees described that their dashboards that are used for decision-making are built on top of the data warehouse where they have centralized all their marketing data. In addition to the databases, the design and structure of databases have a big impact on the capability to use data. The results illustrate that well-designed structure of the database is essential for the efficient use of data in data analyses for creating knowledge.

> *"We have good databases and good database structure. If you do data analyses as a work, those are important to you. [...] As the created knowledge is based on analytics, and during the past year we have been trying to improve the quality of the knowledge created for marketing. For that we have campaigns, and products in those, and medias where the products have been in. We try to combine those and build a relational model based on that, which has been helpful for the use of analytics."* (Interviewee 2 - Customer Insight Manager, Retail)

4.3.7 Data visualization

Big Data technologies are not only used to store and utilize data, but to visualize it for efficient usage as well. Data visualization emerged as one of the subthemes from the interviews. Data visualization was presented in chapter 2.3 as an efficient tool to make big datasets to be understandable and available for interpretation and decision-making (Ducange et al., 2018; Gupta et al., 2021). This was continuously brought up in the interviews in knowledge creation, storage, transfer, and application. As presented throughout the knowledge management processes data is visualized in dashboards, reports, and applications. All interviewees emphasized the importance of data visualization in creation of knowledge as the data or the analyses alone necessarily do not provide knowledge to other than the data analysts or data scientists. Interviewee 2 (Customer Insight Manager, Retail) told that for this they have their own team to make dashboards for the internal teams to use. Other interviewees supported this by stating that all information they create with data analyses are visualized and brought into dashboards for the creation of knowledge in the relevant places.

> *"All of our data is in the cloud, just like everyone else's. And together with data scientists we create actionable insights through visualization. Depending on the dashboard, we personalize them to fit what the use case is."* (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

As stated in the knowledge storage processes, the knowledge is stored in the reports and dashboards where it is visualized. This allows the knowledge to be used when it is needed.

Interviewees agreed that data visualization has an important role in the knowledge transfer and application as the reports and dashboards are used to present and share knowledge within the organizations. Data visualization puts the information from data to an easily understandable format, which allows the knowledge created with Big Data Analytics to be used. Interviewees illustrated this by saying that they use data visualization to make presentations to different executive teams and other teams that are responsible for marketing decision-making. However, interviewee 2 (Customer Insight Manager, Retail) also added that how much the reports and dashboards are utilized varies from individual to another.

"We try to bring the data from the analyses in a reliable way and in a fast pace to the dashboards where it can be browsed and examined for making conclusions based on it. And based on the conclusions people can shape their own operations." (Interviewee 4 - Marketing Technology Architect, Retail)

4.3.8 Context of knowledge created with analytics

According to Amado et al. (2018) Big Data itself does not offer value because it is purely a raw material. Therefore, as the data visualization presented, the data and the data analytics need a context in order to create knowledge. Even though reports and dashboards are efficient instruments to make the data in a more understandable form for interpretation, those are not useful without a context where those are tied to. This was presented in chapter 2.3 as information is a flow of data without context, and knowledge is an authenticated flow of information in a context (Alavi & Leidner, 2001; Nonaka, 1994). Interviewees agreed with this as they described that data analytics is a function that explains or serves a function in the real world. Interviewees described that analyses are made for a certain purpose or to gain a better understanding of a certain situation.

"Data is acquired and visualized. And above all people interpret those through some reports or tools, and then people make better decisions." (Interviewee 4 - Marketing Technology Architect, Retail)

One interviewee presented that the knowledge that is created with data analyses need someone to explain the results in the context for the insights to be usable.

"If you can visualize the data into an easily understandable form. And in a way that it is explained out by someone else than the data scientist. And as I mentioned before the reason and the emotion. The data scientist is the reason, who eats steel to make the analyses, but we need emotion to explain it [the analysis] to someone. And that is the biggest challenge with a lot of firms as either one is missing. And you have to combine these two." (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

The results brought up the role of the technologies creating knowledge. Interviewees described that Big Data and data analytics are important in creating knowledge for better decision-making and to be utilized in marketing operations. One interviewee pointed out that even though Big Data technologies are great tools for creating knowledge but are worthless without the people who know how to get the most out of them.

"Tools are just as good as their users. A good example I've used before is that do you need a Ferrari for something or will a moped be enough. If you have a Ferrari in the garage but no one who can drive it, it is useless. If you have a bicycle or a moped in the garage that everyone knows how to ride, you will get way much more out of that, and you will get further than with the really expensive Ferrari. Many firms invest in the Ferrari, a really expensive tool, but they lack the people who really can drive it." (Interviewee 3 - Senior Manager, Marketing Technologies, Oil refining)

4.4 Dynamic capabilities

As presented in chapter 2.4 Big Data analytics serve as dynamic capabilities that improve strategic decision-making. Big Data Analytics as dynamic capabilities was recognized as one theme in the study. The theme consists of three subthemes: *sensing*, *seizing*, and *transformation*. This follows the elements of dynamic capabilities processes presented by Teece (2007).

4.4.1 Sensing

Sensing emerged as one of the subthemes from the interviews, as Big Data Analytics is used to sense opportunities and threats in markets. Interviewees described using data analytics to sense opportunities and threats in multiple ways. Interviewee 2 (Customer Insight Manager, Retail) stated that data analytics are used to review and verify hunches, and to find new ideas in markets. Especially, when the business environments differ from one geological location to another, the data analytics are vital for recognizing opportunities that have strategical impact in the particular market. Interviewee 3 (Senior Manager, Marketing Technologies, Oil refining) answered among the same lines as he described using data analytics to find new potential to grow market share. Interviewee also added that they gather and analyse data to recognize threats to their brand in the markets.

Interviewees said that data analytics are used to monitor multiple business functions within the firms to recognize opportunities and threats both in the markets and in the marketing. One interviewee also explained using data analytics and predictive analytics to continuously recognize opportunities in the markets and exposing risks.

> *"Yes, continuously in the client work where our modeling platform products, such as digital attribution and sales modeling, are used. When we do those models, we continuously get recommendations that recognize new opportunities in marketing. They also show us what things are not working or what things should be reduced, so what are the risks. These models continuously give us recommendations on how to work."* (Interviewee 5 - Chief Technology Officer, Marketing consultancy)

4.4.2 Seizing

The results illustrate that in addition to sensing opportunities and threats in the markets, Big Data Analytics is also used to seize the opportunities and threats. Seizing refers to the ability to use resources to capture value from the opportunities and to effectively deal with the threats (Teece, 2007). Data analyses are used to create knowledge which enables the firms to react to the opportunities and threats. Interviewees discussed that data gives indication on how to react to the opportunities through differing actions or business functions, such as sales. One interviewee also added that Big Data Analytics have helped reacting to both different opportunities and threats by guiding their firm's actions with increased knowledge.

> *"We have our own risk management unit, that of course review the risk potential and risk scenarios of our different investments. And it is something that is done in many companies of our size. They make all sorts of different data analyses from available data to evaluate the potential business risks."* (Interviewee 4 - Marketing Technology Architect, Retail)

However, some interviewees pointed out that even though Big Data analytics offer the possibility for the firms to react to the opportunities and threats, the human factor restricts the efficient utilization of data analytics to seize opportunities and threats. Interviewee 3 (Senior Manager, Marketing Technologies, Oil refining) noted that even though the tools are there, the lack of human ability or knowhow sometimes restricts the efficient reaction. Interviewee 5 (Chief Technology Officer, Marketing consultancy) explained how they have gained good results by being able to react to the opportunities, people sometimes fail to do right decisions, even though data analytics provides insights and concrete recommendations on what actions should be done in marketing.

> *"Partially we have been able to react [to the opportunities and threats], but at the end of the day it all comes down to the people's decision-making. And not being able to do the measures recommended by data analytics, so that restricts us."* (Interviewee 5 - Chief Technology Officer, Marketing consultancy)

4.4.3 Transformation

The third element of dynamic capabilities processes is transformation. Transformation refers to continuously renewing and reconfiguring assets in a sustainable way to maintain and build competitiveness (Teece, 2007). Transformation emerged as one of the subthemes from the interviews. The results illustrate that Big Data Analytics enables the reconfiguration of assets by providing knowledge where to allocate them, which improves the adaptiveness of the firm.

> *"For example, the situation between Ukraine and Russia has had a big impact on our business and we have been monitoring the situation through data as well. On how the purchasing behaviour has changed in our different functions and how it will probably affect our business. And of course, the same thing applies to COVID-19. Those have radically changed our business environment and we have utilized the acquired data to make better decisions on how to adjust our own operations"* (Interviewee 4 - Marketing Technology Architect, Retail)

One interviewee pointed out that marketing functions can also enhance the reconfiguration of resources by supporting sales of particular goods in particular locations based on data analytics. In the interviews the most common resource to be transformed was money. In addition to money being reconfigured, the interviewees also pointed out that the working amounts on different functions by the experts are also reconfigured. Marketing budget is reconfigured and allocated based on analytical models and predictions.

> *"Data analytics gives us a clear vision on what actions and things are working and what are not working. And how much we get efficiency or sales from a certain client. And based on that we can decide how we allocate our money and resources."* (Interviewee 5 - Chief Technology Officer, Marketing consultancy)

Several interviewees noted that usually the setting is that marketing organizations or departments are given resources and are not able to have a big impact on the reconfiguration or delegation of organizational resources. This restricts the efficient transformation of resources in marketing organizations. However, one interviewee added that there have been situations where the need for resources or need for reorganizing the resources have been able to justify with marketing data analyses.

> *"Resources have always been found if the cause is important enough and we are able to justify it with data analytics. And in the case of internal organizing or anything like that, those will always come across our desk if there is a need for view of the consumer or the market. Those will go through our unit, and we will support the decision-making with data"* (Interviewee 2 - Customer Insight Manager, Retail)

The results demonstrate that Big Data Analytics are dynamic capabilities that improve strategic decision-making through sensing, seizing, and transformation. The analyses and models based on data provide the marketing organizations with a better knowledge and understanding on strategic decisions and actions.

4.5 Summary of the results

Figure 6 demonstrates the findings of the results with a data-driven marketing model of the use of Big Data Analytics in strategic decision-making. The model starts with high-quality and validated data that serves as the source of knowledge. The data is processed and analysed with Big Data Analytics. Big Data Analytics is used to provide improved knowledge management processes through data visualization. Data visualization is utilized in knowledge creation, storage, transfer, and application.

Data analyses are implemented into the decision-making through iterative and cyclical knowledge management processes, which provides the firm dynamic capabilities by providing improved reactivity and adaptiveness through efficient use of data and offering insights. Big Data Analytics is used to sense new opportunities in the markets. Data analyses are used to create knowledge which enables the firms to react by guiding firm's actions. Big Data Analytics enables the reconfiguration of assets by providing knowledge where to allocate them. The knowledge from the analyses is then used in strategic decision-making phases. Big Data Analytics is used to monitor and to predict markets and to make decisions based on the analyses. Strategic decisions that are made based on the knowledge from Big Data Analytics offer the firm a better understanding of their marketing, which is implemented back to the use of Big Data Analytics.

Data-driven marketing provides a basis for the whole process of utilizing Big Data Analytics in strategic marketing decision-making, as the effective use of Big Data Analytics in strategic marketing decision-making requires a good understanding of the marketing and its environment.

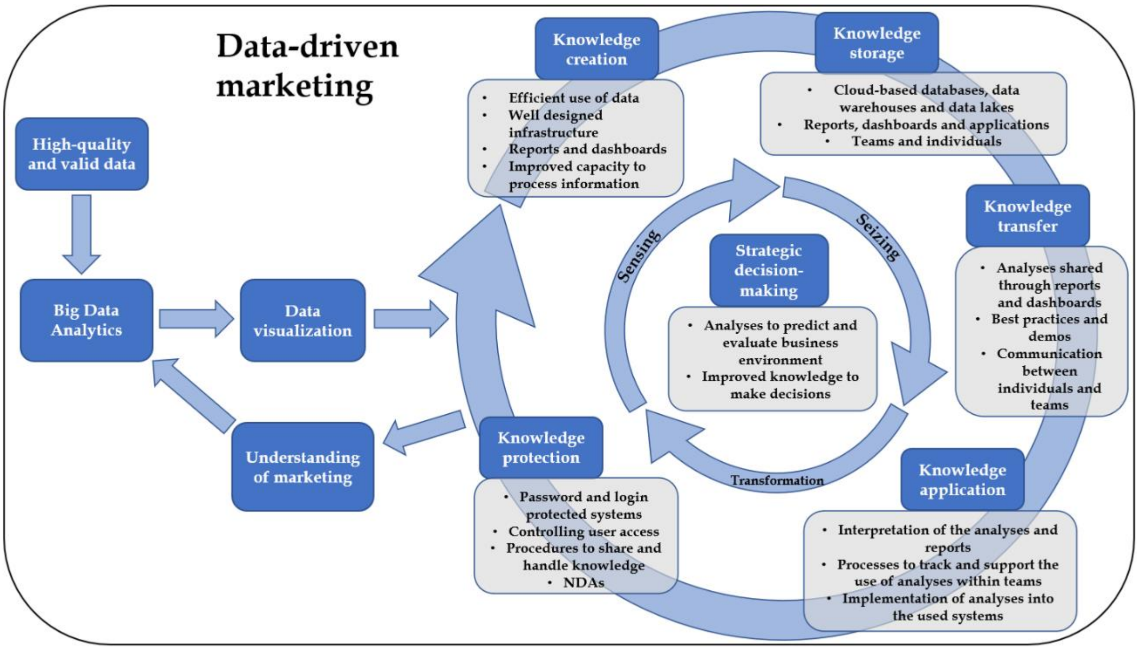

Figure 6: Data-driven marketing model of the use Big Data Analytics in strategic decision-making

5 DISCUSSION

This chapter draws the conclusions of this master's thesis. First, we summarize the findings of the study in light of the research questions and examine the theoretical contributions of this master's thesis. Then the managerial implications are presented. In the last part of the chapter, the limitations of the research are reviewed through reliability and validity, and avenues for future research are suggested.

5.1 Theoretical contributions

The aim of this master's thesis was to describe how Big Data Analytics is utilized in the strategic marketing decision-making. The theoretical framework for the thesis used knowledge-based view, knowledge management, and dynamic capabilities as the theoretical basis. This thesis has two research questions: *How can Big Data Analytics be utilized in the strategic decision-making in marketing organizations?* and *How Big Data Analytics support knowledge creation that generates dynamic capabilities useful for strategic decision-making?* To conclude the results of this research, the research questions of this thesis are answered in this chapter.

The main research question of this thesis was: *How can Big Data Analytics be utilized in the strategic decision-making in marketing organizations?* The results of this study strongly support the findings of existing literature on the use of Big Data Analytics in strategic decision-making that has recognized the improvements that Big Data Analytics have in strategic decision-making (Chen et al., 2015; Ferraris et al., 2019; Gnizy, 2020; Gupta et al., 2021).

The results of the study indicate that data and Big Data Analytics require a good understanding of the organization's marketing to support the strategic decision-making. This allows the data analyses to offer relevant knowledge required for strategic decision-making, which has a direct impact on the business results of the firm. This indicates that the knowledge created with the Big Data Analytics for strategic decision-making is tacit knowledge by the definition of Alavi & Leidner (2001) as it combines the technical elements of knowing Big Data Analytics and the cognitive elements of making effective strategic decisions based on the analyses. In addition, this is supported by knowledge-based view, which sees that a part of firm's knowledge is its ability to apply its tangible resources in its strategic actions (Alavi & Leidner, 2001; Shah, 2022). These findings are also in line with the viewpoint of data-driven marketing according to Johnson et al. (2019) and Sheth & Kellstadt (2021), who state that data-driven marketing combines data analytics and strategic decision-making in marketing to create business value. Based on the evidence of this research, the creation of knowledge with Big Data analytics and implementing it to strategic decision-making creates a feedback loop, which improves the overall understanding of organization's marketing that further improves the use of Big Data Analytics.

The findings illustrate that the combination of high-quality and validated data, a good understanding of the organizations marketing, and knowledge management processes create a basis for the use of Big Data Analytics in strategic decision-making. The analyses done with Big Data Analytics are models and differing analyses, such as scenario and predictive analyses where knowledge for marketing can be created based on different variables. This is supported by Gnizy (2020) and Shah (2022).

Based on the evidence of this research, for the analyses that are created for strategic decision-making to be effectively utilized, the organization needs efficient knowledge management. The results of this study indicate that knowledge management processes include knowledge creation, storage, transfer, application, and protection, like Alavi & Leidner (2001), Gasik (2011), and Gold et al. (2001) present. The results of this study indicate that knowledge management processes support the flow of knowledge from the data to the decision-making. As presented in Figure 6, the flow of knowledge provides a cyclical model of the knowledge management processes, which further includes both the technologies to create knowledge from the Big Data Analytics as well as the people who create and use the knowledge. Efficient knowledge management processes provide the firm with the capability to apply the knowledge into strategic decision-making. Especially efficient knowledge application processes able teams and individuals to understand and use the insights from the Big Data Analytics. Current literature has recognized that Big Data Analytics can create organizational agility through knowledge management (Côrte-Real et al, 2017). This research adds to the literature by recognizing that Big Data Analytics combined with knowledge management can create improved capabilities for strategic decision-making.

In strategic decision-making the scenario and predictive analyses are used to provide the organizations with information on the evolution and changes of the business environment, which gives insights for the decision-making. In the strategic decision-making processes these scenario and predictive analyses are used in the identification phase. The identification phase consists of recognising the opportunities and problems that initiate the decision-making process (Mintzberg et al., 1976). In the diagnosis, the goal is to understand the decision situation and to determine cause-effect relationships (Mintzberg et al., 1976). Based on the evidence of this research these forward-looking analyses through Big Data Analytics are used in the identification phase of the strategic decision-making.

As the findings present the use of Big Data Analytics, especially the modelling solutions, to make better analyses based on different variables it can be used in strategic decision-making in the development phase. These fits the definition of development phase according to Mintzberg et al. (1976), as the development phase consists of developing solutions for the decision-making.

It was found that the biggest contribution by Big Data Analytics in the selection phase of a strategic decision-making, is by providing improved knowledge to the organization's teams and individuals to make and choose solutions for strategic decisions based on verified data. These findings support the findings of Chen et al. (2015), Ferraris et al. (2019), and Gupta et al. (2021), who also found that Big Data Analytics improve the knowledge to make decisions.

The findings in the strategic decision-making phases suggest that the utilization of Big Data Analytics in strategic decision-making establishes data-driven decision-making in the firm. These findings are supported by Brynjolfsson & McElheran (2016), who state that data-driven decision-making is achieved as data and metrics are implemented in strategic decisions. However, as the findings indicate, the strategic decisions come down to the people who interpret and apply the knowledge from the Big Data Analytics, which can lead to making strategic decisions that are opposed to the insights from the analytics. This suggests that the efficient implementation of Big Data Analytics into the strategic decision-making requires efficiently facilitated collaboration between the managers who make strategic decisions, and the data analysts who are responsible for Big Data Analytics, as presented by Intezari & Gressel (2017).

The findings of this study add to the findings of Gupta et al. (2021) who demonstrate that the Big Data Analytics offers the firms dynamic capabilities by enhancing the adaptiveness and reactivity through improved data sources and technical capacity to analyse and manage data for decision-making. The results of this study add on to the findings by adding the cognitive capacity to analyse and manage data for strategic decision-making, in addition to the technical capacity through the required knowledge to effectively utilize Big Data Analytics, as well as the created knowledge from Big Data Analytics that further enhance the use of Big Data Analytics in strategic decision-making. The dynamic capabilities were found in the research to be achieved through sensing, seizing, and transformation, which is in accordance with the dynamic capabilities processes presented by Teece (2007). The sensing of opportunities and threats is done with Big Data Analytics by attaining more information and insights about hypotheses or by discovering those with predictive analyses, which relates to the findings of Chen et al. (2015) and Shah (2022). The seizing and transformation with Big Data analytics was found to take place in this research through the improved knowledge from the analyses, which help the firms to react to the opportunities and threats, as well as to reorganize their resources in a sustainable way. This view of the dynamic capabilities provided combines the findings of Gupta et al. (2021), Chen et al. (2015), who also recognized Big Data Analytics to provide dynamic capabilities with an improved knowledge, and Côrte-Real et al. (2017), who presented that Big Data Analytics can provide dynamic capabilities through knowledge management. These novel competences in organizing the firm's processes to efficiently apply knowledge from multiple sources to gain competitive advantages creates the knowledge-based view in this thesis, as it is supported by Gold et al (2001) and Grant (1996).

Therefore, in this study it was found that Big Data Analytics are used in strategic marketing decision-making by offering improved knowledge for the decision-making with analytical tools that offer insights in all strategic decision-making phases. The utilization of Big Data Analytics is implemented with knowledge management processes, which lead to dynamic capabilities through enhanced adaptiveness and reactivity in the decision-making situation. The efficient use of Big Data Analytics in strategic decision-making is made possible by a good understanding of the organization's marketing.

To help answer the main research question in this thesis, an additional research question was presented. The additional research question for this thesis was: *How Big Data Analytics support knowledge creation that generates dynamic capabilities useful for strategic decision-making?* On this additional research question, the results of this study also support the findings of existing literature, which has recognized that Big Data Analytics provide capabilities to sense, acquire, process, store, and analyse the data, which leads to the creation of knowledge from Big Data (Chen et al., 2015; Côrte-Real et al., 2017; Wright et al., 2019). In addition, this research recognized data veracity and validity as key factors in the characteristics of data, and data visualization was found to have an important role in the knowledge creation.

The whole process of knowledge creation with Big Data Analytics starts with high quality data, which is collected, processed, and analysed with Big Data Analytics. Data-driven marketing places data at the centre of firm's competitiveness (Johnson et al., 2019; Shah & Murthi, 2021). The results of this study are in accordance with this as data was seen as a source of knowledge for strategic decision-making. The findings of this study brought up the veracity and validity of the data as key factors in Big Data analytics. The results of data veracity correspond with Erevelles et al. (2016) stating veracity becomes more important so that firm's and marketers can be sure about their data quality. And validity has been found as a complement to veracity, as it adds to the integrity of the data through the correct use of it (Ducange et al., 2018). This was found as an important aspect in this thesis in the Big Data analytics, especially to guarantee the trustworthiness of the analyses for decision-making.

In addition to high-quality and validated data, the creation of knowledge through Big Data Analytics requires well designed knowledge repositories and infrastructure. This allows for the effective and fast use of Big Data for the data analyses. This corresponds to the viewpoint of de Camargo Fiorini et al. (2018). This is also tied to the finding of having the competent people who are skilled to use Big Data Analytics to make desired analyses, as well as to utilize the insights and to explain those to others. Having the infrastructure as well as the competent people to use and implement it in marketing, improve the knowledge creation and hence, the business value of the Big Data Analytics. This is supported by Intezari & Gressel (2017) who state that Big Data databases and Big Data Analytics alone do not result in successful strategic decision-making but requires the expertise to utilize it as well.

The findings of this study illustrate that the knowledge management processes have a big role in knowledge creation. As the Figure 6 demonstrates the results of the study, the knowledge management processes are iterative and organizational knowledge creation includes other processes than just the knowledge creation process. Based on the results of the study, Big Data Analytics improve knowledge creation through improved capacity to process Big Data and to create knowledge with the analyses. This is in accordance with the findings of Ferraris et al. (2019) and Varadarajan et al. (2020). Like Intezari & Gressel (2017), Jabbar et al. (2020) and Shah (2022) suggest, cloud-based database solutions and Big Data Analytics improve the capacity to store data and information that improves knowledge creation. This is also supported by Côrte-Real et al. (2017) who present that Big Data technologies are utilized to improve the organizational memory by providing a centralized and quickly accessible unit to store, share, and retrieve knowledge. The results of this study were in line with that as cloud-based databases, data warehouses, and data lakes offer a centralized knowledge repository for data, which improves the knowledge creation. In line with Alavi & Leidner (2001), Cormican & O'Sullivan (2003), and Gold et al. (2001), knowledge transfer was found to be an important knowledge management process to support the creation of knowledge. The transfer process was found to have an important role as the purpose of the transfer is to share the knowledge that is gained with the Big Data Analytics to the teams and individuals who are in positions to make strategic decisions. This has also been supported by Ferraris et al. (2019).

Data visualization was found to have an important role in the knowledge creation for strategic decision-making, as the results of the study demonstrate that data visualization is utilized in knowledge creation, storage, transfer, and application processes. Knowledge from the Big Data Analytics are visualized in reports and dashboards that are utilized in many levels of the organizations. These visualized forms of data offer the teams and individuals within the organizations to create deeper knowledge and understandings for the decision-making, as well as directly use the insights from the reports and dashboards. These findings are supported by Gupta et al. (2021).

Therefore, the findings of this research recognize that Big Data Analytics support knowledge creation that generates dynamic capabilities useful for strategic decision-making by using high-quality and validated data to make analyses, which improve the organizational knowledge through knowledge management processes. These knowledge management processes utilize data visualization that helps in the creation of improved knowledge. As presented earlier, the improved knowledge adds to the ability to process and analyse data that creates dynamic capabilities useful for strategic decision-making.

This thesis provides *three distinctive contributions* to the existing literature. *First*, this thesis provides an original theoretical model for the use of Big Data Analytics in strategic decision-making that adds to the existing academic literature on how Big Data Analytics and knowledge management is used in strategic marketing decision-making (Gnizy, 2020; Gupta et al., 2021; Johnson et al., 2021).

The model is based on the empirical findings of the research and the theoretical framework of this study that was built on knowledge-based view, knowledge management, dynamic capabilities, and strategic decision-making literature. In the context of data-driven marketing, the model recognizes the use of Big Data Analytics, as well as the role of data and understanding of marketing, in the strategic decision-making through five iterative and cyclical knowledge management processes. The knowledge management processes further create dynamic capabilities useful for strategic decision-making through sensing, seizing, and transformation. These findings combine the use of knowledge-based view, knowledge management and dynamic capabilities in strategic decision-making, and therefore fills the research gap in the utilization of these theories in Big Data research presented by Côrte-Real et al. (2017) and de Camargo Fiorini et al. (2018).

Second, based on the inadequate literature on the use of Big Data Analytics in the strategic decision-making, presented by Ferraris et al. (2019), Gupta et al. (2021), and Johnson et al. (2021), it can be argued that this thesis provides an original contribution on the implementation of Big Data Analytics into strategic decision-making through the strategic decision-making phases presented by Mintzberg et al. (1976). Previous literature has focused on the use of Big Data Analytics in the strategic decision-making in how to use Big Data Analytics in strategic position approaches (Gnizy, 2020), and how the knowledge management systems can facilitate the strategic decision-making (Intezari & Gressel, 2017). In addition, other studies discuss the strategic benefits of Big Data Analytics without studying how Big Data Analytics are used in the strategic decision-making (Ferraris et al., 2019; Gupta et al., 2021; Johnson et al., 2021). Therefore, this thesis also fills the research gap on how Big Data Analytics is utilized in strategic marketing decision-making presented by Ferraris et al. (2019), Gupta et al. (2021), and Johnson et al. (2021) by offering a theoretical model on how Big Data Analytics is implemented into strategic decision-making through strategic decision-making phases.

Third, this study adds to the findings of Gupta et al. (2021) who recognized that the Big Data Analytics offers the firms dynamic capabilities by enhancing the adaptiveness and reactivity through improved data sources and technical capacity to analyse and manage data for decision-making. This study shines light to the cognitive capacity, in addition to the technical, in analysing and managing the data. Therefore, this adds on to the existing literature of dynamic capabilities.

5.2 Managerial implications

In addition to the theoretical contributions, this thesis provides many managerial implications for practice. This study built a data-driven marketing model for the use of Big Data Analytics in strategic decision-making based on an empirical study that combined the views of data-driven marketing experts and theoretical literature. This model offers the managers and practitioners a deeper understanding of how Big Data Analytics can be implemented intro strategic marketing decision-making. The findings of this study provide insights on what tangible and intangible resources, and what processes are needed for the effective utilization of Big Data Analytics in strategic decision-making.

The insights provided by this study confirm the viewpoint of data-driven marketing by presenting, that the use of Big Data Analytics improve the ability to produce analysis of the results of marketing actions and decisions, as well as the impact of performance of marketing based on the marketing investments. Thus, the empirical findings of this study shine light on that Big Data Analytics enhances the accountability of marketing, which has also been recognized by the existing literature. Hence, the managers and practitioners should include Big Data Analytics and data more into their marketing operations and strategy.

The findings of this study stressed the importance of veracity and validity of the Big Data that is used for the analyses. As many interviewees pointed out that the customer data that is used for decision-making must abide by the GDPR. Therefore, firms must be aware of how they gather and handle the customer data so that the validity of the data ins ensured. This further improves the quality of the Big Data analyses, which have a direct effect on the quality of the organization's decisions, if the analyses are used in the strategic decision-making.

The knowledge and understanding to efficiently use Big Data Analytics in strategic decision-making is arguably the most important insight provided for the managers and practitioners by this thesis. This includes the knowledge to make data analyses from Big Data, the ability to understand what the analyses have to offer in the marketing context, and the capability to utilize the data analyses in strategic decision-making. This requires a data-driven mindset from the whole organization and all people who are connected to the decision-making processes. Otherwise, the Big Data Analytics will fail to reach its full potential and remain underutilized. Therefore, having the technology does not provide any value to the business without the competent people to use and utilize it.

Furthermore, this study highlights and illustrates other applications and advantages of data-driven marketing and the use of Big Data Analytics in decision-making, such as the importance of data visualization in knowledge creation. Managers and practitioners may utilize these insights to improve their data-driven marketing operations.

5.3 Limitations and future research suggestions

The limitations of this research are reviewed through its reliability and validity. Reliability and validity of the research must be assessed to assure the trustworthiness of a study and its outcomes (Eriksson & Kovalainen, 2008). In addition, both reliability and validity have an impact on the quality and impartiality of research, and it is necessary to take them into account at every stage of the research process (Saunders et al., 2019). Reliability refers to the replicability and consistency of the research as the study should be able to produce consistent and identical results despite the identity of the researcher (Eriksson & Kovalainen, 2008).

Key to ensure reliability is well designed and evaluated research process that does not contain logic leaps and false assumptions (Saunders et al., 2019). In this study this is established by selecting fitting research methods that are thoroughly justified in this thesis with a precise presentation of their use and aims. Additionally, to ensure reliability, the research questions are added in the appendices in writing. However, due to the open nature of the semi-structured interviews, the supplementary questions that were asked and were not part of the initial research questions cannot be documented. Error and bias can affect any research and those are a threat to reliability (Saunders et al., 2019). In this study, researcher bias may be a threat to the quality of the research because the interviews were conducted by only one researcher. Researcher bias refers to a phenomenon where the demeanour of the researcher can either induce bias in the answers of the interviewees or the researcher's view or disposition can affect the objective interpretation of the responses (Saunders et al., 2019). The objective interpretation of the interview answers is ensured through carefully and thoroughly designed research process and methods, as was covered earlier, but research bias when conducting the interviews was overcome by the researcher purposefully avoiding implications or statements that may have led the interviewees on their answers. The interviews were recorded and transcribed carefully to support reliability.

Reliability is an important aspect of research quality, but it alone does not ensure the quality and trustworthiness of the research, and therefore the research quality is dependent of validity as well (Saunders et al., 2019). Validity refers to the degree to which study conclusions provide an accurate description of what is measured (Eriksson & Kovalainen, 2008). For research to achieve validity, it must use appropriate measures to collect data, accurately analyse the findings from the data and have generalisable results (Saunders et al., 2019). Validity must be examined throughout the research process to guarantee the validity and to avoid systematic errors.

In this study, validity is gained through appropriate research methods that are used to collect and analyse the data, which includes the thorough planning of the interview questions that are based on the theoretical framework of the thesis. The anonymity of the interviewees increases the validity of the study since anonymity can encourage the interviewees to give more open and honest answers (Krefting, 1991). Furthermore, the interviewees were given the opportunity to add to their answers or give further insights to the themes at the end of the interviews after the interview questions were addressed. This additionally increases the interviews trustworthiness and, hence the validity of the study (Saunders et al., 2019).

The use of online video call as the medium of the interviews decreases the validity of the study since it may have resulted in lost information in the interviews. The generalisability is restricted because the sample size of the study is rather small, and the study only covers Finnish companies. Saunders et al. (2019) note that despite having a small sample size in qualitative research does not automatically lead to the research not being generalisable because generalisability might come in a form of the findings in a research setting being generalisable across other research setting. It is important to highlight that the interviewees' answers are simply reflections of their own experiences and viewpoints.

The findings of the thesis recognized the possible limitations in the utilization of Big Data Analytics in strategic decision-making to be in the decision-makers' ability to adopt the data analyses as a basis for the decision-making. Thus, future research may extend the understanding of the factors and processes that improve the adoption of insights from Big Data Analytics by the decision-makers. This future research avenue is a natural continuum for research in this domain. Further research suggestions emerged from the interviews as well. As a term Big Data Analytics is a broad concept, which covers a lot of technologies and technical skills. Hence, opportunities for future research are in examining the different technologies such as machine learning or artificial intelligence, or practices such as DataOps (an automated approach to data analytics that combines technology and processes to improve the quality and speed of data analytics with data pipelines), in the strategic marketing decision-making. One of the interviewees also pointed out that the strategic decisions differ between B2C businesses to B2B businesses. Thus, future research could study the use of Big Data Analytics in strategic marketing decision-making in either context.

As discussed earlier, this thesis used qualitative methods in the research, and the research only covered Finnish companies in no particular industry. To gain a deeper understanding of this phenomenon, quantitative research would support that. In addition, companies from different countries could improve the generalisability of research on this domain. Choosing a specific industry as a context of the study could provide deeper insights in that context. Therefore, future research could study this domain with quantitative methods. Research focusing on companies from different countries or in a specific industry present interesting avenues for future research as well.

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APPENDIX 1 - Interview questions

THE USE OF BIG DATA

1) Briefly describe the company you work for and your role in it
2) How does your work relate to data and analytics?
3) What kind of data does your company collect and what are the sources you collect it from?
4) How would describe your company's approach to data-driven marketing?
   - How is big data utilized in marketing?
   - What kind of role does data analytics have in your organization's marketing?

KNOWLEDGE MANAGEMENT PROCESSES

5) How do individuals in your organisation create and acquire knowledge from the data they have access to?
   - What kind of programmes and tools do you use in data analytics to create knowledge?
   - What kind of role do those programmes and tools have in your organisation's data-driven marketing?
6) How do you store the created knowledge in your organisation?
7) How do you distribute the created knowledge? / How do you make sure everyone who needs to have access to the information?
8) How are insights generated from data analysis transformed into action in your organisation?
9) How do you protect the created knowledge in your organisation?

DYNAMIC CAPABILITIES

10) Has your organisation been able to recognise certain risks or opportunities in your markets by using data analytics?
11) Has your organisation been able to react to those risks or opportunities?
12) Has your organisation been able to adapt its resources sustainably to the changes?

STRATEGIC DECISION-MAKING

In the earlier situations where risks or opportunities were recognized:
13) Has your organization been able to determine cause-effect relationships for the decision-making process through data analytics?
14) How has your organization utilized data analytics in development of a solution or solutions in decision-making?
15) How has your organization utilized data analytics to make a choice between the solutions?