LAPPEENRANNAN-LAHDEN TEKNILLINEN YLIOPISTO LUT
School of Business and Management
Master’s Degree Program in International Marketing Management (MIMM)

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HARNESSING BIG DATA FOR BUSINESS PURPOSES IN FINNISH SMES – ADAPTIVE MARKETING CAPABILITIES PERSPECTIVE

Examiners: Assistant Professor Joel Mero
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ABSTRACT

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Title	Harnessing big data for business purposes in Finnish SMEs – Adaptive marketing capabilities perspective
Faculty	School of Business and Management
Master's Programme	International Marketing Management (MIMM)
Year	2020
Master's Thesis	Lappeenranta-Lahti University of Technology LUT 70 pages, 9 figures, 1 table and 1 appendix
Examiners	Assistant Professor Joel Mero & Associate Professor Anssi Tarkiainen
Keywords	big data, big data analytics, machine learning, adaptive marketing capabilities, resource-based theory

The purpose of this thesis is to understand what kinds of resources and capabilities small and medium-sized B2B businesses require in order to harness big data for business purposes, and how SMEs with limited resources can gain business benefits with big data. Furthermore, the aim is to study the perceptions and attitudes towards machine learning, since machine learning is not widely adopted in smaller organizations, yet it has several advantages in big data analysis. To achieve these objectives, this thesis follows a qualitative case study research method. The case companies are one born-digital firm and one born-traditional organization.

The findings of the study indicate that in order to exploit big data effectively, SMEs should have certain physical, human and organizational resources, including analytics skills, powerful software, data warehouse for data integration, accurate and high-quality data, and data-driven organizational culture. In addition, vigilant market learning, culture of experimentation, and open innovation capabilities are emphasized, and according to the findings, SMEs with limited resources can compensate the shortage of resources by obtaining adaptive marketing capabilities. Thus, no substantial internal resources are necessarily required. Furthermore, machine learning is perceived as a positive force that can be utilized to derive additional value from big data applications.

TIIVISTELMÄ

Tekijä	Tanja Tammisalo
Tutkielman nimi	Big datan hyödyntäminen liiketoiminnallisiin tarkoituksiin suomalaisissa pk-yrityksissä – Mukautuvien markkinointikyvykkyyksien näkökulma
Tiedekunta	Kauppatieteellinen tiedekunta
Maisteriohjelma	International Marketing Management (MIMM)
Vuosi	2020
Pro gradu -tutkielma	Lappeenrannan-Lahden teknillinen yliopisto LUT 70 sivua, 9 kuvaa, 1 taulukko ja 1 liite
Tarkastajat	Apulaisprofessori Joel Mero & Apulaisprofessori Anssi Tarkiainen
Avainsanat	big data, big data analytiikka, koneoppiminen, mukautuvat markkinointikyvykkyydet, resurssiperusteinen teoria

Tämän pro gradu -tutkielman tarkoituksena on ymmärtää, millaisia resursseja ja kyvykkyyksiä pienet ja keskisuuret B2B-yritykset tarvitsevat jotta voivat hyödyntää big dataa liiketoimintaetujen saavuttamiseksi. Lisäksi tavoitteena on tutkia, miten rajalliset resurssit omaavat pk-yritykset pystyvät hyödyntämään big dataa. Tutkimus myös kartoittaa pk-yritysten asenteita koneoppimiseen, koska koneoppimista ei ole vielä otettu laajasti käyttöön pienissä ja keskisuurissa organisaatioissa, vaikka sillä on useita etuja big datan analysoinnissa. Työ noudattaa laadullista tapaustutkimusmenetelmää. Tapaustutkimukseen osallistui kaksi eri yritystä, yksi born digital -yritys ja yksi perinteinen yritys.

Tutkimuksen tulokset osoittavat, että big datan tehokas hyödyntäminen vaatii pk-yrityksiltä fyysisiä, inhimillisiä ja organisatorisia resursseja, mukaan lukien analysointitaitoja, tehokkaan ohjelmiston, tietovaraston datan integrointia varten, korkealaatuista dataa, sekä datalähtöisen organisaatiokulttuurin. Tuloksissa korostuu myös valpas markkinoilta oppiminen, kokeellinen kulttuuri ja avoin innovaatiokyky, joilla pk-yritykset voivat kompensoida omien resurssiensa rajallisuutta. Jos yrityksellä on vahvat mukautuvat kyvykkyydet, big datan hyödyntäminen ei välttämättä edellytä merkittäviä sisäisiä resursseja. Tutkimuksessa kävi myös ilmi, että koneoppiminen koetaan tärkeänä arvoa lisäävänä tekijänä big data -toteutuksissa.

ACKNOWLEDGEMENTS

I would like to thank everyone who has been a part of my thesis writing journey. Firstly, I would like to express my appreciation to my supervisor, Assistant Professor Joel Mero, whose guidance has been extremely valuable throughout the project.

I would also like to thank the interviewees for taking the time to participate in this research. I highly appreciate all their efforts and the information they shared with me. Without suitable case companies, I wouldn’t have been able to finish this thesis.

Finally, I want to thank my spouse, my friends and my family for all their support, inspiration, encouragement and all the patience they have shown me during this journey.

In Helsinki, 20.6.2020

Tanja Tammisalo

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1 INTRODUCTION

The aim of this study is to understand the key resources and capabilities that small and medium-sized organizations require to harness big data, and eventually machine learning, for business purposes. The topic is approached from resource-based theory and adaptive marketing capabilities perspectives, emphasizing the latter. The introduction part of the research paper presents what is already known of the topic and identifies key concepts and research gaps, providing a greater understanding of the research area.

1.1 Background and research gap

Today, numerous firms are aiming to transform their organization in order to gain novel business benefits. According to Kotler and Armstrong (2018, 17), the recent developments in digital technologies have created a new business environment, where organizations are actively adopting new-age tools that can help to engage customers, build brands, and create relationships and value for customers more effectively. The advances in the Internet of Things, machine learning, marketing analytics and big data have enabled innovative possibilities for organizations (Kotler & Armstrong 2018, 17).

Big data is widely praised as a vital success factor for today's businesses, helping firms to increase customer value and to gain improved business performance in competitive environments. The potential of big data has been receiving tremendous attention in recent years, as data-driven strategies, in which decision-making is based on data instead of opinions or intuitions, are becoming increasingly important in terms of achieving a competitive differentiation and enhancing firm performance (Barton & Court 2012; Wedel & Kannan 2016). Organizations are more data-driven than ever before, since the availability of immense amounts of unstructured and structured data is reinforcing data-driven cultures in firms (Wedel & Kannan 2016).

Big data can potentially help firm to overcome critical organizational barriers and respond to fast-moving signals in the market. According to Sen, Ozturk and Vayvay

(2016), the effective use of data can pose significant benefits for business of all sizes; with big data, companies can gain increased flexibility, productivity, responsiveness and anticipation, and improve their abilities to respond to changing customer needs.

However, firms are facing a high degree of complexity due to the expansion of existing data and the novel customer expectations, indicating that big data exploitation can present extensive challenges for businesses. Utilizing big data means that companies must deal with several data challenges regarding capturing, storing, searching, sharing, analyzing and visualizing data. (Chen & Zhang 2014; Mari 2019; Wedel & Kannan 2016) According to Day (2011), many firms are suffering from data deluge, which refers to a situation in which the amount of available data surpasses the organizations' capabilities to manage and utilize it for business purposes. This indicates that organizations must obtain novel resources and capabilities to exploit big data successfully (Day 2011; Kraaijenbrink, Spender & Groen 2012).

Prior studies regarding big data exploitation in organizations have been conducted mainly from a resource-based theory (Akter, Wamba, Gunasekaran, Dubey & Childe 2016; Erevelles, Fukawa & Swayne 2016; Gupta & George 2016; Mikalef et al. 2020) and dynamic capabilities perspectives (Mikalef et al. 2020). Gupta and George (2016), drawing insights from resource-based theory, propose that there are certain tangible, human and intangible resources that help firms to build big data analytics capabilities; the necessary tangible resources are data, technology and basic resources, such as adequate investments and time, the essential human skills include managerial and technical big data skills, and one of the most important intangible resources is data-driven organizational culture. The studies by Erevelles et al. (2016) and Mikalef et al. (2020) present similar findings, requesting that human, tangible and intangible resources jointly help firms to acquire big data analytics capabilities. Furthermore, Erevelles et al. (2016) and Mikalef et al. (2020) argue that solid big data analytics capabilities can improve organization's dynamic or adaptive capabilities, which potentially leads to enhanced business performance and helps firms to gain competitive advantage.

The prior studies, however, are not sufficient enough to understand how small and medium-sized businesses can address the issue of data deluge and harness big data for business purposes with limited internal resources. This is a valid concern and a very relevant area of research, as many organizations that are attempting to adopt big data are struggling to fully utilize the potential of it (Lunde, Sjusdal & Pappas 2019). Moreover, SMEs often suffer from a lack of appropriate resources causing them to fail in their big data initiatives (Ogbuokiri et al. 2015). Day (2011) stresses that resource-based theory puts too much emphasis on the resources and does not explain how firm's capabilities are established. Hence, this study suggests that adaptive marketing capabilities can reinforce firm's human, physical and organizational resources in big data exploitation. Engels (2017) argues that the only way for SMEs to turn big data into profits is by networking and teaming up with others, since smaller businesses are not capable of managing big data on their own due to resource shortages. This justifies the choice of involving adaptive marketing capabilities in the framework of this study, as strong adaptive marketing capabilities allow businesses to improve the utilization of external capabilities and resources, obtain opportunities through collaboration, and combine network resources to achieve a better business performance (Day 2011).

Academic journals regarding adaptive marketing capabilities are scarce, and Guo, Xu, Tang, Liu-Thompkins, Guo and Dong (2018) highlight that there's a pressing demand for further studies in order to fully explore adaptive marketing capabilities' antecedents and consequences. Furthermore, adaptive marketing capabilities theory hasn't been studied in big data environment, which further emphasizes the importance of this study.

In addition to studying how SMEs can harness big data for business purposes with adaptive marketing capabilities, this thesis aims to understand firms' attitudes towards machine learning. According to Mari (2019), machine learning is a powerful method for turning big data into valuable insights, and it can provide significant benefits for organizations by helping them to make use of a vast amount of unstructured and voluminous data that can't be managed with traditional methods (Davenport, Barth & Bean 2012; Amado, Cortez, Rita & Moro 2017). Typically, firms adopt machine learning to further increase business intelligence, enhance decision-making, discover new vulnerabilities, provide faster processing efficiency, and create cost-savings and profitability (Attaran & Deb 2018). The survey conducted by MIT Technology Review Insights (2019) claims that businesses can identify high-value customers, understand consumer intent and discover new business opportunities with machine learning solutions. Nevertheless, although machine learning is a technical field that grows at a rapid rate (Jordan & Mitchell 2015) and it answers the big data challenges by providing more efficient ways of analyzing data (Amado et al. 2017), it is not extensive exploited in smaller organizations. (Wedel and Kannan 2016).

The survey conducted by Bughin and Hazan (2017) revealed that many executives are not utilizing machine learning as they are uncertain of its business case, and firms are still seeking models for how to utilize machine learning together with big data to gain business advantages. (Bughin & Hazan 2017; Burgess 2018). This thesis aims to provide real-life examples of how case companies have exploited machine learning with big data, while seeking to further understand firm's attitudes and motives for implementing machine learning solutions in big data projects.

Machine learning has been studied in different circumstances, such as in the medical (Cabitza, Rasoini & Gensini 2017; Demasi, Kording & Recht 2017; Krishnan, Wang, Aljabar, Ball, Mirza, Saxena, Counsell, Hajnal, Montana & Edwards 2017) and chemical sciences contexts (Butler, Davies, Cartwright, Isayev & Walsh 2018; Granda, Donina, Dragone, Long & Cronin 2018). However, there are few research papers discussing how SMEs can utilize machine learning in big data analysis. Thus, both big data and machine learning are extremely relevant research topics, especially in the SME environment.

1.2 Aim of the study and research questions

Big data can pose significant benefits for firms, especially when paired with machine learning. Yet, the process of transforming immense amounts of data into business benefits can still seem vague for executives, and many SMEs are failing in their big data initiatives. The aim of this study is to extend the understanding and knowledge of how SMEs can derive value and actionable insights from big data, focusing on the required resources and capabilities. The thesis attempts to answer to the following research questions:

RQ1*: What resources and capabilities SMEs require to seize new business opportunities with big data?*

RQ2*: How SMEs with limited resources can exploit big data to gain business benefits?*

RQ3*: What attitudes firms have towards machine learning?*

Furthermore, the third research question has two sub-questions in order to specify the reasons for adopting machine learning adoption, and to understand what kinds of benefits organizations aim to achieve with it in big data applications:

> ***Sub-RQ1****: What are the main drivers for machine learning adoption in big data applications?*
>
> ***Sub-RQ2****: How machine learning can enhance big data applications?*

1.3 Theoretical framework

The theoretical framework of this thesis builds on resource-based theory and adaptive marketing capabilities approach. The resource-based theory offers a solid foundation for identifying the relevant physical, human and organizational resources for big data adoption, while adaptive marketing capabilities perspective is utilized to further explain how SMEs with limited resources can harness big data for enhanced business benefits.

Resource-based theory is a broadly recognized framework for determining the strategic resources firms need to establish a competitive advantage. The resource-based theory underlines the importance of firm’s physical, human and organizational resources (Barney 1991). However, it’s been argued that resource-based theory alone is not suitable to explain a firm’s competitive edge in complex and unpredictable circumstances, in which new technologies and markets arise. (Day 2011; Kraaijenbrink et al. 2012). According to Priem and Butler (2001), the problem of the resource-based theory is that it lacks the ability to predict and identify capabilities leading to competitive advantage, and it fails to address fundamental connections between the resources and the environment. Resource-based theory has been criticized by researchers, as it involves a static approach (Priem & Butler 2001) and puts little weight on innovation and learning (Teece 2014). Day (2011) and Polat and Akgün (2015) emphasize that organizations must upgrade their static approaches with adaptive strategies to maintain a leadership position in the market.

Adaptive marketing capability is firm's ability to identify and seize novel opportunities that emerge in the market. The three main adaptive marketing capabilities are vigilant market learning that means being able to identify weak market signals, adaptive market experimentation that enhances constant experimentation and learning, and open innovation or open marketing that involves creating relationships with valuable stakeholders that have certain abilities or skills (Day 2011). According to the study conducted by Guo et al. (2018), adaptive marketing capabilities have greater impact on firms' business performance than static resources in fast-changing and complex market conditions, since the adaptive marketing capabilities approach explains how to close the widening gap between the firm's resources and the demands of the environment (Day 2011; Polat & Akgün 2015). However, Mikalef, Krogstie and van de Wetering (2018) believe that both static and adaptive capabilities are critical for firms, arguing that the main difference between static capabilities and adaptive capabilities is that the former supports firm's existing operational capabilities, while the latter enables firms to modify their operational capabilities and resources in response to rapid alterations in the market. Thus, according to prior research, both resource-based theory and adaptive marketing capabilities approach are valid perceptions. Furthermore, as adaptive marketing capabilities theory builds on resource-based view, the theories are not mutually exclusive.

This thesis suggests that in addition to physical, human and organizational resources identified in the resource-based theory, organizations should obtain adaptive marketing capabilities to compensate the lack of internal resources and to further enhance firm's abilities to exploit big data. For example, if the firm lacks internal analytics skills, it's still possible for them to obtain those skills through cooperation with partners or other stakeholders, and by creating the kind of relationships that benefit both parties. Furthermore, vigilant market leaning skills and experimentation can help SMEs to seize emerging market opportunities and harness their existing resources effectively for performance gains. Hence, organizations can establish superior big data capabilities by complementing their existing resources with adaptive marketing capabilities.

The theoretical framework of this thesis proposes that while adaptive marketing capabilities reinforces firm's human, physical and organizational resources leading to enhanced big data capabilities, machine learning can reinforce firm's big data analytics capabilities, which in turn helps companies to generate better business results. The relationships between all the key elements of the theoretical framework are illustrated in Figure 1.

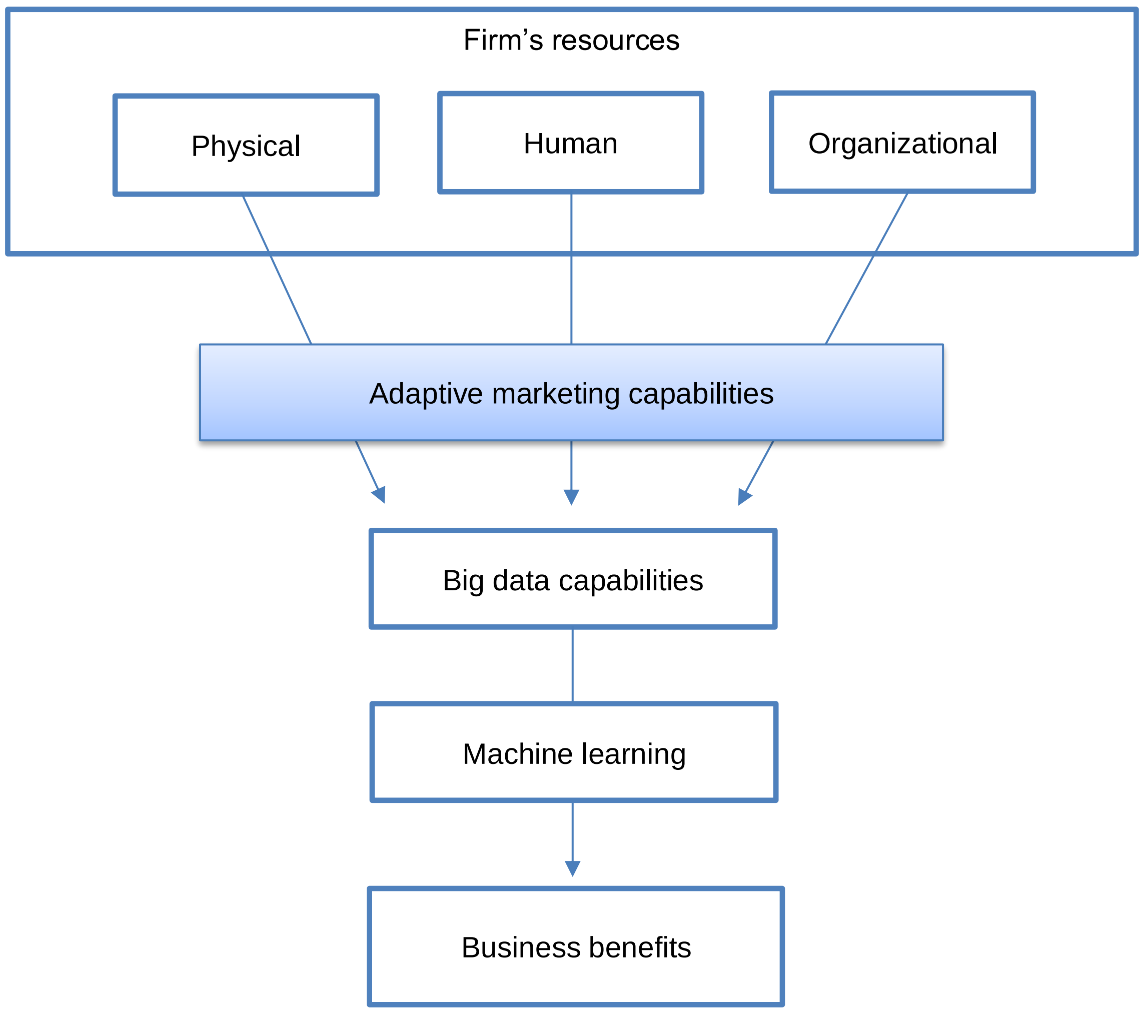

Figure 1. Theoretical framework of the study

1.4 Key definitions

Artificial intelligence (AI): the umbrella term for a several different technologies and methods that can be utilized to sense and perform with the ability to learn and adapt over time. For example, machine learning and deep learning fall under the artificial intelligence concept. (Akerkar 2019, 3; Sterne 2017, 9).

Machine learning (ML): an area of artificial intelligence that involves the computational approaches developed to automatically make sense of data, without requiring much input or assistance from humans (Akerkar 2019, 5). According to Russell and Norvig (2010, 694–695), the three primary kinds of machine learning are unsupervised learning, supervised learning, and reinforcement learning.

Big data (BD): complex and enormous data sets that demand advanced data storage, management and analysis techniques and tools. The three main factors characterizing big data are the volume of data, the variety of data, and the velocity at which data is collected (Chen et al. 2012; McAfee & Brynjolfsson 2012; Shah, Rabhi & Ray 2015).

Big data analytics (BDA): techniques and processes for collecting, managing and analyzing enormous data sets to uncover correlations, hidden patterns, trends, or other insights (Jordan and Mitchell 2015; Knapp 2013; Qiu et al. 2016; Zhou et al. 2017).

Big data analytics capabilities (BDAC): the firm's capability to aggregate and utilize its big data-specific resources throughout the organization. Big data analytics capability is the unique combination of the company's physical, human and organizational resources. (Gupta & George 2016; Mikalef, Krogstie, Pappas & Pavlou 2019)

Resource-based theory (RBT): one of the most acknowledged approaches for understanding and describing organizational relationships and firm's resources that can be exploited to achieve sustainable competitive advantage. Resource-based theory suggests that resources that are valuable, rare, imperfectly imitable and non-substitutable and can potentially generate firm's sustainable competitive advantage.

The resources can be human, physical, organizational or financial (Barney, Ketchen & Wright 2011; Barney 1991).

Adaptive marketing capabilities (AMC): the ability to constantly anticipate and seize novel market opportunities, persistently learning by conducting experiments, and integrating network partner resources to adapt to market changes and to access novel insights (Day 2011; Guo et al. 2018). According to Day (2011), adaptive marketing capabilities include three main aspects: (1) vigilant market capability, (2) adaptive market experimentation capability, and (3) open marketing capability.

1.5 Delimitations

The focus of this study is on small and medium-sized companies operating in the B2B sector in Finland. The empirical research involves one born-digital firm and one born-traditional company, and the aim is to find similarities and differences between these organizations. However, due to small sample size and narrow focus on carefully selected B2B firms, the findings of the results cannot necessarily be applied universally. This study doesn't provide a coherent understanding of the big data methods, tools and techniques, but it concentrates on the resources and capabilities that are driving and enabling big data adoption in organizations.

The findings of this thesis can provide directions for future research and more knowledge of how SMEs have managed to harness big data and machine learning to gain enhanced business benefits. Furthermore, the findings increase the understanding of adaptive marketing capabilities in big data context.

1.6 Research methodology

This chapter explains the research structures and methods used, and offers justification for the chosen research methods. The structure of the research process is visualized in Figure 2.

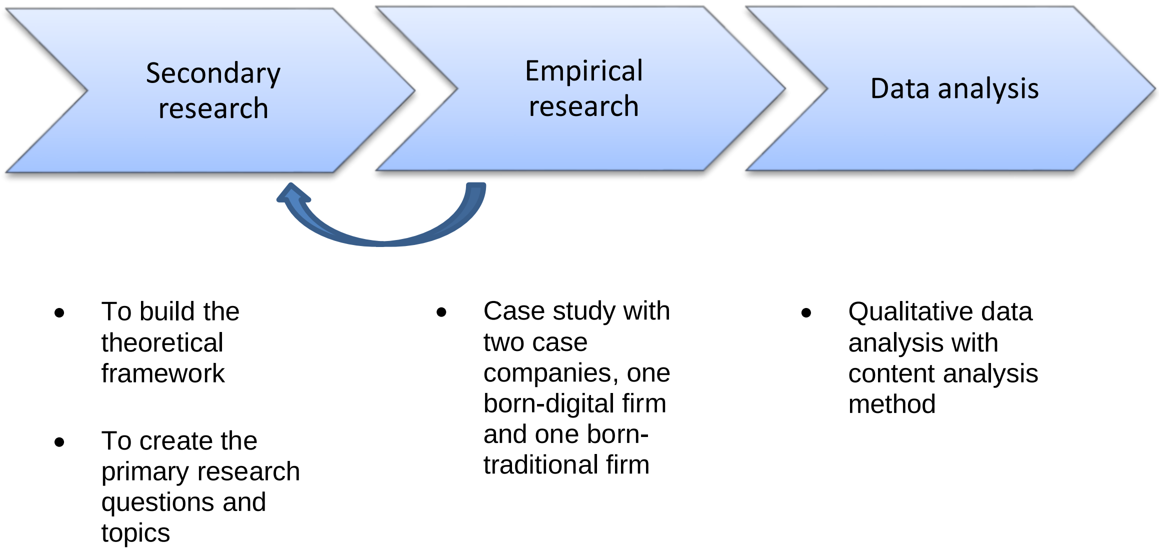

Figure 2. The research process

Since adaptive marketing capabilities theory hasn't been studied extensively in academia, this study follows a qualitative research method and is exploratory by nature. Exploratory study is particularly convenient when the aim is to understand a certain issue or phenomenon, introducing research questions often starting with "how" or "what" (Saunders, Lewis & Thornhill 2016, 174–175).

An exploratory research is flexible and adjustable, which gives the researchers a possibility to change the direction as new data and insights occur. The data can be collected in various ways, such as by examining the existing literature, interviewing experts, or conducting individual or focus group interviews. Typically the interviews are relatively unstructured, as the nature of the research problem is often unclear. (Saunders et al. 2016, 175) In this study, semi-structured interviews were utilized for data collection in order to ensure all the key themes were covered during the interviews. The thesis follows a case study research strategy concentrating on small and medium-sized businesses that operate in the B2B sector in Finland, and public documentation regarding the case firms were exploited as an additional source of secondary data.

According to Saunders et al. (2016, 127), it's often more appropriate to work inductively rather than deductively when the existing literature on the research topic is scarce and the objective is to gain a better understanding of a phenomenon. With inductive approach, data is collected and theory created after conducting the data analysis (Saunders et al. 2016, 124). In this thesis, the preliminary theory was first developed based on the existing literature, but the findings from the empirical research were utilized to complement the theoretical part.

1.7 Structure of the study

This study is divided into two primary sections, which are the theoretical and the empirical parts. The chapter one begins with an introduction; it presents the background and aims of the study, the research gaps as well as the research questions, and the theoretical framework. The introduction also identifies key definitions and delimitations, and introduces the research methodology. The following chapter is the literature review, discussing the main topics of the study in more detail and presenting findings of the earlier studies. The theoretical literature section is followed by the empirical part of the study, in which research designs and methods are presented in more detail. The findings section covers the research findings in relation to the theoretical framework of the study. Finally, the last chapter discusses the conclusions, as well as the limitations and recommendations for future research.

2 BIG DATA, MACHINE LEARNING AND RELATED CONCEPTS

The purpose of this literature review is to deliver a greater understanding of the main concepts of the study, including big data and big data analytics, artificial intelligence, machine learning and deep learning, and to discuss the relationships between these concepts. Moreover, the chapter introduces business opportunities and challenges associated with big data exploitation.

2.1 Big data and big data analytics

Big data and big data analytics refer to voluminous data and complex analytical techniques that demand unique and powerful data storage, management and analysis systems and methods (Chen, Chiang & Storey 2012). Big data consists of structured, unstructured and semi-structed data (Gandomi & Haider 2015). Several big data definitions have emerged in recent years, but the three generally accepted features of big data are volume, variety, and velocity, also known as three Vs (Chen et al. 2012; McAfee & Brynjolfsson 2012; Shah, Rabhi & Ray 2015). The study of big data is constantly evolving, and according to Tiwari, Wee and Daryanto (2018), the main characteristics of big data are nowadays best described with a 5V framework, which involves veracity and value in addition to the attributes included in the 3V model. Sivarajah, Kamal, Irani and Weerakkody (2017) add also variability and visualization as features of big data to the 5V concept.

Volume refers to the magnitude of data (Gandomi & Haider 2015). McAfee and Brynjolfsson (2012) discuss how approximately 2.5 exabytes of data was generated on a daily basis in 2012, and today, the quantity of data is constantly growing. *Variety* of big data sources is enormous, as technological advantages allow business to utilize various types of structured, semi-structured and unstructured data, such as conversations and messages on social media, images, audio, and video (Gandomi & Haider 2015). *Velocity* refers to the speed of creation and the rate it moves around. With real-time analytics, firms can be much more agile and have advantage over competitors. (Gandomi & Haider 2015; McAfee & Brynjolfsson 2012) *Veracity* deals with the trustworthiness of the data. Since many valuable big data sources, for example social media, involve human judgement, the quality is less controllable. The necessity of dealing with inaccurate information is a critical factor in big data processes, and veracity refers to understanding the data and coping with the biases and imperfections in the data. (Gandomi & Haider 2015; Sivarajah et al. 2017) *Value* can also be defined as one characteristic of big data. The original data typically has low value in relation to its volume, but it's possible to increase the value by analyzing a vast amount of such data (Gandomi & Haider 2015). *Variability* refers to data whose meaning continuously changes, and *visualization* involves presenting the data and key information in a readable manner (Sivarajah et al. 2017).

Big data analytics is a process that involves collecting, managing and analyzing immense amounts of data (Jordan and Mitchell 2015; Qiu et al. 2016; Zhou et al. 2017). According to Ferraris, Mazzoleni, Devalle and Couturier (2019), the main objective of big data analytics is to create actionable insights and to generate valuable knowledge in order to achieve performance gains and competitive edge in organizations. The advent of big data has developed an extensive interest towards machine learning, as fully making sense of massive data sets requires novel learning techniques. (Jordan & Mitchell 2015; Qiu et al. 2016; Zhou et al. 2017) Thus, machine learning can be utilized as one particular way to analyze the data. Since machine leaning thrives on large data sets and powerful computing systems along with efficient learning algorithms, big data enables machine learning algorithms to extract underlying patters and build more accurate and timely prediction models at much faster rate than ever before. (Davenport 2013; Zhou et al. 2017) Hence, machine learning can pose significant benefits for big data analysis and vice versa.

2.1.1 Big data business opportunities for SMEs

There are multiple ways big data can be utilized for value creation across organizations. For example, big data and machine learning technologies can be used to design solutions for pricing (Bhadani & Kotkar 2015; Davenport 2013), customer segmentation (Davenport 2013; Sterne 2017, 313), as well as experimentations and innovations leading to new business models and offerings (Chen et a. 2014; Davenport 2013; Manyika et al. 2011). Chen et al. (2014) state there are various business advantages that can be established through exploiting big data, such as improved operational efficiency, information regarding strategic direction, superior customer experience, discovery of new markets, and abilities to comply with rules and regulations.

According to existing studies (Attaran & Deb 2018; Burgess 2018; Bhadani & Kotkar 2015; Davenport 2013; Manyika et al 2011; McAfee & Brynjolfsson 2012), big data along with machine learning can also provide effective tools for enhanced decision-making. Basing decisions on data rather than opinions and intuitions can be referred as data-driven decision making (Provost & Fawcett 2013). According to Amado et al. (2017), data-driven decision making is crucial for businesses, and data can assist for example marketers in answering vital questions, such as “what is the most appropriate product and service for a specific market”, and “how to advertise such product or service in the market”. Alshura et al. (2018) highlight that big data can potentially provide organizations with real-time and complete understanding of the customers and their behaviors, which allows firms to improve their decision-making effectively.

2.1.2 Big data challenges

As discussed, big data holds great potential for organizations. However, there are several challenges that firms must address to harness big data for business opportunities. According to Sivarajah et al. (2017), the foremost challenges of big data can be categorized into challenges regarding the data, the processes and the management. Data-related challenges refer to the characteristics of the data itself, such as data volume, variety, velocity, volatility and value. Process-related challenges involve a set of different challenges, such as acquiring, mining, warehousing, integrating, aggregating, analyzing and interpreting the data. Management-related challenges contain the challenges related to data security, privacy, governance and ethical aspects. The primary challenges are presented in Figure 3.

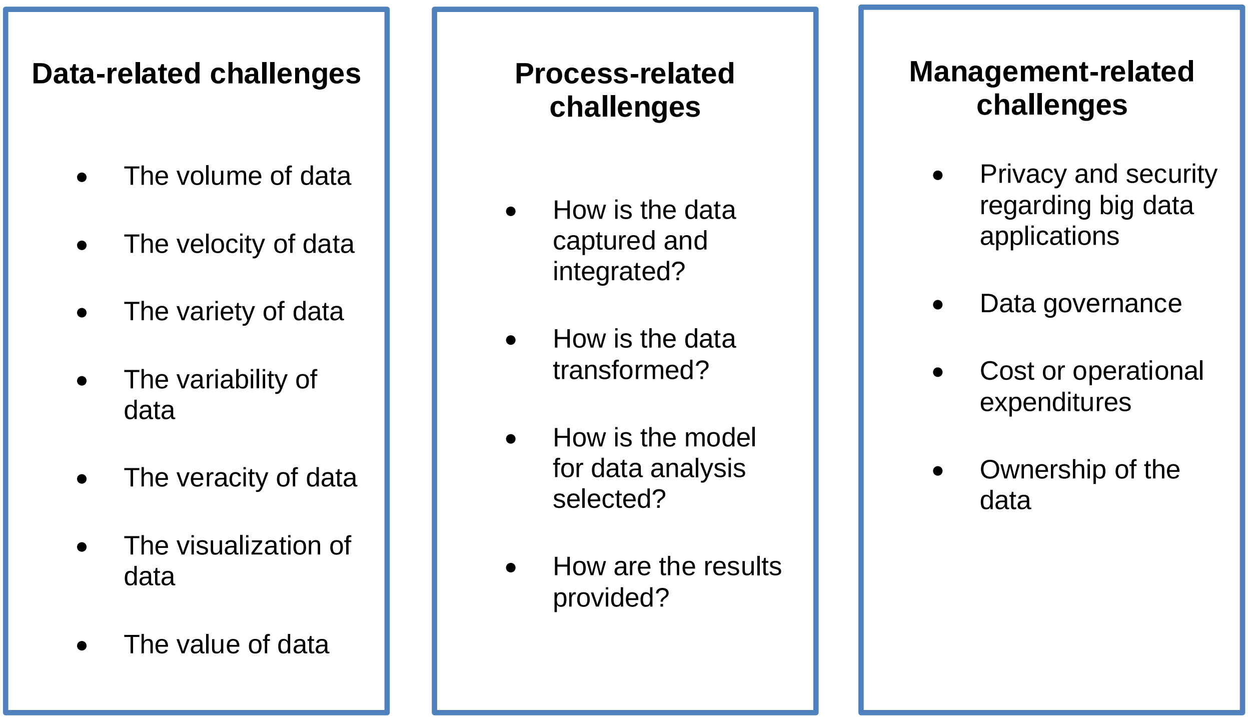

Figure 3. Big data challenges (adapted from Sivarajah et al. 2017)

According to Engels (2017), there are several barriers that keep especially small and medium companies from exploiting big data. These barriers include the lack of data security, high costs, missing know-how, the lack of common standards, and an uncertain regulatory framework. However, Engels (2017) stresses that big data projects are not elite projects that are constrained to large organizations; in fact, SMEs often have more flexible decision-making processes due to lower internal hierarchy and agile strategies, indicating that smaller firms may be able to transform data into business opportunities more rapidly compared to multinational companies.

Lunde et al. (2019) stress that often organizations that exploit big data gain only limited benefits from it, indicating that firms are not able to fully harness big data for business purposes. One factor that can be perceived as a major barrier for big data applications is the culture of the firm. An effective exploitation of big data throughout the company demands a data-driven organizational culture in which the decisions are based on data rather than one's opinion (Erevelles et al. 2016; Gupta & George 2016; Wedel & Kannan 2016), yet changing the company culture can be extremely difficult, since it contains deeply embedded goals, values, processes, rules, practices, and attitudes (Denning 2011).

2.2 Artificial intelligence

Artificial intelligence includes an extensive variety of technologies, but generally artificial intelligence refers to the domain of computer science that studies how machines can be made to perform human-like tasks intelligently. The term emerged first in 1950s, coined by John McCarthy. (Jackson 1985, xiii; Sterne 2017, 9) Artificial intelligence can be categorized into the following types: narrow intelligence, artificial general intelligence, and artificial superintelligence. Narrow intelligence is applied to perform a specific task, such as segmenting a wide audience into target groups or choosing an action that can convince a prospect to buy. (Paradiso 2016, 16; Sterne 2017, 71) In case the behavior specification or context is altered, narrow AI typically demands human reprogramming in order to maintain its level of intelligence (Goertzel 2015). When artificial intelligence is capable of learning across a wide scale and it's not tied to a highly specific tasks, we can talk about artificial general intelligence. (Goertzel 2015; Paradiso 2016, 16) Third form of AI, artificial superintelligence, doesn't currently exist, but it refers to a situation when the capabilities of machines surpass human brains. Today's AI applications in businesses are mainly limited to the narrow AI. (Paradiso 2016, 16)

2.3 Machine learning

While artificial intelligence is an extensive field covering multiple approaches on how to make machines intelligent, machine learning concentrates on the technologies that enables machines to perform tasks by learning from data and making intelligent decisions automatically (Attaran & Deb 2018; Chen & Zhang 2014; Rebala, Ravi & Churiwala 2019, 3). Machine learning can be understood as a subset of artificial intelligence. (Rebala et al. 2019, 3) Russell and Norvig (2010, 694–695) define the three primary kinds of machine learning as unsupervised learning, supervised learning, and reinforcement learning. In unsupervised learning the machine is able to learn from the training data without explicit feedback, whereas in supervised learning the learning happens when the algorithm is provided a large sets of data along with correct answers. In reinforcement learning the machine learns from reinforcements, rewards or punishments. Semi-supervised learning can be placed somewhere between supervised and unsupervised learning, and it refers to a situation when the machine is given a few labeled examples and it must make use of massive amounts of unlabeled training data. (Rebala et al. 2019, 19; Russell & Norvig 2010, 694–695)

According to Attaran and Deb (2018), machine learning has unique features related to speed, accuracy, reliability, consistency and transparency, which can help firms to overcome human limitations effectively. Speed refers to cloud-based machine learning's ability to go through a vast amount of data at a rapid rate, allowing the algorithms to discover insights and patterns much faster. Also, machine learning can create thousands of models in a week, whereas a human is able to produce one or two model in the same period of time. When programmed properly, machines are not as prone making errors as humans are, which gives machines the benefit of accuracy, and they can effectively provide reliable and consistent insights from gigantic structured, semi-structured and unstructured data sets. Machine learning algorithms also enhance transparency, allowing the decisions to be evaluated and developed in the future. (Attaran & Deb 2018)

Since machine learning can be utilized to extract insights from massive data sets, the advent of big data is one key driver of machine learning (Jordan & Mitchell 2015; Qiu, Wu, Ding, Xu & Feng 2016; Zhou, Pan, Wang, Vasilakos 2017). There are also other market forces driving machines learning within organizations, such as advances in computational processing, development of new learning algorithms, affordable data storage, and increased understanding of the value of technology (Attaran & Deb 2018; Jordan & Mitchell 2015).

Machine learning can offer various benefits for organizations, and it can be used for gaining insights and detecting patterns within large data sets, predicting outcomes or behavior, or selecting actions when aiming to achieve a specific goal (Pillow & Sahani 2019; Rebala et al. 2019, 4). Classification, clustering and prediction are examples of common machine learning problems (Rebala et al. 2019, 4). Classification means classifying something into categories, and it's vastly useful with various applications; for example, credit card companies can utilize classification when deciding whether a transaction is good or fraudulent (Rebala et al. 2019, 4; Forsyth 2019, 3). Clustering divides a large set of data into clusters in a way that objects in one particular cluster are somewhat similar, and it differs from classification by the fact that the number of clusters can't be known beforehand. Prediction is based on historical data and it's used to build models to forecast a future value. (Rebala et al. 2019, 4)

According to the survey conducted by MIT Technology Review Insights (2016) in partnership with Google Cloud, most organizations are still struggling to apply machine learning for gaining business benefits. Concurrently, the survey revealed that firms with advanced machine learning strategies are demonstrating genuine ROI with their machine learning initiatives. Several survey respondents reported that machine learning technologies have already led to more extensive data analysis and insights, and companies planning to use machine learning are mainly seeking to gain competitive advantage and better understanding of customers or prospects. (MIT Technology Review Insights 2016) A better understanding of customers can lead to valuable insights regarding customer needs and behavior, which allows firms to offer more value to customers by providing improved products and services. (Bhadani & Kotkar 2015; Edwards 2013; Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh, & Byers 2011)

Machine learning applications on big data are primary done in large corporations, since it's a rather novel development. (Attaran & Deb 2018). Yet, Attaran and Deb (2018) believe that there are numerous smaller organizations that would benefit from machine learning techniques, as machine learning allows firms to harness the unexploited potential or value in their unstructured data.

According to Qiu et al. (2016), the three primary issues of machine learning for big data are 1) learning for large scale of data, 2) learning for incomplete and high speed of data, and 3) learning for deriving valuable information from enormous data sets. Although the growth of big data has driven significant developments in terms of enhanced data storage, analysis, and visualization, majority of the traditional machine learning techniques are still not capable of handling data with the features of large volume, variety, velocity, veracity and low value density. This has risen the interest of advanced machine learning techniques and methods, such as deep learning. (Qiu et al. 2016)

2.4 Deep learning

While machine learning is a branch of AI, deep learning is a subcategory of machine learning that stems from computer science, mathematics and neuroscience (Sejnowski 2018, 3). Deep learning utilizes artificial neural networks that are multi-layer neural nets consisting of input layer, numerous hidden layers and an output layer. That is the base of dynamic neural networks where the information flows in less controlled manner and the machine is able to reprogram itself dynamically, allowing the system to form conclusions more rapidly and create accurate models from raw data (Beam & Kohane 2018; Khan, Jan & Farman 2019; Sterne 2017, 86). According to Khan et al. (2019), deep learning techniques are successfully used in several fields such as image processing, transportation, healthcare and agriculture, and it's increasingly adopted in big data analytics due to its capability to process voluminous data in real time. Figure 4 illustrates the relationship between artificial intelligence, machine learning and deep learning.

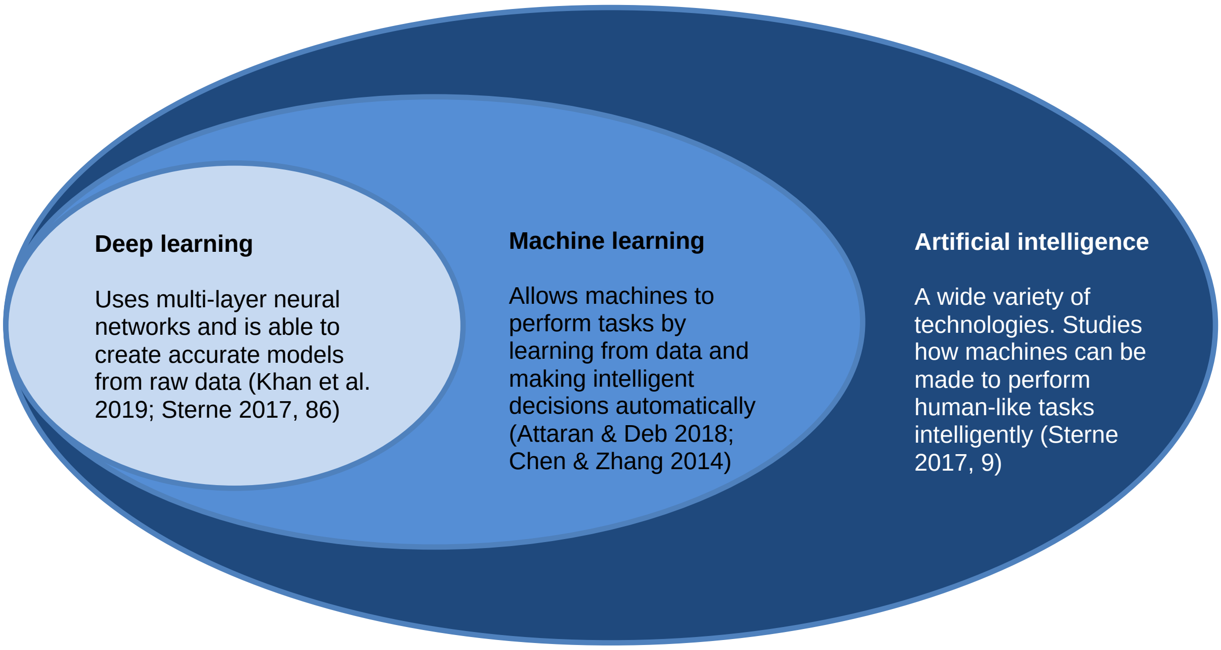

Figure 4. The relationship between artificial intelligence, machine learning and deep learning

3 RESOURCES AND CAPABILITIES

This section discusses prior academic studies in the fields of resource-based theory and adaptive capabilities approach. A dynamic capabilities theory is also introduced briefly, as adaptive capabilities approach stems from dynamic capabilities.

3.1 Resource-based theory

Resource-based theory is one of the most dominant academic perspectives for understanding and describing organizational relationships, and it is used to explore firm's resources that can potentially lead to sustainable competitive advantage (Barney et al. 2011; Barney 1991). According to Barney (1991), a firm can reach a superior business performance when it's executing a unique value creating strategy and when current or potential rivals can't imitate the profits of that particular approach. For the resource to be heterogeneous and immobile and thus relevant for generating competitive advantages, it must be valuable, uncommon, imperfectly imitable and non-substitutable (Barney 1991).

Firm's resources entail tangible and intangible assets, capabilities, information, knowledge, management skills and processes (Barney 1991; Barney et al. 2011). These resources can be divided into the following groups: physical capital resources, human capital resources, organizational capital resources and financial resources. *Physical resources* involve all the physical technology utilized within the organization, such as computer hardware and software technology, automated warehouses and robots for manufacturing (Barney 1991; Barney & Hesterly 2015, 86–87). *Human resources* contain the training, judgement, experience, intelligence and relationships. It also involves insights of individuals such as data scientists and strategists who are able to manage and obtain insights from data (Barney 1991; Barney & Hesterly 2015, 86–87; Erevelles et al. 2016). *Organizational resources* refer to firm's planning, coordinating and controlling systems, culture and reputation, as well as a structure that allows the company to convert insights into action (Barney 1991; Barney & Hesterly 2015, 86–87; Erevelles et al. 2016). Finally, *financial resources* encompass all the money organizations utilize to implement strategies. (Barney 1991; Barney & Hesterly

2015, 86–87). The focus of this study is on physical, human and organizational resources.

3.2 From resource-based theory to adaptive marketing capabilities

According to Day (2011), resource-based view fails to explain how capabilities are established or modified to changing market conditions and disruptions, such as digitalization. Dynamic capabilities theory was created to address these limitations. Similarly to resource-based theory, dynamic capabilities approach presumes that firms' strategic resources within an industry are heterogeneous. These resources are deeply rooted in organization's processes, which indicates they are hard to duplicate. Thus, heterogeneity can provide a long-lasting competitive advantage. (Day 2011)

Teece (2014) describes dynamic capabilities with three primary characteristics: sensing, seizing and transforming. Sensing refers to identifying environmental changes and developing new technological opportunities, seizing means exploiting the opportunities while capturing value from doing so, and transforming advocates continuous renewal. Dynamic capabilities can be described as the capacity of organizations to design, grow and adjust their resources to respond to the demands of the firm's environment (Day 2011; Helfat & Martin 2015). Day (2011) describes dynamic capabilities as "repeatable and deeply embedded set of skills and knowledge exercised through a process", allowing firms to respond to market changes and outdistance the nearest rivals. However, dynamic capabilities entail an inside-out perception that assumes that the inner abilities of the firm are the foremost keys to success, which limits the firm's readiness to anticipate sudden changes in the environment and be resilient when complexity accelerates (Day 2011). Consequently, Day (2011) argues that organizations must concentrate on augmenting and extending their dynamic capabilities by building adaptive capabilities with outside-in perspective that looks first to the market, enabling the firm to make more rapid adjustments. Thus, this study concentrates on adaptive marketing capabilities, since firms with adaptive capabilities have enhances abilities to identify emerging market opportunities and it's perceived as a suitable approach in big data context that often involves complex and highly competitive circumstances and environments (Day 2011; Guo et al. 2018).

3.3 Adaptive marketing capabilities

To respond to the accelerating complexity and velocity of the markets, firms must adopt adaptive marketing capabilities, which allows them to anticipate trends and react to the constant market changes effectively (Day 2011). Lu, Zhou, Bruton and Li (2010) describe adaptive capabilities as the firm's abilities to manage, integrate and allocate resources to fulfill the requirements of customers or suppliers. The adaptive marketing capabilities approach follows an outside-in strategy, which enables organizations to match the novel business demands fostered by the disruptive innovations and tech-savvy consumers combined with the expansion of digital touchpoints. Outside-in approach looks first to the market and proactively detects changes in customer needs and emerging competitors, providing firms with enhanced business opportunities. (Day 2011) The role of adaptive marketing capabilities is increasingly important in today's dynamic and extremely competitive business environments, in which firms must constantly renew themselves (Hunt & Madhavaram 2019). This is extremely relevant for firms utilizing big data and machine learning, since those fields are constantly evolving.

Day (2011) argues that the three essential adaptive capabilities for firms are vigilant market learning, adaptive market experimentation and open marketing. *Vigilant market learning* refers to firm's capabilities to anticipate changes in their market environment; a firm must adapt a sense-to-sense approach, meaning that decision-making is driven by current and future customer behavior and needs. Vigilant organizations have a strong market orientation, they are capable of asking the right questions and are committed to learn more about interesting signals and patterns that can lead to innovative business solutions. Vigilant market listening requires an open-minded approach and customer-orientation, as well as abilities to detect and exploit weak opportunities in the market. The *adaptive market experimentation* capability entails an experimental mindset, including curiosity and willingness to test novel things while challenging old beliefs. To gain business opportunities, firms must share insights throughout the organization and learn from the experiences of the network partners. With *open marketing*, companies can access new capabilities and talent, richer microlever responses and novel insights, and improve the information flow within and outside the firm. (Day 2011) According to Day (2011), the adaptive capabilities have a greater leverage when an organization has an adaptive business model capable of responding to fast-changing market signals, vigilant leaders, as well as an appropriate organizational structure in relation to the firm’s business environments.

The study by Guo et al. (2018) emphasizes the importance of adaptive marketing capabilities in turbulent circumstances. The study supports Day’s (2011) arguments, and suggests that organizations should include their clients into the product development processes to anticipate changing customer needs, conduct experiments in the market to avoid new product failures and to identify opportunities, and to develop an open innovation methods by integrating firm’s internal capabilities with external stakeholders, which involves enhancing the relationships with, for example, customers and suppliers. (Guo et al. 2018) However, the adaptive marketing capabilities hasn’t been extensively studied in big data or machine learning contexts, which poses a significant research gap. This study attempts to close that gap and increase the understanding of adaptive marketing capabilities’ role in big data projects.

3.4 Big data analytics resources and capabilities

This section reviews the acknowledged fundamental resources and capabilities that have been associated with big data analytics in prior research. The resources are discussed from the resource-based theory perspective, and the capabilities from adaptive marketing capabilities perspective.

3.4.1 Big data analytics resources

According to Erevelles et al. (2016), the process of big data exploitation is moderated by physical, human, and organizational capital resources. This particular process involves gathering and managing records of consumer activities, analyzing and extracting insights from data, and utilizing those insights to gain business opportunities (Erevelles et al. 2016). The big data process is visualized in Figure 5.

Figure 5. Big data process (adapted from Erevelles et al. 2016)

To be able to collect and analyze data and harness it for business purposes, firms should obtain certain resources and capabilities. Regarding physical resources, it's essential for the SMEs to have an appropriate technological infrastructure that enables them to process data and form networks that support scale and efficiency (Mikalef, Fjørtoft & Torvatn 2019). According to Zhou et al. (2017), big data introduces critical challenges to data analysis methods, forcing organizations to deal with data dimensionality, model scalability, adaptability, usability and distributed computing. Firms utilizing big data must handle massive data sets and have a software or platform that is capable of managing the volume, velocity and variety of data, and is powerful enough to store and analyze large amounts of real-time data from various different sources (Chui, Manyika & Miremadi 2018; Erevelles et al. 2016). Applying data analysis methods, such as machine learning, to enormous and complex data sets consumes a lot of logical and physical resources, including data file space, central processing unit and memory, and it can be computationally expensive (Assefi, Behravesh, Guangchi & Tahti 2017). Furthermore, the organization must have resources to manage the data quality effectively, since valuable business insights are based on accurate information. (Lim, Kim, Kim, Kim, Maglio 2018; Mikalef et al. 2019a). Thus, appropriate physical resources are essential in big data exploitation.

In addition to physical resources, the appropriate human and organizational resources are crucial for seizing business opportunities with big data. Training of employees and analytics professionals, as well as adopting novel organizational culture and structure are critical factors for big data exploitation (Barton & Court 2012; Gupta & George 2016; Shah, Horne & Capellá 2012; Wedel & Kannan 2016). Furthermore, organizations must be equipped with the know-how of novel technologies to extract intelligent insights from big data. This know-how can include skills and competencies in machine learning, data extraction, cleaning and analysis, as well as programming (Gupta & George 2016).

Harnessing big data for business purposes demands data-driven organizational culture, which allows organizational members to practice decision-making that relies on the insights obtained from data. (Erevelles et al. 2016; Gupta & George 2016; Wedel & Kannan 2016). According to Bhadani and Kotkar (2015), the implementation of big data requires a development of organizational culture that fosters transparent communication system and innovation, and motivates employees to embrace new technologies. Furthermore, the culture and capabilities need to be aligned across the whole organization for the firms to be able to obtain the full potential of big data (Ferraris et al. 2019; Gupta & George 2016).

Bughin and Hazan (2017) believe that new leadership and management skills are needed to successfully align data-driven organizational culture across the firm. According to McAfee and Brynjolfsson (2012), management skills are also required in the extents of leadership, talent management, technology and decision-making. Managers must also be able to utilize the data and have a clear idea of how to exploit the insights derived from it. Furthermore, managers should be able to comprehend the current and future needs of customers, organizational departments, and other stakeholders (Gupta & George 2016).

3.4.2 Big data analytics capabilities

According to the existing research, firms can build big data analytics capabilities by merging and deploying their physical, organizational and human resources through processes, roles and structures throughout the firm (Gupta & George 2016; Mikalef et al. 2020). The studies suggest that to create big data analytics capabilities, the firm needs more than one or two kinds of resources, as big data analytics capability is an unique combination of physical, human and organizational resources. For instance, an organization that has a powerful platform or software that is capable of storing and analyzing voluminous data can’t obtain the full benefit of big data in case it lacks managerial and technical skills. Concurrently, the presence of data and technology along with human skills will not be sufficient if the firm doesn't have a data-driven culture in which decisions are based on data instead of opinions or intuitions. (Gupta and George 2016) Furthermore, according to prior studies, having strong big data analytics capabilities can enhance firm's adaptive or dynamic capabilities, which in turn leads to improved competitive performance (Erevelles et al. 2016; Liao, Kickul & Ma 2009; Mikalef et al. 2020; Wei & Lau 2010).

This thesis approaches the topic from different perspective, suggesting that SMEs with limited resources can compensate the shortage of resources with adaptive marketing capabilities. Thus, firms can develop big data capabilities although they would lack some fundamental internal resources, as long as they are able to obtain adaptive marketing capabilities that include vigilant market learning, open innovation, and a culture of experimentation. These capabilities can reinforce the firm's existing physical, human and organizational resources, which leads to strong big data analytics capabilities. This process of building big data analytics capabilities is illustrated in Figure 6.

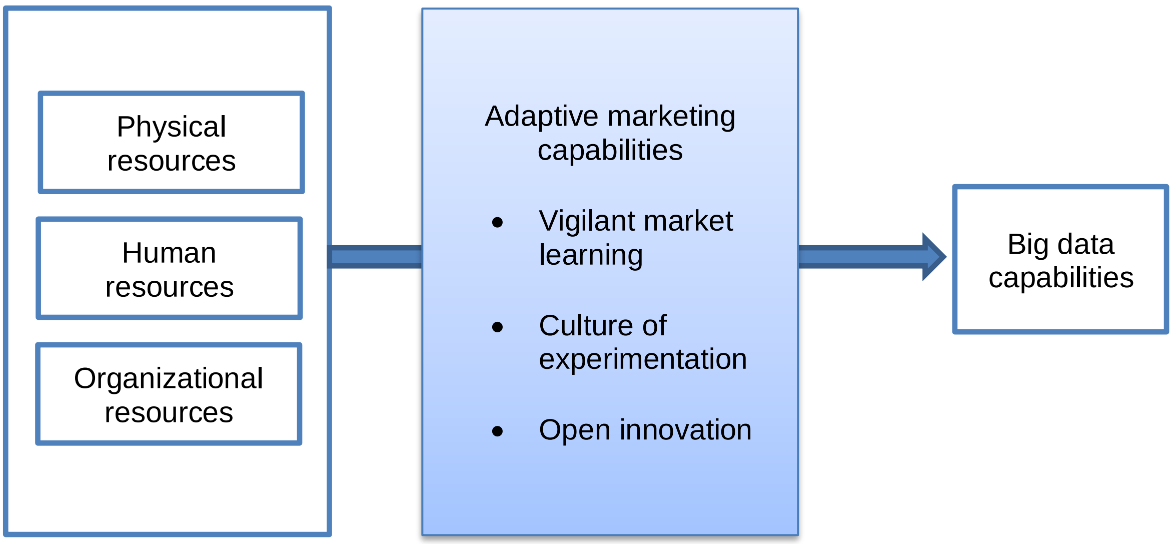

Figure 6. The process of building big data capabilities

4 RESEARCH DESIGN AND METHODS

This study exploits a case study research strategy. Case study is often recommended when the purpose is to attain a solid understanding of the context of the research and the processes related to it (Saunders et al. 2016, 146). Case study is an in-dept inquiry into a phenomenon with real-life examples, which can lead to rich empirical descriptions as well as the creation of the theory. “Case” may refer to, for instance, a person, a group, a firm, or an event (Saunders et al. 2016, 184–185). Case study research includes investigating single or multiple units of study, using for example interviews or surveys as data collection methods (Farquhar 2012, 6).

Case studies can utilize more than one different sources of primary and secondary data, such as internal documentation, industry reports and interview data. Using several data sources or research methods is recommended, as investigating the phenomenon from different perspectives strengthens findings. The limitation of studying a single case or a small number of cases is that the research can’t necessarily be extended to other situations. However, case studies can contribute to knowledge in business by providing a deep understanding of the phenomenon, which offsets this limitation. (Farquhar 2012, 7)

Case study was a logical choice for this research, as the relationship between adaptive marketing capabilities and big data is yet unknown. Furthermore, a case study research method was selected due to the acknowledged demand for further case studies in the field of adaptive marketing capabilities (Guo et al. 2018) as well as in big data environment (Sivarajah et al. 2017). In this thesis, the case study was built by using two case companies from two different industries. The idea was to compare a born-digital company to a more traditional firm, and examine and identify their key resources and capabilities for big data adoption, and additionally gain an understanding of their attitudes towards machine learning. The case companies were chosen according to the criteria that both organizations had to be small or medium-sized businesses and operate in the B2B sector in Finland.

4.1 Data collection methods

The data was mainly collected by utilizing one-to-one semi-structured interviews with experts. Semi-structured interviews often include predetermined questions, but the use of them may vary between the interviews. Semi-structured interviews were chosen as the primary data collection method to ensure all the key themes were covered, yet to have the possibility to modify and add additional questions to reach the research objectives in particular interviews and in different organizational contexts. (Saunders et al. 2016, 391) Secondary data in the form of public documents was exploited as an additional data source, to strengthen the research findings derived from the primary data.

To gain relevant insights of the SMEs resources and capabilities in regards to big data adoption, the requirement was to involve interviewees with a solid understanding of the company's big data processes. The interview data consists of an interview with Leadfeeder's Chief Technology Officer and Glaston's Digitalization manager. Hence, the sample size was small but carefully selected. The semi-structured interviews involved the following predetermined themes: background information, big data's role in organization, resources and capabilities, organizational culture, opportunities and challenges, and machine learning in big data projects. The interview questions are presented in Appendix 1. Table 1 includes the interview details, including the firm, interviewee's position, type of firm, interview length and interview method.

Table 1. Interview details

Firm	Position	Type of firm	Length (min)	Interview method
Glaston	Digitalization manager	Born-traditional	113	Face-to-face interview
Leadfeeder	Chief Technology Officer	Born-digital	43	Teams interview

The primary idea was to conduct both interviews in person, but since the Covid-19 outbreak prevented physical contacts, only the first interview was conducted face-to-face and the second one by Teams application. Both interviews were recorded to ensure reliability.

4.2 Case company descriptions

This thesis focuses on SMEs operating in the B2B sector in Finland. Since smaller organizations often fail in their big data initiatives due to lack of resources and capabilities, the idea was to gain a deeper knowledge of how small and medium-sized organizations can overcome the acknowledged barriers of big data adoption by conducting in-depth interviews at carefully chosen case companies. Thus, the interviews were conducted with data-driven SMEs, in order to gain a good understanding of how these firms had managed to harness big data for business purposes, and identify the key resources and capabilities that had enabled the successful execution of their big data initiatives.

The aim was to select two different case companies to attain a broad understanding of the nature of the resources and capabilities across industries. More specifically, the data was collected from one born-digital firm and one more traditional enterprise; this approach was chosen to understand how the big data -related resources and capabilities vary between digital natives and companies that were born-traditional. The chosen case companies are Leadfeeder and Glaston.

Leadfeeder is a born-digital startup found in 2012, and they have approximately 186 employees worldwide. The company is based in Finland, but they also have offices in the United States. The company operates in the web analytics technology field and offers an online lead generation tool for organizations. With Leadfeeder’s website visitor tracking software, companies can track their website visitors and convert promising visitors into sales leads.

Glaston is a traditional company operating in a glass processing industry. Glaston was founded in 1870, but the glass processing business started only a century later in 1970. The firm has approximately 800 employees and headquarters in Helsinki. Glaston grew significantly in spring 2019 as a result of its acquisition of Bystronic Glass, and today, Glaston has factories in Europe, Asia and the United States. The firm utilizes big data along with cloud services and IoT to help its customers to use Glaston's machinery as efficiently as possible and monitor production in real time.

4.3 Data analysis methods

This study follows a content analysis method, which is a typical choice for qualitative case studies. Content analysis is a technique that categorizes qualitative data so that it can be analyzed quantitively. (Saunders et al. 2016, 608) Empirical analysis was guided by the existing theory, and the idea was to reach the research objectives by comparing empirical findings to the literature review of the study. The theoretical framework presents the key themes of this paper, and these themes were used for creating a foundation for the empirical analysis and for forming the interview questions, as well as coding the data. (Hsieh & Shannon 2005) The key categories were:

- Big data and physical, human and organizational resources
- Big data and adaptive marketing capabilities
- Big data and machine learning

All the interviews were transcribed into text files, and the interview transcriptions were read through carefully. After coding each theme separately according to the key categories, several additional coding rounds were executed in order to discover possible subthemes. Once having a good understanding of the main themes and subthemes, a short overview was written regarding each theme. The key categories identified during the coding were aligned with the theoretical framework. The adaptive marketing capabilities identified from the interviews were vigilant market learning, a culture of experimentation, and open innovation capabilities, and as for the resources, each type of resource presented in the resource-based theory emerged from the discussions, too. Furthermore, the perceptions of machine learning were discussed.

4.4 Reliability and validity

While the concepts reliability and validity are typically associated with quantitative research, there are ongoing debates about whether reliability and validity as criteria are appropriate in qualitative research. Quantitative studies apply statistical methods for defining reliability and validity of the research findings, whereas qualitative researchers aim to ensure the trustworthiness of the findings with methodological strategies. When studying a phenomenon, there are multiple ways of establishing truth, and the observations made during the empirical research are always, to some extent, inimitable. Thus, instead of reliability and validity, this thesis focuses on ‘trustworthiness’ as criteria, as it has been argued to be a more suitable descriptor in qualitative studies. (Golafshani 2003; Noble & Smith 2015)

The empirical study of this thesis focuses on comparing the big data -related resources and capabilities of born-digital companies and traditional enterprises. The purpose is to have a deep understanding of each firm’s big data processes and concentrate on the key resources and capabilities that allow the exploitation of big data in organizations. Also, the empirical part aims to understand the attitudes small and medium-sized businesses have towards machine learning. The study intents to find similarities between the interviews, but as the case companies operating models differ significantly from one another, it’s expected that the key resources and capabilities enabling big data initiatives may vary between the selected firms. Thus, this thesis reflects the findings on the existing theory, primarily on the resource-based theory and the adaptive marketing capabilities theory. The research can’t necessarily be applied to other situations as the sample size is limited to only two cases, but the findings can provide valuable insights of the novel phenomenon and set a foundation for the further studies regarding adaptive marketing capabilities in big data exploitation (Farquhar 2012, 7).

Both interviews were conducted either face-to-face or by phone, which allowed both the researcher and interviewees to ask any additional questions or clarifications to avoid misinterpretations. The selected interviewees have a good understanding of that particular case company's big data journey, which increases the trustworthiness of the findings. Additionally, all interviews were recorded, and the audio files were transcribed into text prior to the data analysis in order to ensure reliability.

5 FINDINGS

This chapter presents the findings of the empirical research. The chapter is divided into subchapters according to the coding categories and the main themes presented in the theoretical framework, to ensure all the key aspects of this thesis are covered accordingly and research questions answered appropriately. However, the section begins with an overview of the findings regarding born-digital and born-traditional firms' resources and capabilities in big data adoption.

According to the findings, born-digital and born-traditional firms' fundamental resources and capabilities in big data exploitation slightly differ from one another. To be more specific, although all the resources and capabilities presented in the theoretical framework emerged during the discussions, internal resources are considered somewhat more valuable for born-digital firms than for born-traditional businesses. The identified key resources and capabilities are presented in Figure 7.

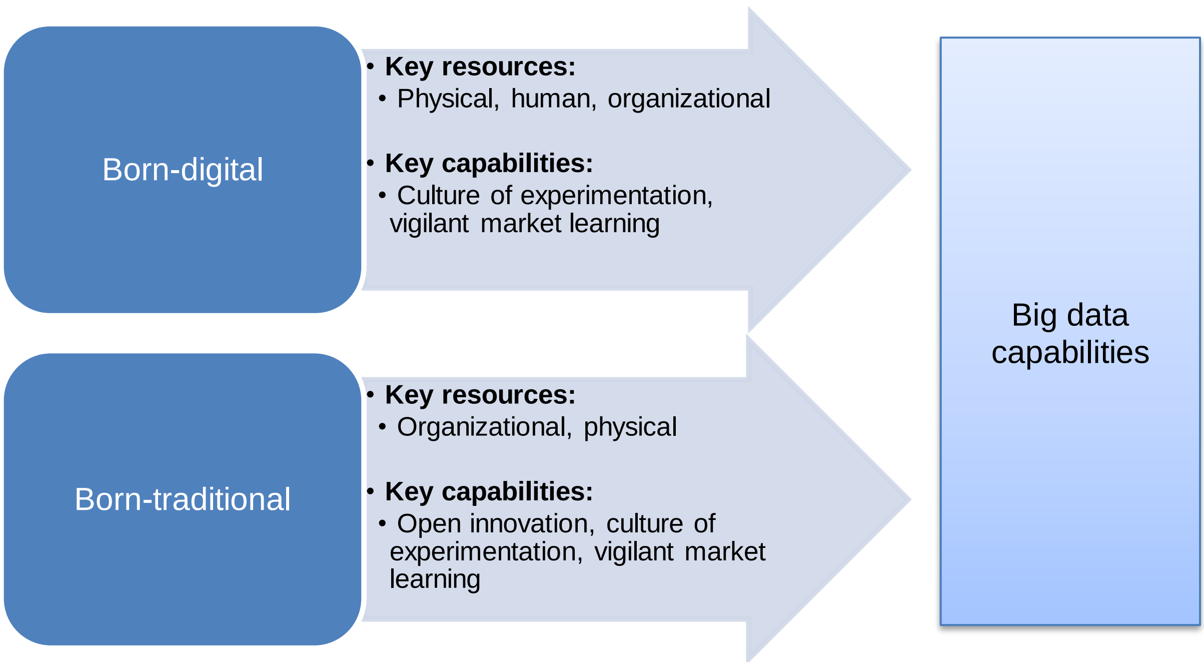

Figure 7. The key resources and capabilities for big data exploitation

The main differences between born-digital and born-traditional firms were regarding human capital resources and open innovation capability. While the born-digital firm emphasizes strong internal resources and skills, the born-traditional company relies heavily on outsourcing and external knowledge regarding the adoption of big data and related technologies. Thus, the born-digital business have robust open innovation capability, which compensates the lack of internal human resources. The following sections will discuss the findings in more detail, beginning with the findings associated with resource-based theory.

5.1 Big data and resource-based theory

This subchapter presents the resources that emerged during the interviews, following the resource-based theory framework and including human, physical and organizational resources. The overview of the main findings regarding the key resources are presented in Figure 8. The identified resources are discussed in more detail below.

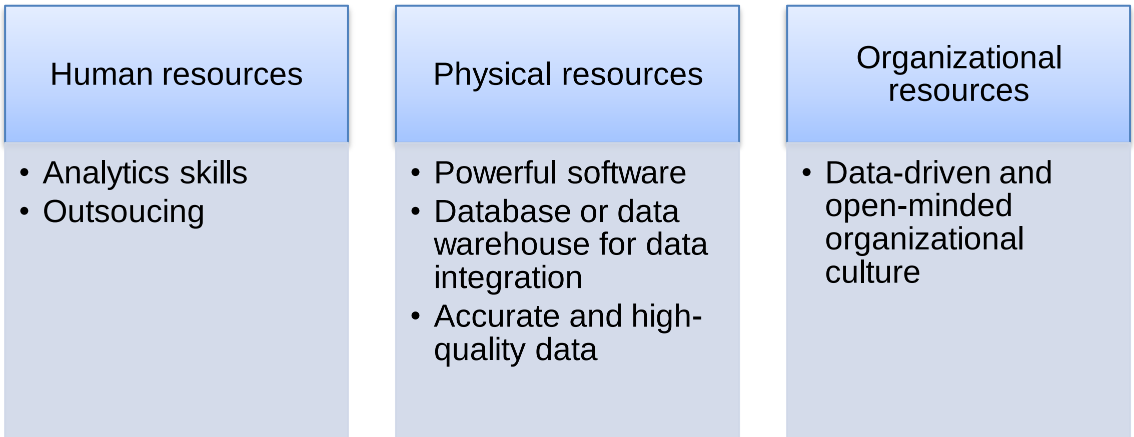

Figure 8. The key human, physical and organizational resources

5.1.1 Human resources

According to the findings of the empirical research, both the born-digital firm and the born-traditional organization emphasize the need of know-how of novel technologies and software, and skilled analytics professionals who have competencies in, for instance, data extraction, data cleaning and data analysis, and are able to extract valuable insights from big data.

> *"In order to use the data intelligently, it's essential to have appropriate resources. The exploitation of our internal data expanded significantly after hiring an analytics professional to our team."* (CTO, Leadfeeder)

For the born-digital Leadfeeder, acquiring new skills and building a data warehouse have been the most crucial enablers on the company's big data journey. Although Leadfeeder has always had its roots in web analytics, the firm started truly exploiting big data effectively after employing experienced analysts and designing a data warehouse, which allowed to pull together all the data from different sources within the organization for analysis and reporting.

Correspondingly, skilled analytics and software professionals are required in more traditional companies when harnessing big data for business benefits. However, since SMEs often have limited resources and internal skills, the crucial know-how can also be acquired through partnerships, as Glaston's digitalization manager specifies:

> *"Of course you need to have software professionals in-house, or alternatively you can acquire partners who are willing to co-operate. The most important thing is that you have the courage to start doing something."*

Glaston's example shows that SMEs with limited in-house resources can also exploit big data successfully by cooperation. In fact, networking and teaming up with others is crucial for SMEs, since smaller companies are often not capable of managing large amounts of data on their own. Networking seems to be especially vital for born-traditional firms, where analytics skills are not profoundly integrated into the core of the business.

Glaston's digitalization manager believes that one of the firm's core strengths is its skilled personnel with extensive experience in glass processing field, and the ability to combine those existing skills with advanced technologies such as big data and machine learning. This combination allows Glaston to create innovative automation functionalities and software updates that differentiate the firm from its primary competitors.

The born-digital Leadfeeder's core competencies are based on digital technologies, and rather than relying on outsourcing, firm's in-house analysts have an active role in the big data exploitation. To convert masses of data into business benefits, the analysts don't solely analyze the existing data, but also consistently present novel ideas of how to effectively utilize the data in different areas of the organization, such as in sales. Since in-house business analysts have a good understanding of that particular firm's business domains and they consistently work with the same data, they can easily detect new opportunities and extract valuable insights from that data.

5.1.2 Physical resources

The case companies identified a few critical physical resources regarding their big data initiatives. First, in order to extract valuable insights from big data, firms must obtain an appropriate platform or software to manage and analyze data with the characteristics of high volume, velocity and variety. Both of the case firms are dealing with machine learning in their big data initiatives, which implies that the importance of having a powerful software further increases, since applying machine learning to massive data sets typically consumes a lot of physical and logical resources.

The born-digital organization has a data warehouse that pulls all the data together from various different sources. Being able to gather all the analyzable data in one place was one of the greatest challenges for the firm in terms of exploiting the data effectively, since building the data warehouse required multiple resources, such as novel skills. Today, the data warehouse is recognized as one of the most crucial components in the firm's big data utilization, since it provides high-level reporting and analysis that allow the company to make well-informed business decisions.

The born-traditional firm Glaston aims to differentiate from its rivals as the innovative technology leader in the glass processing industry, and they have also been able to combine their sales, logistics and customer relationship data into an integrated cloud database. In addition, by exploiting Internet-of-things (IoT), Glaston has managed to connect their machinery to a cloud service, which enables them to collect almost real-time data on how their machinery are being used by customers. This, in turn, allows the firm to provide new products or services for their customers, while improving customer experience by helping their clients to maximize the production efficiency with the company's machinery. Thus, integrating the data into a unified database or data warehouse is considered as one of the key physical resources among SMEs.

When it comes to the data itself, both case companies highlight the importance of data quality. As Glaston's digitalization manager states, "the bottom line is you collect the right data and it's of high quality". This is a critical component on one's big data journey, since valuable insights can only be derived from accurate data. Data quality problems generally increase as the data volume and variety grow, which implies that SMEs exploiting big data must be prepared to monitor and manage the data quality effectively, ensuring only truthful information enters the analytics systems.

5.1.3 Organizational resources

Data-driven and open-minded organizational culture is emphasized as one of the crucial enablers of big data exploitation. Data-driven organizational culture is vital for SMEs exploiting big data, since data-driven culture encourages organizational members to make decisions based on the insights obtained from data. Furthermore, the culture has to be aligned across the whole firm. The case companies aim to ensure that all the employees are able to practice data-driven thinking and have the ability to utilize the existing resources, such as the data warehouse, for decision-making.

When a company first starts exploiting big data, changes in the organizational culture are often required. Changing an organizational culture can be very challenging, since company's culture encompasses a complex set of values, attitudes and practices. The born-digital Leadfeeder's organizational culture has always been very data-driven, since all the three founders have a background in analytics – thus, thinking with data has been at the core of the company's strategy since day one. Nevertheless, as the firm developed over the years and new functions emerged along with a growing number of employees, company's processes and practices had to be reviewed in order to ensure the data-driven approach was embraced throughout the company. Today, it's essential to guarantee that every member of the organization has visibility and access to relevant data, which encourages organizational members to practice data-driven thinking.

> *"For example, when hiring a new team leader in our marketing function, we wanted to ensure that the person understands data and knows how to exploit it, although no practical data skills are required since we already have those kinds of resources and skills in the firm. But data-driven thinking is essential."* (CTO, Leadfeeder)

The exploitation of big data has had a consuderable impact on Glaston's organizational culture. Currently, the firm's revenue essentially comes from selling machinery and maintenance services, yet the adoption of advanced technologies has fostered new ideas regarding a novel revenue model that focuses on big data -based software, indicating that the firm would mainly sell software instead of machinery. Creating a new business model is a great challenge for Glaston; the firm's culture involves deeply embedded values and attitudes, as the company has concentrated on selling machinery for decades.

Transforming a machinery firm into a software company demands a substantial organizational change, which can be an extensive and rigid process. According to Glaston's digitalization manager, developing new technological solutions is relatively straightforward with suitable capabilities and partners, yet changing the company practices and especially the attitudes of the employees is one of the biggest challenges for the firm regarding their big data initiatives.

> *"When one aims to change a firm's identity from a hardware company to a software company, it is difficult for many. And it's especially difficult for a sales person who has been selling machinery for 30 years."* (Digitalization manager, Glaston)

The company believes in "seeing is believing" mentality, indicating that in the organizational members will eventually adapt to the new culture. However, although Glaston has already managed to harness big data for business opportunities, the organizational change is still an ongoing process in the firm.

5.2 Big data and adaptive marketing capabilities

This subchapter presents the findings of the empirical study from the perspective of adaptive marketing capabilities theory. Adaptive marketing capabilities are further divided into three main capabilities: vigilant market learning, culture of experimentation, and open innovation.

5.2.1 Vigilant market learning

In order to harness big data for business benefits, SMEs must have the ability to anticipate market trends and changing customer needs, and actively generate new ideas of how to utilize the existing data. At both case companies, emerging trends are closely monitored throughout the company, and analysts and engineers are constantly proposing fresh ideas of how to gain valuable business insights from data. For example, at Leadfeeder, analysts constantly communicate with the sales and marketing departments and introduce new opportunities.

> *"Our analysts have an active role in data utilization. They constantly tell for example to the sales leader how the data could be used intelligently, and whenever new possibilities occur from the data. The communication between the analysts and the sales function is extremely important, since those possibilities are not always evident."* (CTO, Leadfeeder)

Also at Glaston, designers and engineers are committed to generating fresh ideas and opportunities, and the teams vigorously identify technological developments. Glaston is a pioneer in the glass processing industry, but in order to stay ahead of the rivals, the firm realizes that it's crucial to constantly follow market trends and anticipate new opportunities. The firm actively monitors competitors' and other companies' activities in the field to gain valuable insights and ideas that can potentially generate new business benefits.

> *“We are constantly learning and listening what others do in the market, and we try to identify novel trends. There are always fresh ideas and start-ups that are trying something new.”* (Digitalization manager, Glaston)

Thus, Glaston actively listens to their partners and other stakeholders to identify weak market signals. The firm also follows large technology pioneers, such as Microsoft and Google, and reaps the benefits of the solutions generated by these multinational organizations. This implies that smaller firms with limited resources are not forced to create all the solutions by themselves in big data -related projects, but they can effectively learn from other players with vigilant market learning capability. With this approach, firms don’t necessarily need to obtain substantial internal resources.

5.2.2 Culture of experimentation

Culture of experimentation is another critical adaptive marketing capability for SMEs with limited resources when harnessing big data for business purposes. Careful testing is essential in big data applications to ensure the data is relevant and of high quality. With a company culture that fosters experimentation, firms can turn new ideas and solutions into action across the company.

Testing is a vital aspect for Leadfeeder’s website visitor tracking software and the website development, and the company always runs tests prior to making any changes on the website to ensure the decisions are made based on data instead of opinions or beliefs. The born-digital organization increases customer value by proving their clients solutions that can detect the most valuable leads on one’s website. Currently Leadfeeder is developing a new machine learning model that offers more information regarding the website leads, which further improves the firm’s value offering. Developing such solutions and finding new innovative ways to create customer value requires internal testing and most importantly, a will to experiment, which is possible to achieve by building a culture of experimentation.

A more traditional firm Glaston also emphasizes the importance of building a company culture that nurtures experimentation. Glaston’s testing process involves several stages, starting with small internal tests with simulators and eventually introducing the ideas to a “friendly user” customer. Finally, the solution is presented to a final customer after proof-of-concept experimentation is carried out to demonstrate the functionality. Careful testing process can effectively prevent firms from failing, although failures are inevitable – however, by adopting a culture of experimentation, SMEs can see failures as opportunities for learning rather than mistakes.

> *“You just have to be brave enough to start testing ideas, first with small tests. You shouldn’t be worried even if you don’t really know anything about the topic – if you have skilled partners, they can advise you. Also universities are often a good source of information and capabilities.”* (Digitalization manager, Glaston)

According to the findings, an experimental organizational culture is one of the key success factors for big data exploitation. Typically, born-digital firms’ culture can be very innovation-driven and management open to experimentation, while traditional businesses that are not born in the digital era may struggle in building a culture that nurtures testing of novel technological solutions. Thus, to gain business opportunities with big data, it’s especially important for born-traditional firms to learn from network partners and other stakeholders, and follow the examples of pioneers in the field.

5.2.3 Open innovation

Open innovation capability allows organizations to access new talent, capabilities and insights. According to the findings of the empirical research, open innovation is especially important for traditional SMEs with limited in-house resources for big data exploitation. While the born-digital Leadfeeder relies heavily on their in-house resources, Glaston’s strategy has always involved collaboration with partners, suppliers, universities, and other stakeholders.

Glaston’s digitalization manager emphasizes that it’s possible for a small or medium enterprise with inadequate resources to utilize advanced technologies, as long as the firm finds suitable partners:

> *“With collaboration, it’s been easy for a firm like us to proceed. There are a lot of organizations in the field that can advise you, that’s very clear. There are also several subcontractors and service and technology providers that are willing to help. So it’s possible to start exploiting even if the firm’s own resources are somewhat limited.”*

The firm believes in open innovation and has actively participated in innovation events and conferences. Once in every two years Glaston organizes Glass Performance Days (GPD) conference in Tampere, focusing on the development of the global glass industry. The event allows all the industry experts to share learning and business ideas, and to solve problems collectively. Rather than solely relying on their own internal knowledge and resources, a fundamental part of Glaston’s identity is to actively utilize several external sources to tackle big data -related challenges and to drive innovation and glass processing solutions.

> *“If you do everything alone, you might lose your direction – it’s like staying in your own silo and not really knowing what everyone else is doing. For that reason, I believe that these kinds of collaborations with stakeholders are very good, and it gives you the confidence that you are heading to the right direction.”* (Digitalization manager, Glaston)

Thus, cooperation with appropriate stakeholders is often a major success factor for SMEs in big data projects, especially in traditional organizations. Firms can seek talents from universities or companies that are not direct competitors. The case company Glaston has worked intensively with universities over the years, which has provided them new technological skills and valuable competencies in the domains of big data, machine learning and neural networks. Glaston arranged the world’s first glass industry hackathon, *Hack the Glass – hackathon*, in 2017 in collaboration with Business Tampere to have application developers and technical university students to try to solve a predetermined technological challenge. The purpose of the event was to discover new glass processing solutions with the aid of over 70 skilled participants and 24 teams, and the winning team’s contribution resulted in a novel business idea. Furthermore, Glaston hired a thesis worker from the hackathon to start working on the firm’s big data and machine learning solutions.

“Thesis projects have been very fruitful for us. We can give challenging tasks to students and young talents, while they get familiar with our problem areas and understand the background of the issues. And often we have noticed that a certain task is not as challenging for the students as we thought it would be, since the students are used to solving similar problems in their studies on a daily basis. So hiring thesis workers is working very well for us, and it provides us critical capabilities.” (Digitalization manager, Glaston)

5.3 Firms’ attitudes towards machine learning

This subchapter focuses on discussing the case firms’ perceptions and attitudes towards machine learning. As argued in the theoretical section of this thesis, machine learning can offer several benefits for SMEs, such as gaining better insights and detecting patterns from big data, predicting outcomes or behaviors, or enhancing decision-making. Currently, machine learning is mainly used in large organizations, but the usage is expected to increase as technologies mature and a growing number of companies can gain access to advanced analytics solutions. Thus, the goal of this part of the empirical study was to understand SMEs’ attitudes and readiness for machine learning adoption, and increase the knowledge of the main drivers for machine learning exploitation.

In this thesis, both born-digital and traditional case companies recognize the importance of machine learning in big data projects. The attitudes towards machine learning are aligned with the theoretical framework of this study, meaning that machine learning is considered as an important factor that can result in improved business performance in big data applications by enhancing the value of big data. The role of machine learning is illustrated in Figure 9.

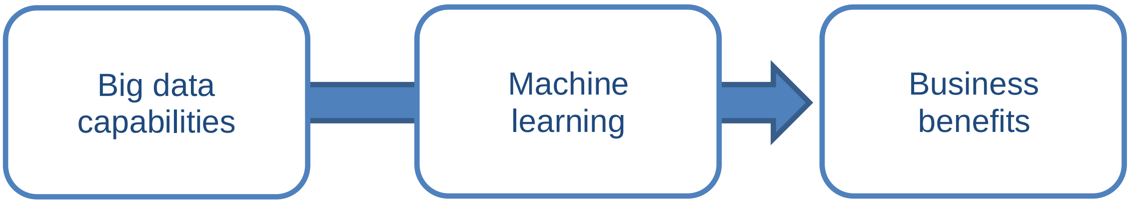

Figure 9. The role of machine learning in big data applications

According to the findings, machine learning is extremely useful in automating tasks and processes; while certain tasks consume a significant amount of time and resources when done by humans, machine learning can offer valuable solutions to increase efficiency. For example, machine learning is an ideal solution for dealing with data quality issues. Evaluating the quality of data can be tremendously resource-intensive and tedious when done by humans, but with machine learning, organizations are able to assess the quality of data effectively. This is considered as one of the main benefits of machine learning in big data projects.

> *"We have a large database that includes a lot of irrelevant or incorrect data. Evaluating and assessing all the data is a very manual task though, which is why we first started implementing machine learning solutions – to replace human work."* (CTO, Leadfeeder)

Machine learning along with big data is a powerful method for automating certain business processes and manual activities. By automation, firms can improve productivity, quality and robustness, and replace dull and time-consuming tasks that are normally done by humans. Nevertheless, although certain tasks can be performed more accurately and efficiently with the use of machine learning and neural networks, the case companies realize that the fear of intelligent machines replacing all the human work is not relevant. Instead, machines and humans can work in collaboration and complement each other, which results in increased productivity. Furthermore, if applied successfully, automation enabled by machine learning allows organizations to develop a competitive advantage in highly competitive industries.

> *"We have been manufacturing these tempering lines for 50 years, and there are many people who have been working for us for decades. Therefore, we have a*

> *very strong expertise and we excel at tempering glass. When you add big data along with machine leaning and neural network models to that setting, we believe that it is the kind of combination that can provide us advanced automation solutions and software upgrades to our machinery, which in turn helps us to stay ahead of the competition."* (Digitalization manager, Glaston)

Both born-digital and traditional companies' main driver for machine learning adoption is clear: to increase customer value, which leads to business benefits. Nevertheless, the case companies underline that in order for the machine learning solutions to perform these kinds of tasks flawlessly, the models require a substantial amount of high-quality training data that is used to train the algorithm. This indicates that prior to beginning implement machine learning solutions, firms must ensure the data sets are large enough, and organizations may first have to gather a sufficient amount of training data with human labor. In addition, developing machine learning models requires data science expertise, implying the firm may have to obtain new knowledge by recruits or outsourcing. Thus, there are certain requirements that SMEs must be able to meet in order to harness machine learning opportunities.

Nevertheless, although machine learning adoption requires tangible and intangible resources, implementing machine learning solutions can be relatively simple with adaptive marketing capabilities. One example of a straightforward AI-based solution is *Glaston Siru*, a mobile application utilized in the glass tempering industry to conduct glass fragmentation tests. Glaston developed the application in collaboration with a university, which means the developing process was inexpensive and easy for the firm, yet providing substantial business benefits and perceptions for future machine learning and neural network projects. Hence, firms can achieve valuable opportunities with limited resources, as long as they have the ability to generate ideas, experiment and cooperate with suitable partners.

5.4 Current and future business opportunities

Although both case companies have managed to create success stories with big data, machine learning and other advanced technologies, the firms are willing to further improve their big data and machine learning offerings. The born-digital Leadfeeder is constantly improving their analytics capabilities in order to deliver enhanced opportunities for the customer to detect and identify the most valuable leads on the website, while the more traditional Glaston is the frontrunner in their field of bringing latest technological possibilities to complement their machinery.

Based on the empirical research as well as the existing literature, all the finest big data solutions are powered by machine learning or other advanced technologies. For example, firms can develop churn prediction models that can help organizations to take actions to prevent customers from leaving the firm, automate processes, assure quality, or optimize performance with machine learning. Moreover, firms that manage to harness machine learning for big data projects are able to deliver enhanced customer experience and value, which is the main driver for machine learning adoption.

The amount of big data is constantly growing, which indicates that novel business opportunities will arise in the future. As this research shows, in order to stay ahead of the competition and seize the arising opportunities, SMEs with limited resources should focus on obtaining vigilant market learning, culture of experimentation, and open innovation capabilities. With these capabilities, big data and machine learning exploitation can be relatively straightforward even for smaller organizations.

6 DISCUSSION AND CONCLUSIONS

This section discusses the findings and draws conclusions. First, empirical findings are summarized and theoretical contributions presented. After, managerial implications are discussed. Finally, limitations and suggestions for future research are provided.

6.1 Summary

The aim of this thesis is to realize what kinds of resources and capabilities small and medium-sized firms in the B2B sector need to utilize big data for business benefits, and how SMEs with limited resources can exploit big data. In addition, the objective is to study the perceptions and attitudes SMEs have towards machine learning and to increase the understanding of SMEs' readiness for machine learning adoption as well as the main drivers for exploiting it. This summary presents the key findings for each research question.

***RQ1**: What resources and capabilities SMEs need to seize new business opportunities with big data?*

According to the findings of this study, both born-digital and more traditional organizations require physical, human and organizational capital resources to adopt big data successfully, as also presented in the existing literature (Erevelles et al. 2016; Gupta & George 2016; Mikalef et al. 2020; Wedel & Kannan 2016). These resources include analytics skills, powerful software, database or data warehouse for data integration, accurate and high-quality data, and data-driven organizational culture. However, since resource-based theory concentrates solely on the resources and doesn't properly explain the role of capabilities (Day 2011), this study attempts to close this knowledge gap by utilizing adaptive marketing capabilities approach. According to the findings, capabilities driving big data exploitation are vigilant market learning, culture of experimentation, and open innovation.

A noteworthy subtheme regarding big data challenges emerged during the interviews, which is closely related to the required resources and capabilities; changing an organizational culture was considered as one of the main barriers for big data utilization. The born-traditional case company emphasized that adopting a novel organizational culture that fosters data-driven thinking can be extremely difficult, since changing a company culture is a fundamental shift that has a substantial impact on the way the entire organization operates. Thus, it’s often a slow and demanding process, as also stated on the existing literature (Denning 2011). Although the change can be eventually accelerated, for example, by training or recruiting new talents with a data-driven mindset, changing an organizational culture is an ongoing challenge for the born-traditional enterprise.

RQ2: How SMEs with limited resources can exploit big data to gain business benefits?

The findings of the study indicate that SMEs with limited resources can obtain adaptive marketing capabilities in order to complement and reinforce the existing physical, human or organizational resources. The adaptive marketing capabilities include vigilant market learning, culture of experimentation, and open innovation. Vigilant market learning enables businesses to identify weak market signals and arising opportunities, and with a culture of experimentation, firms can turn ideas and insights into action. Open innovation fosters the adoption of novel technologies and allows SMEs to access new talent and capabilities that are critical for successful big data exploitation. The open innovation capability involving cooperation with partners, companies and other stakeholders is especially important for traditional organizations that are not born in the digital age, and whose core business is not in analytics. Meanwhile, born-digital firms may rely more on their own internal physical resources. Therefore, instead of acquiring all the resources in-house, firms can obtain the necessary resources by collaboration and outsourcing.

RQ3: What attitudes firms have towards machine learning?

Both the born-digital and born-traditional case firms realize the potential of machine learning and utilize it actively in their big data projects. The main drivers for machine learning adoption is to enhance customer experience and value, which benefits both parties, the customer and the firm. Machine learning is used in companies for different reasons, such as for automating processes, improving and assuring quality data quality, and optimizing performance. Machine learning and other advanced technologies can bring significant additional value to big data applications, and although machine learning is not yet widely adopted in SMEs, machine learning exploitation can be relatively straightforward with adaptive marketing capabilities. Thus, SMEs should focus on improving their vigilant market learning, culture of experimentation, and open innovation capabilities in order to exploit machine learning -powered big data solutions.

6.2 Theoretical contributions

The findings of this study are well aligned with the previous studies regarding resource-based theory in big data context (Erevelles et al. 2016; Gupta & George 2016; Mikalef et al. 2020; Wedel & Kannan 2016). Most importantly, this study contributes to the adaptive marketing capabilities literature that is scarce. According to Day (2011) and Guo et al. (2018), adaptive marketing capabilities provide businesses enhanced possibilities to explore external resources and capabilities, obtain opportunities through cooperation, and combine network resources. The findings of this study agree with Day (2011), presenting the findings from a novel perspective, involving big data and machine learning context. Furthermore, this thesis responds to the demand of Guo et al. (2018), who stress that there's a pressing need for further studies in the field of adaptive marketing capabilities in order to fully understand the consequences of those. The adaptive marketing capabilities identified in this research were vigilant market learning, a culture of experimentation, and open innovation, which corresponds to Day's (2011) findings.

This thesis reinforces the existing studies regarding resource-based theory, while creating ground for the future studies in the field of adaptive marketing capabilities. Day (2011) argues that resource-based theory is not sufficient to explain how firm's capabilities are created, and thus this research aims to close this knowledge gap by including adaptive marketing capabilities perspective. Adaptive marketing capabilities is a novel research topic that hasn't been thoroughly examined in academia, indicating that this study's contribution to adaptive marketing capabilities literature is of great importance. Furthermore, this study increases the understanding of how to leverage resource-based theory in order to respond to the demands of the modern business world, where firms are facing increasing complexity and competition in the market.

According to existing studies, having strong big data analytics capabilities enhances firm's adaptive or dynamic capabilities, which allows firms to gain a competitive edge (Erevelles et al. 2016; Liao, Kickul & Ma 2009; Mikalef et al. 2020; Wei & Lau 2010). The findings of this thesis, however, reveal that SMEs with limited resources should gain adaptive marketing capabilities in order to exploit big data successfully, leading to improved business performance. Thus, even firms with scarce internal resources can seize business opportunities with big data by adopting adaptive marketing capabilities and reinforcing the existing resources with vigilant market learning, culture of experimentation and open innovation capabilities. This thesis adopts an unique approach regarding a novel phenomenon, which provides a greater understanding of the phenomenon and further enhances the importance of this study in academic literature.

Furthermore, this thesis contributes to big data and machine learning literature, responding to the demand for further case studies in the field (Sivarajah et al. 2017). Existing studies have recognized the benefits of machine learning in big data applications (Davenport 2013; Jordan & Mitchell 2015; Qiu et al. 2016; Zhou et al. 2017), but this study provides novel insights on the management's attitudes regarding machine learning exploitation in SMEs, since machine learning is not yet extensively utilized or studied in the context of smaller B2B enterprises in Finland.

6.3 Managerial implications

The selected case companies are pioneers in the field of big data and machine learning, which implies that the findings of this thesis provide valuable insights for small and medium-sized enterprises that have not yet fully succeeded in their big data or machine learning initiatives. By taking the findings into consideration, managers at SMEs can potentially improve their big data readiness effectively.

Many SMEs in Finland suffer from a shortage of physical, human and organizational capital resources, which prevents them from exploiting big data opportunities. The findings of this thesis imply that organizations with limited resources can harness big data for business benefits, too, by adopting adaptive marketing capabilities. The critical adaptive marketing capabilities include vigilant market learning, culture of experimentation, and open innovation. Since SMEs are often relatively flexible and they can quickly adapt to changes towards efficiency (Iqbal, Kazmi, Manzoor, Soomrani, Butt and Shaikh 2018), SMEs have enhanced abilities to adopt adaptive marketing capabilities compared to multinational companies with rigid organizational structures.

Furthermore, by adopting adaptive marketing capabilities, SMEs can effectively improve their for readiness for exploiting machine learning in big data applications. In fact, implementing machine learning solutions can be relatively straightforward with appropriate partners, vigilant market listening and a courage to experiment.

6.4 Limitations and future research

The research context is limited to SMEs operating in the B2B sector in Finland, which poses certain limitations to the study. As the objective was to find companies that have successfully managed to harness big data and machine learning to gain business benefits, finding suitable organizations was rather difficult, as big data along with machine learning is not yet extensively exploited in small or medium-sized organizations in Finland. Thus, the sample size was small, yet the case companies were carefully selected.

The focus of the research was on managerial level, indicating that only people with management positions were interviewed. Furthermore, the interviews were conducted only with persons who have a coherent understanding of the company’s big data processes. For the future studies, it’s suggested to aim for a larger sample sizes and include more organizational members from each case company in order to attain a wider view along with different perspectives regarding the research topic.

Since the empirical research includes only one born-digital firm and one traditional organizations, the findings of the study may not apply to all companies. Therefore, the future studies should concentrate on conducting more in-depth interviews with companies operating in different industries. Moreover, the study revealed that adaptive marketing capabilities can improve machine learning readiness in addition to big data analytics capabilities, indicating there’s a demand for further studies regarding adaptive marketing capabilities in both big data and machine learning contexts.

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APPENDICES

Appendix 1 – Interview questions

Background questions

- Company, the nature of the company, position in the company, etc.

Big data in the organization

- What kind of role big data has in the organization?
- From what sources big data is collected?
- How is big data exploited?
- What kind of role big data has in company's competitive performance?

Resources and capabilities

- What have been the most critical success factors or enablers for big data exploitation?
- Does big data exploitation involve cooperation with partners or other stakeholders?
- Does big data exploitation involve experimentation?
- How is the company monitoring and identifying emerging market trends?
- Are there some capabilities that should be improved to foster big data exploitation?

Organizational culture

- What kind of impact big data exploitation has had on the company's culture, structures or behaviors?
- How has the organizational culture been transformed to support data-driven thinking and exploitation of big data?
- Is big data applied throughout the organization or in certain projects or departments only?

Challenges and benefits

- What have been the main challenges regarding big data exploitation?
- What have been the primary benefits gained through big data exploitation?
- Have you been able to measure the benefits?

Machine learning with big data

- What systems or methods are utilized in big data exploitation and data analysis?
- How and with what methods will big data be exploited in the future?
- What have been the main benefits derived from machine learning?
- What is the role of machine learning in big data exploitation?