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Implementation and Exploitation of Data and Data Driven Decisions in B2B sales and marketing - A Case Study

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Abstract

Despite the increasing reliance on data in decision making, firms have issues turning their organisations data driven. Even though data driven decision making have an increasing impact on marketing and sales practices in all industries, a greater focus is given to consumer centered firms. This paper investigates the implementation of data analytics and digital transformations in B2B sales and marketing from a managerial approach. Based on interviews from practitioners working in the field of IT, the findings indicate that implementing data analytics and data driven processes require resources that connects IT with the core business. If successful, implementation of data analytics can lead to improved business performance. Specifically for B2B marketing and sales this can result in improved customer relationships, more accurate and valuable leads and increased brand awareness.

Keywords: Big data, Data driven, Data Analytics, Digital transformation, Change management

Introduction

Technology is evolving and growing at a speed which is hard to ignore. Marketing and sales are two areas within business which are very much influenced by this (Thomson, 2019; Chaine, 2019). A big part of this development is the increasing meaning and reliance on data, which is widely discussed in both academia and among business practitioners. Big Data, digital marketing and data driven decision making are all concepts that are becoming increasingly recognized in a wide range of industries. There are, however, some distinctions that influences how companies can exploit the advantages of data in their business. First, the setting which companies are operating in, which can either be Business to Business (B2B), or Business to Consumer (B2C) (Cannon, 2019). Second, the product companies provide to its customers, which can either be a physical product or a service (Vargo, Lusch, Archpru Akaka, & He, 2010).

These distinctions have to be made due to the belief that B2B and B2C marketing are two separate topics where the type of customer, either businesses or consumers, influence the characteristics of the external communication (Dant & Brown, 2008; Rėklaitis & Pilelienė, 2019). However, it is not solely the type of customers that differentiate B2B marketing from B2C. Lilien (2016) stresses the complexity, in terms of number of people involved in B2B purchases, with varied incentives. B2B companies also tend to meet more variation in customer demand, the corporate brand will be of greater importance, than product level marketing (Liu, Foscht, Eisingerich & Tsai, 2018). Additionally, Lilien (2016) emphasise heterogeneity among customers that concern the size of the company and varied performance requirements. Moreover, there is, in general, a lower amount of data in the B2B industry compared to the other, which can lead to implications in analysis of data (Schimel, 2020; El Deeb, 2015).

These distinctions are also relevant as product and service marketing differs. Service marketing strives to build a relationship between a company and its customers, which is mutually beneficial (Kumar, Chattaraman, Neghina, Skiera, Aksoy, Buoye & Hensler, 2013). Liu et al. (2018) found that firm profit in the B2B industry are enhanced when the relationship to its customers increase with product extensions. Specifically relevant in this field technology services implies a novel dimension to the field of service development as characteristics of these services differs from traditional services (Sandström, Edvardsson, Kristensson & Magnusson, 2008). These characteristics, referred to as IHIP; intangible, heterogeneity, inseparability and perishability (Blut, Beatty, Evanschitzky & Brock, 2014) are common in service marketing research. They are, however, not applicable for technology services (Sandström et al., 2008) since technology enables the service to be consumed repeated times and in similar ways.

Despite this, both B2B, compared to B2C, and service marketing, compared to product marketing, have not gained the same focus. B2B research started to appear in publications far later than the one for B2C, and the amount of those publications were until the turn of the 21st century, still just a fraction of the consumer centred (Lilien, 2016). Wedel and Kannan (2016) describe the history of data and analytics in marketing, but their emphasis and focus is directed towards data and concepts used in B2C contexts. The little attention B2B research obtains is however not justified considering the large fraction of the GDP it constitutes (Wiserma, 2013; Cortez & Johnston, 2017). Furthermore, the field of data driven service management is yet rather unexplored. This indicates that there is a gap in this field of research (Kumar et al., 2013), which was confirmed in 2019, when there was a call for research in the intersect of B2B and service innovation (Dayan & Ndubisi, 2019). Emphasized by Cortez and Johnston (2017) both data analytics and exploiting technology are areas that call for more research attention due to the challenges B2B marketing practitioners encounter. Hence, this paper will focus on a B2B service company.

Within the field of data analytics "Big Data" is currently focal. Without undermining the importance of large amounts of data, there seems to be a common misunderstanding that size is a prerequisite for data to be meaningful (Bosacci, 2018; SaS, n.d; Aurugia, 2017). Instead, there are other characteristics that are more crucial than volume in categorising data as big; Variety - the different forms and sources of data, Velocity - the speed at which data is collected and managed, Value - the potential of turning data into useful insights and Veracity - quality of data (Sas, n.d; Aurugia, 2017; Ishwarappa & Anuradha, 2015). For example, internal customer and operations data can be used to obtain insight (Fitzpatrick, 2019), without it necessary being "big". Accordingly, big data does not relate to the number of byte, but rather of what the data is telling in terms of insights (Xu, Frankwick & Ramirez, 2016). It cannot be ignored though, that the larger a dataset is, increasing volume of data points, the better the distribution of that population will be presented (Prakash-Maheswari, 2018; Gallo, 2016). However, as the standpoint of this article is managerial, rather than technical, there will be no further distinction of big data analytics and data analytics, meaning that the concepts will be synonymously treated throughout the paper.

As technology have become an obvious part of life and business (Kumar, Ramachandran & Kumar, 2020), becoming digitalized is crucial (Gale & Aarons, 2018). Therefore, companies turn to data and data science to gain competitive advantages (Provost & Fawcett, 2013). To stay competitive, most companies today are aware of digital marketing as a prerequisite (Quinton, & Simkin 2017). The importance of data is thus influencing marketing practices and the emergence of information technologies (IT) have transformed how firms search for and collect data as information (Järvinen & Taiminen, 2016). Likewise, the advancement and adoption of artificial intelligence, or AI technology has reshaped the market and customer experiences (Conick, 2017). AI as a concept is often a victim of misconceptions, much because of an image created by popular culture (Kaplan & Haenlein, 2020) and even though AI is at the centre of attention, it is not equal to IT or data analytics (Reavie, 2018).

What must be considered, is that no matter the value data and technology contribute with, there are challenges too. As data and the number of sources of data are increasing, the need of verifying the accuracy of that data is too (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Consequently, poor data inputs lead to unreliable information and poor data driven decisions (Kwon, Lee & Shin, 2014). Hence, data accuracy and reliability is crucial to make proper decisions based on data and data analytics (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Data has come to be considered a type of capital, just like more traditional types, such as intellectual and financial (Lau, Zhao, Chen & Guo, 2016). To maximize the value of data, expertise of data and data science should be combined with domain knowledge, i.e. knowledge of the specific area in which the data is retrieved from (Medium, 2019). Thus, regardless of the data quality, skilled personnel must make sense of the data and draw accurate conclusion from it (Sun, Hall & Ceglieski, 2019). Capabilities to use data in this manner, to extract value in terms of insights and knowledge from it, can be viewed as a key strategic asset (Provost & Fawcett, 2013). This is leading to a paradigm shift that requires an increasing understanding of the principles of data science (Kumar, Ramachandran & Kumar, 2020). Accordingly, new roles are taking shape, and traditional roles are becoming more analytical (Sun, Hall & Ceglieski, 2019; Carillo, 2017). However, even though data scientist has been called the sexiest job of the 21st century, companies cannot solely rely on the IT-department to successfully transform businesses to data driven organizations (Carillo, 2017), but digital transformations require both technical and cultural change (Shaughnessy, 2018). Since the latter composes a possible barrier for change (Panetta, 2019), the mindset and thinking must be transformed, not only the technical infrastructure (Gale & Aarons, 2018). The cultural challenges concerns developing a culture that is data driven (Tabesh, Mousavidin & Hasani, 2019), which implies decisions being made with data as support, rather than instinct and intuition (Gupta & George, 2016; McAfee & Brynjolfsson, 2012). Yet, many organizations have poorly working data management and lack data and analytical know-how (Gentner, Stelzer, Ramosaj & Brecht, 2018). Digital transformations with positive outcomes is therefore not obvious (Gale & Aarons, 2018). Hence, regardless the potential benefits of data and data science in business (Carillo, 2017) there are a large fraction of digital transformations and big data analytics implementations that fail (Kesari, 2019; Capgemini, 2015).

To further investigate how firms can include data and IT to improve their performance we will turn to the resource based view of the firm. Despite the extensive focus on big data analytics, the influence on performance is still challenging for both academia and businesses (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019). As data driven decision making is related to economic benefits (Brynjolfsson & Mcelheran, 2016) and improved business performance (Akhtar, Frynas, Mellahi & Ullah, 2019) it is surprising that there is a lack of research considering service providing firms and the implementation of data and technology in the B2B marketing field.

Purpose and Research Questions

The objective of this paper is to identify resources crucial for implementing data driven decision making and data analytics in B2B firms. More specifically we will investigate the influences of data in a marketing and sales context by conducting a case study at the IT consultancy firm, Findwise. The ambition is to provide an extensive guide for managers in data analytics implementation projects, with the main focus on which resources that are central for data driven decision making. The structure of the paper will be based on the big data analytics cycle of Tabesh, Mousavidin & Hasani (2019). For all phases there are activities vital for digital transformation, which the resources will be based on. The big data analytics cycle will thus enable an overarching framework of data implementation projects.

RQ: *What resources are central for implementation of data driven processes and decision making in B2B sales and marketing?*

Theoretical Framework

To provide a profound understanding of both data influences in B2B sales and marketing and implementation of data driven processes, this section will describe each phase of the big data analytics cycle as well as the fundamentals of the resource-based theory and change management.

Big Data Analytics Cycle

This section will be structured in accordance with the big data analytics cycle (Figure 1.) of Tabesh, Mousavidin & Hasani (2019). The cycle consists of four different phases of data analytics implementation, phase 1-4. These describes the transformation of data to insights, insights to decision, decisions to actions, and actions to data, where each phase itself require specific activities, resources and organizational actors.

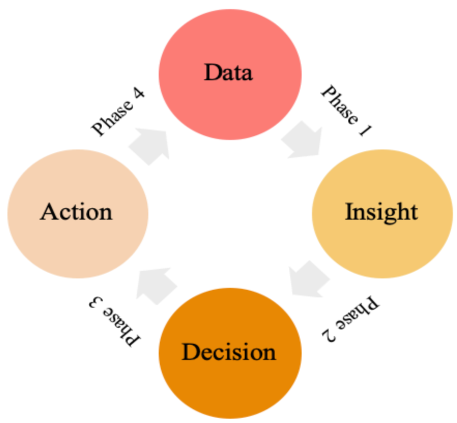

Figure 1. Big data analytics cycle (Tabesh, Mousavidin and Hasani 2019, p. 349), revised.

Phase 1 - Data to Insight

Data as in data collection is the first phase in the analytics cycle. Data is collected from internal or external sources and are thereafter processed with the help of analytical tools (Tabesh, Mousavidin & Hasani 2019). However, to first understand what data to extract we turn to Wright, Robin, Stone and Aravopoulou, (2019) who identified several requirements to successfully use and exploit data. First, equipment to collect, store and analyse the data. Second, the expertise and knowledge of how to manage it and extract valuable insights. To achieve the first of their requirements, the firm thus need to invest in technologies and tools to collect data, such as Artificial Intelligence, AI or marketing automation. AI started to gain much focus relatively recently, which can help marketers to collect and transform data into knowledge (Paschen, Kietzmann & Kietzmann, 2019). AI will most likely have a large impact on digital marketing (Davenport, Guha, Grewal & Bressgott, 2020), however as previously mentioned, there is a common misconception of what AI really is (Kaplan & Haenlein, 2020). Thus, what sometimes is referred to as AI, might be more IA, intelligent automation, as machines are good at repetitive tasks and have an ability of making sense of large sets of data, but not yet thinking like humans (Fleishman, 2020). Marketing automation is another tool that can be used in marketers and sales to collect and manage customer data (Hubspot, n.d.; Järvinen & Taiminen, 2016). Even though there is an increasing focus on marketing automation in B2B (Järvinen & Taiminen, 2016), Lilien (2016) stresses that the majority of applications developed are adjusted to B2C.

New data can be retrieved from a variety of sources such as logs, click streams and social media (Sun, Hall & Cegielski, 2019). Once companies start collecting data, which should be a continuous process, more information about newly generated data will occur (Provost & Fawcett, 2013). Using technologies to retrieve and provide real time data and perform data analytics is proven to enhance data driven decision making (Xu et al., 2016). Hence, the main problem in this process is how to extract what is relevant for those decisions and thus to have data of high quality. Data quality is according to Kwon, Lee and Shin (2014) determined by the consistency and completeness of data, which in turn will be a determinant of the accuracy of the insights produced using that data. These insights can be of market, consumer, product or competitor characteristic (Xu et al., 2016), which can be used to increase sales and customer relationships (Hallikainen, Savimäki & Laukkanen, 2020). In a marketing context, the importance of data is strongly related to its ability to provide insights to tactical and strategic marketing decisions (Kumar et al., 2013). Therefore, data should not only disclose history, but also do predictions (Kumar et al., 2013).

Phase 2 - Insight to Decision

The largest issue concerning big data comes after the collection and is related to the processing of data and turning insights to decisions and later, actions (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Thus, the capability to contextualize the generated insights are of utmost importance (Tabesh, Mousavidin & Hasani, 2019). Critical actors in this phase are, according to Tabesh, Mousavidin and Hasani (2019) managers and data scientists. Lilien (2016) also identify the shortage of data scientists for B2B businesses, making companies undersupplied with human resources. The decisions made in this phase will reflect the quality of the insights generated from phase one. In addition to data quality and analytic capabilities, decision makers must be able to determine what insights to turn into decisions and govern the process onwards (Tabesh, Mousavidin & Hasani, 2019). Hence the importance of having a competent team that can turn data into insights and decisions (Bartosik-Purgat & Ratajczak-Mrożek, 2018).

Managers working with data driven decision making should use data-analytical thinking as a basis for business decisions (Troisi, Maione, Grimaldi, Loia, 2019). However, there seems to be a lack of tech - and analytic experts who have sufficient business knowledge, which limits the potential of becoming data driven (Fleming, Fountaine, Henke & Saleh, 2018). For a marketing department, knowledge of the domain will be advantageously alongside data analytic know how. As data driven marketing, according to Gartner (n.d.) is *"acquiring, analyzing and applying all information about customer and consumer wants, needs, motivations and behaviours",* interpretation of this information will be done, and put into a context in which the firm operates (Tabesh, Mousavidin & Hasani, 2019).

Phase 3 - Decision to Action

While the techniques that enable these processes are being adapted and digital marketing is more present than ever, some companies are still not developing marketing strategies which are centred on digitalization (Quinton & Simkin 2017). The complexity of the marketing field has increased as a consequence of the "technicalization" of marketing (Quinton, & Simkin 2017, p. 461). Furthermore, this technicalization can explain the reason of many failed data initiatives - managerial misunderstanding or lack of knowledge in how to turn insights into decisions that thus prevents actions (Tabesh, Mousavidin & Hasani, 2019). Kesari (2019) argues that there is too little focus on business issues, and too much technical emphasis. Business issues refer to the overall challenges that the company face, rather than the technical ones (Kesari, 2019). The "technicalization" has led to specialization, and creation of subsections of marketing. A more fragmented, silo-structured organisation is the consequence, as deep special know-how is required (Quinton & Simkin, 2017). The silo structure is contradictory to what Carillo (2017, pp. 611) identified as necessary to become data driven; establish an "analytics-based DNA", integrating knowledge of concepts such as data management to employees' areas of expertise. Additionally, implementation of analytical tools requires middle- and senior managers to have knowledge and an understanding of the solutions required (Tabesh, Mousavidin & Hasani, 2019). Thus, the mindset of employees, and more specifically decision makers must be more analytical and take on a wider perspective. Even though new methods and technologies are being adapted, it's simply not enough to hire data scientists, but the data driven paradigm requires a shift in corporate culture (Carillo, 2017). This is supported by Tabesh, Mousavidin and Hasani (2019) who stress culture the second barrier to prevent successful implementation as exploitation of data initiatives. The importance of technology and information management is unquestionable. Brinker and McLellan (2014), describe the emergence of the chief marketing technologist (CMT) and their role as change agents. This validates the managerial aspect of change and a too narrow focus on technologies risk an unsatisfactory outcome.

To ease the implementation Tabesh, Mousavidin and Hasani (2019) identify three levers; structural-, relational- and knowledge influences (Tabesh, Mousavidin & Hasani, 2019). The first of these three levers refers to managing support in these transformations, or implementation projects. This is managed through budgets, planning, acquisition of talent and management systems, with the purpose of reducing cultural- and technical barriers (Tabesh, Mousadivin & Hasani, 2019). Second, relational influence concerns interpersonal mechanisms such as communication and coordination, while the last one implies managing the expertise required to achieve the objectives of a project (Tabesh, Mousadivin & Hasani, 2019).

This phase, executing the business decisions, is however not easy. According to Monauni (2017) this is one of the largest challenge. The execution refers to combining the components needed for a decision to turn into practice (Margherita, 2014), and is influenced by the employees and their actions (Neilson, Martin & Powers, 2008). Reasons why companies struggle can relate to vague responsibility directives and insufficient communication of the strategy to be performed (Monauni, 2017). Resource management is according to Margherita (2014) the activities which allocates the right knowledge, physical resources and actors, so that an activity can be properly implemented.

During the last decade, marketing strategy have been increasingly characterised by becoming more data-influenced and digital (Sridhar & Fang, 2019). Digital marketing is becoming more fragmented where different sub-areas are emerging (Busca & Bertrandias, 2020). In practice, digital marketing is related to brand awareness and lead generation throughout the digital channels available (Alexander, 2020). Thus, this phase implies acting on information that is produced and interpreted in previous phases, and that is aligned with the marketing strategy.

Phase 4 - Action to Data

The fourth and last phase of the big data analytics cycle implies bringing data points, both external and internal, back into phase one. The phase imply analysing the actions that were carried through, and thus, account for the outcomes of these initiatives (Tabesh, Mosuavidin & Hasani, 2019). Furthermore, the authors stress this process as self-perpetuating, meaning that new insights are generated and decisions are being evaluated. Internal data is produced directly or indirectly when a business is operating, while external data is retrieved from sources the firm cannot influence (Kwon, Lee & Shin, 2014). The data brought back to phase one, thus depend on what type of decisions and actions that have been made, and what measures that are taken. Likewise, the key activities in this phase refers to data collection and evaluation and take on technical capabilities since they require technical infrastructure such as data collection and storage (Tabesh, Mousavidin & Hasani, 2019). The evaluations and outcomes from the actions taken in phase three is thus now cycled back and can be used for future decision making.

Resource based theory and dynamic capabilities

The resource based theory explain why companies perform differently by investigating their internal resources. The theory have been widely spread to several managerial fields to cross-fertilize insights (Lioukas, Reuer & Zollo, 2016). By building on this theory and its intersect with IT, it will help us to sort out the relevant resources throughout the data analytics cycle.

In the 1980s the resource based view of the firm started to emerge (Kozlenkova, Samaha & Palmatier, (2014). This view later became the resource based theory, RBT, developed by Barney (2001). RBT can help to answer the question why firms within an industry performs differently (Zott, 2003) considering their valuable, rare, inimitable and non-substitutable (VRIN) resources (Nason & Wiklund, 2018; Lin & Wu, 2014). A resource is according to Wernerfelt (1984) either a strength or a weakness of a company. The categorisation of resources can vary; Barney (2001) refers to resources as tangible or intangible, while Gupta and George (2016) identifies tangible-, intangible and human resources, all required to build an IT-capability. Hall (1992) incorporates human dependent resources, know-how and organisational culture to his definition of intangible resources. Considering this definition, we will use Barney’s (2001), tangible and intangible resources throughout the remainder of this paper.

Barney’s (2001) research show that firms focusing on the intangible resources seems to outperform firms that focuses on the tangible resources, hence; intangible assets evidently have a larger impact of a firm's performance. Assets such as management skills, organizational processes and routines, information and knowledge, skilled personnel and technology know-how (Wernefelt, 1984; Barney, Ketchen & Wright, 2011) could thus turn into competitive advantages for firms. Central to RBT is the internal factors, which determines the profits of a company that lead to competitive advantages (Wernerfelt, 1984; Shan et al., 2019). Additionally, Kozlenkova, Samaha and Palmatier (2014) argue that intangible resources such as brand awareness, customer relationship and knowledge and information are all marketing related resources that can be improved with data initiatives.

Dynamic capabilities refer to the ability of adapting capabilities within the firm. The capabilities should be aligned with the changing business environment and the role of strategic management that arranges internal and external resources, functional competence and skills suited to the setting in which the firm acts (Teece, Pisano & Shuen, 1997). Thus, to achieve big data capabilities, big data as a resource is a prerequisite, without big data alone being sufficient (Gupta & George, 2016). According to Lin and Wu (2014) dynamic capabilities can be used to allocate resources to enhance the performance of a business. Within the field of IT, Shan et al. (2019) identifies and stresses the importance of three key resources, namely IT technology resources, IT relationship resources and idle resources. The first one relates to knowledge of IT, and is similar to Gupta and George (2016) who refers to technical skills and experience. IT relationship resources refers to the ability of connecting IT with the business itself and how it enables good relationship with other stakeholders (Shan et al., 2019). The idle resources concerns a strategic and innovative view of IT and the ability of financing IT activities (Shan et al., 2019).

Kwon, Lee and Shin (2014) refers to IT-infrastructure as a tangible resource, while competence, know-how and experience as intangible resources derived from a combination of investments. The investments needed to exploit these analytic techniques are large and can take years to turn into a profitable return (Wright et al., 2019). Found by Lee and Kim (2006) was a positive effect on firm financial performance when investing in IT, however there is a lagged effect, implying that an immediate pay off might not be realistic.

Change Management

The standpoint of this paper is managerial, and the aim is to investigate resources that are crucial in exploiting data and implementing data analytics for data driven decision making. How to manage change is therefore important in organisational transformations as people have to change their behaviour and routines.

Muluneh and Gedifew (2018) differentiates technical and adaptive problems within an organization. The former is in general easy to identify and solve due their straight-forward characteristics (Randall & Coakley, 2007). Adaptive challenges, on the other hand, requires a more in depth approach where values, beliefs and relationship all have to change (Bernstein & Linsky, 2016). Adaptive leadership is complex and has a focus that goes beyond person, and instead looking at processes (Randall & Coakley, 2007; Bernstein & Linsky, 2016). The adaptive leadership strives to engage employees to participate in finding and implementing solutions that improves the business, thus participating in change (Randall & Coakley, 2007).

Adaptive leadership can achieve change sustained over time and is beneficial when combined with design thinking, something referred to as adaptive design (Bernstein & Linsky, 2016). Design thinking is centred around the human aspect of change where the initial step is to figure out the actual need of users (Bernstein & Linsky, 2016). The approach is gaining popularity and attention for its ability to solve organizational issues (Muluneh & Gedifew, 2018).

For digital transformations, change management is fundamental. Ivančić, Vukšić and Spremić (2019) advocate managers to organisationally foster a digital enthusiasm through education, feedback, evaluation and employee conversations. A two-way conversation can thus contribute to a digital culture that enables change since people gain an understanding and share the vision promoted by their managers. Furthermore, the concept of digital readiness will play a role in success of implementation of digital tools. Besides adaptive leadership and intangible resources there are some factors that influence the outcome of change initiatives. According to Sirkin, Keenan and Jackson (2005) those are sufficient amount of time and people and satisfactory financial outcomes.

Methodology

This paper is based on a qualitative research method with an abductive approach. The empirical material is composed through interviews from a case study.

Research design

Since data, data analytics and implementation of related IT-solutions is studied as a phenomenon, a single case study (Dubois & Gadde, 2014) was an appropriate method for this paper. A case study enables a deeper insight (Bryman & Bell, 2017) of how data can be used within B2B firms and provide a better understanding of its impact within organisations. Aligned with Halinen and Törnroos (2005) this case study enabled a closer view of the studied object. Additionally, Dubois and Gadde (2002) describe systematic combining as the process of matching theory and reality, which were applied. Furthermore, Lilien (2016) stresses qualitative and case study methods being particularly suitable for B2B research, rather than traditional B2C research methods.

By conducting a case study, we were able to be flexible in our research process (Dubois & Gadde, 2002), meaning moving back and forth between phases of retrieving theory and data collection. The theoretical section itself was based on research that contributed to answer our research questions. The literature review was conducted in a systematic manner, using databases provided by the university and additional relevant online sources. The information search have had three main areas; change management, data driven marketing and sales, and resource based theory (RBT). As the technological development is rapid, the articles concerning data and IT were mainly published in the last few years to be as relevant as possible. The other two areas, change management and RBT does not have the same ever-changing characteristics, and therefore some older publications and scholars have been cited.

Choice of Case

The company studied was Findwise, an IT-consultancy firm with focus areas in artificial intelligence, enterprise search, analytics and big data (Findwise, n.d.).

Findwise made an appropriate case since they are working with data within various industries for companies with different objectives. They are, thus, aware of how data can be used to provide value in varied contexts. Moreover, they are experts within the field which we were studying, and were judged to be able to contribute with practical expertise. As the purpose of this paper was to investigate relevant resources for data and data analytics, mainly in sales and marketing functions - our interview guides (appendix A-C) were adjusted to the respondent and their role at Findwise.

Sampling strategy

In accordance to Eriksson and Kovalainen (2008) the empirical material was obtained through qualitative and semi-structured interviews with employees at Findwise working with sales, marketing and IT at the Gothenburg office. The interviewees were chosen based on their expertise within the three different areas. Eight interviews were conducted until saturation was reached. Two of the interviews was with the same person, (table 1), and all had a duration of 30 minutes to one hour. The interviews were all conducted digitally between the 17th - 26th of March. All interviews were recorded after approval from each interviewee, thereafter transcribed. As the interviewees were all fluent in Swedish, the interviews were transcribed and translated to English when cited. Due to the size of the company studied, we decided to reveal as brief information as possible of the respondents in order to preserve anonymity. Therefore table 1 below only includes the respondent's department, reference and duration of each interview. Each respondent will, later on in this paper, be referenced to accordingly.

Analysis Method

Once the empirical material was transcribed, the analysis process began. The transcriptions were coded into themes - the four phases of the big data analytics cycle. Later, the resources and activities discussed in the interviews were analysed in order to know how to allocate them to each theme, some relevant for more than one theme. This thematic analysis (Bell, Bryman and Harley, 2019) enabled an understanding and overview of the most important activities and resources throughout the big data analytics cycle. As all information that were gathered were not applicable in this case, we highlighted the parts related to one or several phases, which later became the foundation for our findings. In the thematic analysis quotes from the interviews have been translated from Swedish to English.

Even though we strived to preserve the original phrasings, some wordings have been slightly adjusted to retain the context.

Table1. Interview respondents

Respondent	Reference	Duration
IT	*IT 1*	33 min
IT	*IT 2*	42 min
IT	*IT 3*	46 min
Marketing	*Marketing*	45 min
Marketing	*Marketing*	30 min
Sales	*Sales 1*	52 min
Sales	*Sales 2*	40 min
Sales	*Sales 3*	58 min

The coding process reduced the amount of information and enabled us to link the empirical material to the theoretical framework. To easier follow our arguments throughout the paper, the structure of the theoretical section was continued in our findings. This made it easier for us to, in the analysis process, connect the themes to each section in the paper. The overarching framework - the big data analytics cycle - can be decomposed in several activities per phase that we identified in our findings. However, these activities require certain resources and as the objective of this paper was to identify these resources, our discussion is structured in accordance to them.

Ethical Considerations

There are some ethical considerations that has to be made while conducting a qualitative study. The first is the changed meaning as translation is done (Resch & Enzenhofer, 2018). To overcome this we tried not to alter the wordings in the citations and if the wordings had to be changed we still managed to preserve the context and the original statements. Second, our influence of the interview sessions and the interactions with the interviewees might have affected the data gathered (Maxwell, 2018). A third aspect to be considered is the preconceptions of the study that we, as interviewers, might bring that might undermine the objectivity of the study (Maxwell, 2018). To overcome the second and third issue that might arise we asked one respondent to read through our findings to minimize the risk of misconceptions and to make sure the findings were reproduced in a fair and correct manner.

Findings

Our findings suggest that there are ten resources that are most relevant in data analytics implementation projects. These resources are summarized in the table 2. Furthermore, the findings indicate that data in sales and marketing serves various purposes, which vary among companies. The purposes often relate to more qualified tasks for employees, more efficient use of time and money, more up-to-date information and leads qualification as well as improved customer relations. Working data driven is a challenge, especially for service firms due to the need for customizing the services for each client

The intention of implementing digital tools is to find more profitable ways to perform simple tasks which enables the people to have more complex responsibilities
(Marketing)

This section consist of the key insights retrieved from the conducted interviews. The structure follows the big data analytics cycle where each phase will be divided into two parts - key activities and the resources required to perform those activities. Some are relevant and connected to several phases and will thus appear in more than one phase. The identified activities and resources are built on our analysis of the empirical material and have been allocated to the phase or phases where they were fundamental.

Table 2. Summary of vital activities and resources connected to each phase of the big data analytics cycle

Phase	Resources	Activities
1. Data - Insight	Technical Infrastructure IT Competence High Quality Data Domain Knowledge Time	Identify business case Collect relevant data Structure & clean data Analyse Create & communicate insights
2. Insight - Decision	IT Competence IT Relationship Resource Domain Knowledge Inspirational leaders	Evaluate insights Include other relevant information Change management - establish a data driven culture
3. Decision - Action	Domain Knowledge Structural Influences Relational Influence Knowledge Influence	Execute decisions Change management - establish a data driven culture
4. Action - Data	Technical Infrastructure Domain Knowledge IT Competence	Collect data Analyse & Evaluate/Measure Actions Create & communicate insights

Phase 1 - Data to Insight

During the analysis of the empirical material we identified five activities and five resources related to phase 1 (table 2). The five activities are; identify a business case, collect relevant data, structure and clean data, analyse data and create and communicate insights. Additionally, the five resource identified were; technical infrastructure, IT competence, data quality, domain knowledge and time.

Activities

A starting point of digital transformation projects is to **identify a business case** from which data collection and investment of digital tools should be centred around. The findings indicate that digital projects should be dealt with from a business point of view rather than from an IT-perspective. Technical features might obscure the solutions for the business issue. Similarly, IT itself create value first when it enables solving the business problem. A misconception of the technicalization that isn't too unfamiliar is that AI will overcome all obstacles and issues of a firm, while the reality is quite different. The contemporary AI hype has distorted the perception of what can and cannot be done with AI:

*I think there is a great ignorance out there, an unrealistic picture. Looking at the AI-bubble that is very current, for example, people think AI is going to solve all of their problems (*Marketing)

Oftentimes less complex solutions are needed to improve a business. This hype can therefore also over-emphasise the digital tool itself:

AI is a popular word used to describe something, like a smart system for example, but from a technical point of view it doesn't necessarily have to be AI (IT 3)

Unfortunately employees with an interest in technology are often eager to implement advanced digital tools, consequently, the transformation project fail due to the absence of a purpose. This is often not due to bad developed tools, but rather because it won't bring any real value. The presence of a business case on the other hand, create a purpose and preferably a hypothesis:

You need a hypothesis to evaluate data, and that doesn't always exist, you don't just analyze data for the sake of analyzing (Sales 2)

The hypothesis will function as an objective for a transformation project and the digital tool will enable that purpose to be fulfilled. Additionally, the hypothesis will ease the **data collection** process as it will reveal data relevant to study and analyse:

Is this data relevant for what we try to accomplish? (IT 3)

Hence, you do not collect data for the sake of collecting but for what the firm wants to achieve.

The data collected must thereafter be **structured and cleaned**, which is an activity that for non IT employees often is characterised by ignorance. Although, the structure does not have to be perfect when digital transformations begin. A small effort to structure and clean data can make an IT project go faster and be more efficient. To structure and clean datasets can take up to 80% of the time in digital transformations, while the creation and integration of data and digital tools is claimed to be the "easy" part. Several firms are unaware of this and will be affected financially since the projects will be more time consuming and therefore more expensive. Additionally, this might lead to unrealistic expectations of what digital tools can achieve since the technologies themselves will not automatically solve issues related to data structure.

As a final activity the **analysis** process begins, combining all activities and resources mentioned in this phase and use them to **create and communicate** the insights gained from data.

Resources

Companies today differ in their IT condition, or digital readiness, one aspect of this is the condition of the technical infrastructure. However, our findings suggest that there is no clear correlation between industry and digital readiness:

> *There are definitely some B2B firms that are very mature and then there are some B2C firms that are somewhat immature, so there are differences, but they probably vary more within the groups than between them* (IT 2)

The IT condition can vary more within the industries and the size of the companies. There are also variations between the private and the public sector Hence, there are indications that the maturity is higher in the private sector as the former tend to "ask the right questions". There are differences observed, both concerning ownership and size. More importantly, however, is that the **technical infrastructure** differs more within these groups than between them and the assessment of the technical infrastructure and digital readiness should be done individually. The technical infrastructure is therefore a central resource that can determine the IT condition and enable firms to work automated with collecting and analysing data.

The IT condition is also determined by the ability to use digital tools correctly, IT **competence.** For some companies the knowledge of what IT and data can do is lacking. Therefore there can be somewhat unrealistic expectations of what becoming data driven implies. A higher degree of data- and analytical knowledge is therefore required, not only by managers in a strategic level, but also for employees as the digital tools become integrated in the daily work. Thus, those competences that was solely associated with the IT department are now a necessity in other divisions. For marketing and sales this implies more analytical skills as they have to construe information given from these tools. The analytical competencies that need to be attained can be divided into two categories. First as there is a need to have a more in depth knowledge of IT, technical solutions and statistics. Second, an analytical mindset and knowledge of how to use these tools to perform the tasks.

A resource that relates to collecting data is **data quality**, which is claimed to be one of the most important resources. In order to turn data into insights, data used as an input must be of high quality. Additionally, data must be findable. The respondents emphasise the complexity of defining data quality but refer it to six aspects; (1) Include similar information, (2) be structured in similar ways, (3) be frequently generated, (4) not contain missing values, (5) generate correct information that is relevant for its purpose and (6) be easily accessible - data findability. If the data quality is poor data will be of no help for decision makers. Large amount of data is not per se good as data must contain the information that is valuable for a company and its objectives.

An aspect of data quality is data findability. Data findability is a large obstacle for digitalisation as firms either lack appropriate data or existing data cannot be found or used for its intended purpose:

You can think of data as a library; if everything is structured and sorted, people can find what they search for (Sales 2)

The main problem with data findability is that firms are not traditionally built to optimize cross-functional interactions. As a consequence, data can exists several times but in different forms and shapes. As there can be multiple systems for different divisions, complications can arise with firms' internal interactions and thus their data sharing:

Data might be used to support one process at a time but if those processes never communicate with each other you'll never get a holistic view of your data assets (Sales 3)

Consequently, relevant data can be lost and thus important insights are too. Data should, ideally, optimize, support and be able to fulfil several purposes in various divisions.

To integrate data sharing it is important to adapt the system or tool for its use and context in which the tool will be applied - requiring **domain knowledge**. Data must be collected to serve the right purpose, and thus, the need to know the business and the domain is further emphasised in this phase. As the main objective in phase 1 relates to identifying a business issue, the idea, or knowledge, of what data that might overcome that issue will be crucial:

Another important thing, it depends on the context of course, but knowledge of the domain. You need someone who knows the domain in order to make sense of the subject area and better understand and use the information that is given

(IT 2)

The last resource for phase 1 is **time**. As already mentioned, some processes in digital transformations take more time than others. However, it is not always clear what process that that are more time consuming in the beginning of an implementation project. Each firm has its own needs and structure, which makes the allocation of time very individual. No project will be successful if the amount of time is insufficient and one should never stress through change. As a consequence of insufficient time, either the data quality or the application and adoption of technologies will suffer.

Time is quite important, without time you can't do anything (IT 2)

Phase 2 - Insight to Decision

There are three key activities central for turning insights into actions. First activity is to evaluate insights gained from phase 1. Second, the importance to include other relevant information. Lastly, change management - to establish a data driven culture has the ability to make data driven decisions. Additionally, to execute decisions from the insights four resources are identified as central; IT competences, domain knowledge, IT relationship resources and inspirational leaders.

Activities

As a last activity in phase 1 we have the creation and communication of insights. In phase 2, these insights are **evaluated** and work as a base for data driven decisions. Evaluation of insights should, however, not solely be based on data. There is a risk with looking at numbers at a screen, as other unmeasured information will be excluded from the analysis regardless of the importance of that information. Data is therefore not always the truth as **including other relevant information** can enhance the view of a situation, and thus also the decisions:

It is a bit naive to think that the data you have is the truth. Instead I like to think of it as 'data informed' where you include data as a base for a decision, but you are aware that it does not replicate the whole truth (IT 1)

Using data as one aspect in decision making, combining that with more qualitative information, could imply a more holistic view of a situation and result in a more suitable decision. Evaluation of insights should thus include knowledge of the business and, in a marketing and sales context, its customers.

A data driven culture cannot be forced. But there has to be a willingness to change and a willingness to become digital and data driven. That willingness is heavily dependent on what values a solution will bring to each and every business, and how **change is managed.** Even though technical solutions tend to bring value to a firm, it is the people within the organisation, and their ability to adopt new tools or processes that have the largest impact on the outcome:

People make the largest difference! I think one factor to reach success is to have a strong visionary and/or leader to make people more susceptible for change (Marketing)

Resources

When data have been turned into insights, those insights can be used as a basis to make decisions. Basing decisions on a rational foundation is not something new but the availability of data and technology is still relatively novel. Therefore, the tools and capabilities of managing new sources and larger amounts of data have to be adjusted. The **IT competence** is therefore needed, as adapting to new ways of working with data and knowing how to include data in decision making.

The **IT relationship resource** connects IT to the business. This can be viewed as the link between the IT department and the employees with domain knowledge. For companies to be able to use data as a part of a decision, there has to be an understanding of what data really is. Data in sales and marketing are often rather basic and concern contact information, company information and tracking visitors' activities on the homepage etc. However, if it is not tracked in a sales or marketing tool, such as a CRM or marketing automation, it won't be visible for someone within the company. If there are no clear directives of how to collect data, and what data to collect, there will most likely be hard to use in a consistent way. As a consequence, the quality of data and information will suffer. Additionally, the sales and marketing tools themselves must be easy to use and navigate in. Similar to phase one, **domain knowledge** is focal for the tool or system itself to be adjusted to the users.

Lastly, there has to be support from higher management in order for change to happen, partly in approving budgets and making necessary decision supporting a data driven culture, partly in inspiring the employees. **Inspirational leaders** with clear visions can be a great driving force, especially when it comes to anchoring a mindset within an organisation and engaging employees. Crucial for change management is to thus to make people participate in change.

Phase 3 - Decision to Action

To turn decisions to actions there are several resources and activities required. Specifically for this phase are the resources structural-, relational- and knowledge influence. These alongside domain knowledge were proven to be of importance when executing actions. The central activity in this phase is to perform activities which are aligned with the system which is being implemented - a task that is highly dependent on engaging employees in adapting to new ways of working. Therefore, the key activities in this phase are determined to be decision execution and change management.

Activities

Executing decisions or put decisions into actions does not have to be a complicated task. However, to become data driven the actions should be guided by the insights provided by data. Data driven decision making itself isn't wrong, however among experts there seems to be an over-reliance on data. Thus, rather than basing decisions solely on data, firms should preferably let data be one source of information that is supplemented with other type of information. There is an inherent risk when looking to narrow at available data as other information that might bring value to the conducted actions will be excluded.

In the specific context of B2B sales and marketing there seems to be a vicious cycle where there is a need to track data and store digitally to improve and optimize data analytics. At the same time there is a need to get to know customers personally, and much contact is interpersonal and therefore information related to customers not stored digital. Given this, if strictly basing decisions on data, some information will be excluded and therefore left out when executing decisions. For marketing and sales, phase 3 can include activities such as reacting to leads and planning for marketing communication such as creating digital and customized campaigns or other inspirational material. Consequently these activities will not bring any value if data is inadequate or biased.

To anchor digital tools and digital work tasks, **change management** is focal. Implementation of digital tools can lead to businesses not only saving money, but it can also be timesaving and give the employees more meaningful tasks. However, as good as it might sound, there are indeed quite a few digital transformation projects that fail to succeed. If the culture cannot be transformed or assimilate with the digital changes, it will not be a positive outcome, regardless of the quality of the new systems or processes. One issue with transformations is that people are reluctant to break their routines due to deep imprinted habits:

If they can't break their routines it won't be used in the right way (IT 2)

Managers must therefore educate their employees to understand why changes have to be made. This can be done through change management:

Change management, you'll have to start thinking in new ways, and there can be a great resistance towards that (Sales 1)

However, due to imprinted habits there can sometimes be a resistance towards change. Resistance towards digitalisation often exist due to ignorance and fear. The ignorance often lead to a misconception of what a technology does. Similarly, the fear often relates to a belief that it will lead to lost job opportunities as digitalisation sometimes lead to some sort of automation, reducing the number of workers needed. That is, however, seldom the case since new roles and tasks emerge with technology.

Resources

A resource being relevant throughout the entire big data analytics cycle is **domain knowledge**. When executing decisions the actions should be aligned with the objectives of the business which requires an understanding of the environment in which the organisation is operating in. For marketing and sales departments this is important as the cooperation between the departments often are close. That goes for the respective departments and IT as well. The shared expertise between departments can further lead to an organisation better exploiting the potential of an IT solutions:

I think it's wrong to separate divisions too much, because, it was not until I sat down with a system developer that I realized the true potential with the system, and he didn't realize it either until he sat with me. It was a perfect combo! (Marketing)

The **structural influence** is relating to the managerial support of an implementation project. For a project to be realised there are decisions that have to be made, and the people who has the mandate to make those decision have to be on board. Additionally, it is important with clear directives of what the aim of the project is, and how that is being reached. Strategical, and cross functional initiatives tend to be more successful than projects that are initiated for single departments or sections of a firm. Additionally, working with a committed team, and inspired leaders tend to ease and enable a successful implementation and change of behaviour and culture. Thus, the structural influence includes the coordination of an implementation project, and the support making sure that it is feasible. Time- and financial budgets goes hand in hand and are included in this resource as the length of a transformation project also determines the cost of that project. However, even though time can have a negative short term effect on the bottom line, the potential of what to achieve in a data analytics project is greater. The time it takes to build a holistic IT-solution is often split up as starting small can be beneficial for the outcome:

If you'll try to do everything at once, you definitely will not succeed. Start with one smaller case and if it works well you can introduce more functions (Sales 3)

Relational influence relates to the coordination and communication within the organisations. This is of great importance as people need to understand the objectives when a firm anchors new processes of how to work through new systems. To truly become data driven, or digital, an organisation is dependent on the actions of the employees, and not only the IT department. What is proven to engage employees in adapting to new ways of working is the communication of inspirational leaders. Failed implementation is seldom related to a badly developed IT system, but rather an incorrect usage of that system.

For a sales and marketing department in a B2B setting, the opportunities of using IT systems are large. Nevertheless, the resistance towards IT is often related to the interpersonal relationships employees have with potential- and current clients. As a large fraction of information and data regarding clients aren't stored digitally, there are no standardized process of how to track and manage customer data. This inhibits the full potential of the systems that are developed to provide other employees and/or departments with information. The underlying explanation of this relates to complexity in B2B service delivery as a process that are often customized to each and every customer and their needs. Therefore, a deeper understanding of the customer, their needs, IT condition etc, often requires a more qualitative assessment of clients and basis for a beneficial relationship.

Knowledge influence is about making sure that the required competence and expertise is available to achieve an objective. As IT is becoming more present throughout the various departments in an organisation, including sales and marketing, there is a need to increase analytical and technical capabilities as well.

Phase 4 - Action to Data

As the final step of the cycle is turning actions into data, it is similar to phase 1. The major difference between the phases is that in phase 4 the data driven decision and actions are being evaluated. Due to similar characteristics of the phases the resources and activities are alike. Technical infrastructure, IT competence and domain knowledge are the focal resources in this phase, while data collection, data analysis and communicating insights are central activities. A new dimension on data analysis is to evaluate the actions that have been executed.

Activities

Data is not something that every company receives without actively collecting it. Therefore there have to be continuous **data collection** and a culture supporting working data driven. The data collection in phase 4 have the purpose of evaluating the actions that were made based on the data driven processes in previous phases. The evaluation of data serves a purpose as the effect of an implementation can be used as support for further actions, but also to support an idea that might exist, or to find patterns that were yet not thought of. From a marketing and sales perspective This can imply a more extensive understanding of what customers search for but can't find, what services or products that are bought together, what are the main interest among clients etc. When not using data as support for your decisions there is a risk that important insights and connections can be missed.

When data reveals an unexpected, useful result, that's when you get the wow-factor
(IT 3)

Analysing and measuring the impact of an implementation can, however, be hard to conduct depending on the characteristics of the implemented IT solution. Not only can measurements confirm whether the project was successful or not, it might also reveal what the firm should focus on next. It can, however, be hard to measure the outcome of certain implementation projects due to the complexity of those specific cases, or lack of cases to compare it with.

We always make an effort to evaluate the effect of an improvement, but sometimes it can be more difficult than you think
(Sales 2)

To measure the outcome of an implemented process or digital tool is a way to validate whether the money and time spent on a project was worth it, and whether it should continue or be developed. Despite the importance of measuring the implementation of a new IT solution or digital tool there is still not an obvious activity, much because of complexity. The more tangible a solution is, e.g. saving money, time or increasing sales, the easier it is to measure and evaluate.

Communication of insights are relevant for two main reasons. First, as previously mentioned, it validates the money and time spent on a project, which can be used as a base to initiate future projects. Second, to make the information available to other departments and employees internally and work to resolve the silo-structure that exist among some companies today.

Resources

Data does not simply just exist for companies, but it has to be collected. Therefore, **technical infrastructure** that supports an ongoing collection and analysis of data is focal.

Domain knowledge, as for every phase, is required to analyse data and evaluate insights. In marketing and sales that can imply information on the customers engaged in campaign material, visitations on the webpage, read social media posts and other interactions with the company. Unless there is a knowledge of the domain it is likely that there can be a lack of knowledge in how to interpret that information and its true value for the business. To overcome this, **IT competence** is indirectly required as the collection and analysis of data is conducted using digital tools.

Discussion

The four phases of the big data analytics cycle can be considered as an overarching framework for digital transformations, in which activities are initiated. To perform these activities there is a need for certain resources, that naturally will become components in becoming data driven. Ten resources were identified in the findings, all focal in the implementation process of data analytics, to serve the purpose of creating data driven processes. These resources are technical infrastructure, IT competence, High data quality, Domain knowledge, Time, IT relationship resource, Inspirational leaders, Structural influence, Relational influence and Knowledge influence. As the resources are key for being data driven, the discussion will be based on these resources.

Technical infrastructure

Technical infrastructure is a prerequisite that enables working with data in a digital way. Even though the emphasis on technical infrastructure lies in phase 1 and 4, it would be impossible to conduct the "non-technical" activities related to the other phases without this tangible resource. The condition of the technical infrastructure can vary between companies. While previous research has emphasised B2C companies being more mature and that more digital applications are developed for that industry (Lilien, 2016) our findings indicate that simply differentiating B2B companies from B2C is a simplification since more factors must be included when determining the digital readiness. When developing the technical infrastructure, it is important that data is accessible and overcome the silo structure that inhibits the potential of using data throughout the organisation. This issue was emphasised by Quinton and Simkin (2017), as a consequence of the technicalization of marketing. A challenge for B2B marketing and sales is to adapt business processes to the technical infrastructure, as much of their tasks are conducted manually.

Technical infrastructure is important as no data collection, and thus no data analysis can be done without it. Building analytical capabilities require both tangible- and intangible resources (Gupta & George, 2016). Nevertheless, it is the usage of the system that makes the greatest impact. This is in line with Barney (2001), who states that firms focusing on intangible resources tend to outperform the ones who put more emphasis on their tangible ones.

IT competence

IT competence is a resource that some organisations is lacking. One of the main issues are related to the unrealistic expectations of what being data driven implies, and what can be solved by integrating data analytics in the daily tasks. Our findings indicate that there is a belief that AI can solve and be applied to anything, which is partly explained by ignorance, and partly by the present AI (Kaplan & Haenlein, 2020; Reavie, 2018).

IT competence is required as knowledge of more technical characteristics is needed to implement IT systems and digital tools, as well as understanding data and statistics. This have been confirmed by several scholars such as Gupta and George (2016) and Wernefelt (1984). The knowledge of IT and working with data must be spread throughout the organisation as the presence of data isn't restricted to the IT department, in line with Carillo's (2017) findings. The types of knowledge does however seem to be divided in two, as there is a need to have an in depth technological and statistical knowledge among IT staff, emphasized by Gupta and George (2016). Although, dispersing more basic analytical skills and knowledge is required in the rest of the business. Our findings therefore suggest that a combination of these will lead to enhanced data processes.

From a marketing and sales perspective this implies understanding data that concerns customers and their needs, as well as what to do with that data and thus how to act on the insights that are obtained. The objective with digital marketing is related to lead generation and increasing brand awareness (Alexander, 2020), in line with our findings. Additionally, data can improve the relationship with customers, which is confirmed by Kozlenkova, Samaha and Palmatier (2014).

High Quality Data

Data quality have been identified as one of the most important aspects to succeed with data analytics initiatives, as the quality of the data also determines the quality of the decisions and actions based on data. Even though it might be a concept that is not completely straightforward to define, six characteristics were proven to relate to data quality; (1) Include similar information, (2) be structured in similar ways, (3) be frequently generated, (4) not contain missing values, (5) generate correct information that is relevant for its purpose and (6) be easily accessible - data findability. This is much alike what Kwon, Lee and Shin (2014) and Bartosik-Purgat and Ratajczak-Mrożek (2018) refers to when they mention consistency, completeness, reliability and accuracy. The differences to what we have identified is characteristic (5) and (6), as data per se is not good, but it have to be collected to serve a specific purpose. It should further be accessible for various employees who might make good use of it. High data quality, unlike technical infrastructure, is therefore not a tangible resource that limits data analytics if absent. Hence, "bad" data can be used as an input but will not lead to a desirable outcome.

Even though the quality of data is central to perform high quality data analysis, and the fact that this paper is centred around data there is a need to be critical towards the data that exist. Not due to the data per se being wrong, or of bad quality, but due to the risk of biased decision making. According to our perception this aspect is lacking critique, and the main focus is directed towards the advantages that comes with data, such as financial benefits and improved business performance (Brynjolfsson & Mcelheran, 2016; Akhtar, Frynas, Mellahi & Ullah, 2019). However, if solely basing decisions on data, the data not being included in the analysis will be excluded from further activities and phases such as decision making and actions even though that could provide valuable input.

Domain knowledge

Domain knowledge is the only resource that have been emphasised throughout all phases of the big data analytics cycle. Domain knowledge implies knowledge of the industry that the business is operating in, as well as the departments within a business and their related tasks and objectives (Medium, 2019). Knowledge of the domain works as an enabler of making statistics and numbers valuable to the business as the interpretation can be used alongside practical experience within a field to makes sense on the decisions based on data, and later act on it. This have been identified as a key strategic asset (Provost & Fawcett, 2013). Our findings suggest that domain knowledge have a strong connection to successful implementation of data analytics. Rather than being initiated from a technical perspective, implementation should stem from the business perspective. Thus, whether it turns out being successful depends on the value it brings, and whether the return will outweigh the financial cost and time. This is where our findings differ from previous research. Tabesh, Mousavidin and Hasani (2019) framework is on a general level displaying the process of working with data and the implementation of tools which supports that. Accordingly, their first phase relates to analysing data, not identifying an issue or improvement. To overcome the lack of business connections, managers could turn to the field of change management, and specifically design thinking. This approach has its "point of departure" in the need of the users (Bernstein & Linsky, 2016) and could therefore identify areas of improvement or issues related to the tasks of the employees. Hence, domain knowledge is important to gain these insights.

Time

Time is a resource that is of great importance for an implementation project. Time is a factor that has a strong connection to the cost of a project, and thus with the success of it as well. The more time a project is given, the more advanced and well-developed processes and systems can be created. Much of the time that is given to data analytic projects are often related to the first phase of the cycle, as cleaning and structuring data can take up to 80 % of the total project. The time of an IT project varies much and depends on what kind of project it is as well as the overall IT condition and digital readiness within the organisation. Making sure data is of high quality is aiming at improving the tangible resource of data quality. Managing change, for adaptive challenges (Randall & Coakley, 2007) is complex and requires the involvement of the employees. Therefore, in line with our findings, Sirkin, Keenan and Jackson (2005) argues that letting change take time is often related to the success of the change. Time should also be evaluated after an implementation as the effect of IT investments often tend to be lagged (Lee & Kim, 2006).

IT relationship resource

IT relationship resource is central as it enhances the relationship between IT and the business (Shan et al., 2019).

As sales and marketing in B2B firms heavily rely on interpersonal relationship between buyer and seller the IT relationship resource could enhance that by providing IT support which enables more analytics to be integrated without undermining old processes and interpersonal communication. For example, learning about customer behaviour can be done through digital interaction e.g. tracking web page clicks, and see what customers search for. It can indeed, accordingly to the Kozlenkova, Samaha and Palmatier (2014), enhance customer relations, and target the customers based on their online behaviour. When IT have a strong connection to the departments, the cooperation will most likely lead to more optimized systems, similar to the idea of Shan et al. (2019).

Especially for B2B sales, there tend to be many of the tasks that are still rather manual, and non-data-oriented. Our findings suggest that this is related to the need of getting to know the customers and maintain that relationship. Emphasised by Kumar et al. (2013) is the need to preserve a human aspect in service marketing. Thus, our findings seem to favour previous research in this aspect. Customer relations according to Kozlenkova, Samaha and Palmatier (2014) can be enhanced, however, as B2B purchases tend to be more complex, especially in a service context where the service delivery often is customized and long term projects. Therefore, it can be argued that some tasks such as brand awareness and lead generation (Alexander, 2020) can be more influenced by data and technical infrastructure, in combination with domain knowledge while maintenance of relationships with recurring customers are more qualitative. When IT is involved in the sales and marketing technology and analytics development, there is a greater chance that these initiatives will succeed.

Inspirational leaders

A strong leader or visionary make people more engaged in change. A data driven culture cannot be forced and an unsupported employees will most likely not enable change. This is familiar to what Randall and Coakley (2007) and Barnstein and Linsky (2016) mentions as adaptive leadership, as this concerns changing values and beliefs, while engaging employees in change. That leaders are key persons in change is supported by Tabesh, Mousavidin and Hasani (2019) who argues that not only employees, but managers having mandate to make decisions requires data knowledge and skills, indicating that there has to be an interest in higher positions for a data driven culture. According to our findings it is the people who make the largest difference - employees and leaders, as change is difficult without managerial support, and that execution of actions are much relying on employees (Neilson, Martin & Powers, 2008). How to practically anchor the mindset is further described by Ivančić, Vukšić and Spremić (2019) who determine conversation, communication and education as key. Thus, what we identify as a key resource - inspirational leaders, are supporting previous research on managers involvement in change.

Structural influence

The structural influence includes the managerial support of an implementation project, and our findings are much related to previous research. Tabesh, Mousavidin and Hasani (2019) refers to structural influence as a lever, which eases the implementation, alongside the two following resources; knowledge- and relational influence. Our findings suggests that this is a resource that is overarching and enables a project in the sense that it coordinates activities and resources that is required for a project to run according to plan. It includes having mandate to make decision which are required and having resources, both tangible and intangible in place. What both our findings, and Tabesh, Moudavidin and Hasani (2019) argue for is that structural influence coordinates what several other scholar refers to as necessary resources in creating IT capabilities, such as skilled personnel, technology know-how, data, financial capital etc. (Barney, 2001; Gupta & George, 2016; Wernefelt, 1984; Shan et al., 2019). Therefore, we argue that this is the resource that constitutes planning and coordination of an implementation project, and is also similar to what Margherita (2014) identifies as resource management. What seems to differ, however, is that resource management is defined more narrowly, managing the knowledge and other inputs to execute a decision, while the structural influence implies support throughout the entire implementation project, including planning, directives, objectives, budgets etc.

Relational influence

Interpersonal communication within organisations is important for adapting to change. Specifically, it is important for becoming data driven as the information will disperse faster if the communication and coordination is good. Not only can digital tools support processes like these but they can help to spread the message that data enable an easier way to communicate. The findings suggest that divisions should work more closely together that enable collaborations between their specific expertise. This will lead to shared insights that can improve each department but also the entire organisation holistically. For sales and marketing this implies a stronger collaboration between the departments. Furthermore it implies that both departments work more closely with IT as it can enhance the exploitation of potential of a system and data analytics. As Tabesh Mousadivin and Hasani (2019) identified relational influence as a lever to ease implementation of digital tools, our findings enable an extended analysis of the resource. Relational influence is confirmed to ease the digital transformation, but it also enables the firm to become more integrated, enabling a better collaboration between all divisions. As a consequence of a limited relational influence resource, there will not be a holistic solution of the digital system and the system will not be exploited to its full potential.

Knowledge influence

For sales and marketing analytical and technical abilities are important when decisions will be based on data. As IT is becoming more present in all divisions, knowledge of tools and their functions are important. In addition to IT competences, this resource refers to the ability to manage the expertise needed to turn decisions into actions and thus realizing the business objective. The knowledge influence resource does further require domain knowledge and IT relationship resource as the actions will be executed accordingly. The ability to contextualize the data is thus important. Sales and marketing actions require knowledge of the business and its stakeholders. Separating the divisions too much will most likely lead to isolating knowledge of system functions to the IT department, while the IT department will lack the understanding of the field in which the system is implemented. Additionally, knowledge influence is an important resource for change management as people will adapt changes better. Similar to Ivančić, Vukšić and Spremić (2019) our findings indicate that knowledgeable leaders that can influence and educate employees in working data driven is an important driving force. This support Wernefelt 1984; Barney, Ketchen and Wright (2011) idea that management skills, skilled personnel and technology know how is of utmost importance to perform actions from decisions based on data.

Conclusion

The purpose of this paper was to identify resources central for implementing data driven decision making and data analytics for sales and marketing in B2B firms. By using the big data analytics cycle we identified vital activities for each phase of the cycle, and to perform those activities we identified 10 central resources; Technical infrastructure, IT competence, High quality data, Domain knowledge, Time, IT relationship resource, Inspirational leaders, Structural influence, Relational influence and Knowledge influence. Each resource appears in one or several phases of the big data analytics cycle and can help to guide firms through digital transformations as the resources are required to perform the various activities.

Scholars have previously argued that the digital readiness is lower for B2B companies. However, we found that this does not reflect the reality as there are larger differences within the industries than between them. Even though there might be a smaller amount of data available for B2B, it is still influencing the industry as they become more and more dependent on technology. Though, the main incentive for implementing digital tools for the two industries can differ. Specifically for B2B service firms, digital tools and data analytics are a complement to personal encounters as the purchasing process can be more complex compared to B2C. Data can thus be used for creating valuable leads and brand awareness. Additionally, it can be used as a complement to improve customer relationships since long lasting relationships sometimes require more than what data can offer today. A large incentive to become data driven for B2B firms is to improve the core business and its activities. IT knowledge and analytical thinking is no longer solely isolated to the IT department but integrated in sales and marketing practices as well, which require a stronger collaboration between these three. An integration of these division will enhance an exchange of experience and knowledge that can improve the work of these respective departments, and thus, their performance.

To begin the digital transformation firms should invest in time to structure their IT infrastructure and data quality as this can be very time consuming. The data quality is an important building block since it later will reflect the decision making and actions. Hence, poor quality data will result in inadequate information and thus lead to poor decision making. To make sense of the retrieved data, people must have IT competences such as IT knowledge and analytical thinking, which is achieved through change management including inspirational leaders, education and strong cooperation between departments. Even though technical know-how is significant for data driven decision making, knowledge of the business and stakeholders have to be considered as well. Domain knowledge, which is central in all four phases, implies knowledge of the industry, the organization and the objectives within the organization. Likewise, the IT relationship require knowledge of the context in which the business operates in. Structural-, relation- and knowledge influence are together enablers for change, as they support managers in the coordination of implementation projects. Consequently, all resources are vital to perform the activities that build each phase in the big data analytics cycle. To follow these activities and invest in the resources, firms can transform digitally and thus become data driven.

Limitations & Future Research

The approach of this paper was to, in a qualitative manner, find what can foster an implementation of data analytics and IT solutions supporting collection and data analysis to be performed. Additionally, our aim was to investigate what that might bring to marketing and sales in B2B organisations. Future research could quantitatively investigate the impact and relationship between these resources and financial performance. More specifically, the interrelationship between these resources as there are indications of correlations.

As this is a case study we cannot state that these insights are generalizable, even though this case is an organization which operates in several industries with companies with various characteristics. Furthermore, as the standpoint of this paper being managerial and some technical aspects being left out of the discussion, there might be implications for business practitioners working within the field of data science. Thus, taking on a more technical approach in investigating the relationship between these resources and the marketing and sales field, could potentially imply important complementary evidence.

Even though a case study approach has been argued for due to its characteristic being suitable for this research, there are considerations that has to be made. As a case study has been conducted under a limited amount of time, the time will differ from the period under which the studied objective will be operative, and that will influence the results and conclusions made (Dubois & Gadde, 2002; Halinen & Törnroos, 2005).

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References

Akhtar, P., Frynas, J., Mellahi, K., & Ullah, S. (2019). Big Data-Savvy Teams' Skills, Big Data-Driven Actions and Business Performance. British Journal of Management, 30(2), 252-271.

Alexander, L. (2020). The Who, What, Why, & How of Digital Marketing. Hubspot. Retrieved 200517 from https://blog.hubspot.com/marketing/what-is-digital-marketing

Aurugia. (2017). Top 5 Misconceptions about Big Data. Retrieved 200213 from https://auriga.com/blog/2017/top-5-misconceptions-about-big-data/.

Barney, J. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. Journal of Management, 27(6), 643-650.

Barney, J., Ketchen, D., & Wright, M. (2011). The Future of Resource-Based Theory: Revitalization or Decline? Journal of Management, 37(5), 1299-1315.

Bartosik-Purgat, M., & Ratajczak-Mrożek, M. (2018). Big data analysis as a source of companies' competitive advantage: A review. Entrepreneurial Business and Economics Review, 6(4), 197-215.

Bell, E., Bryman, A., Harley, A., & Harley, Bill. (2019). Business research methods (Fifth edition Emma Bell, Alan Bryman, Bill Harley ed.).

Bernstein, M., & Linsky, M. (2016). Leading Change Through Adaptive Design. Stanford Social Innovation Review, 14(1), 48-54.

Blut, M., Beatty, S., Evanschitzky, H., & Brock, C. (2014). The Impact of Service Characteristics on the Switching Costs–Customer Loyalty Link. Journal of Retailing, 90(2), 275-290.

Bosacci, R. (2018). Small Data, and Getting It. Towards Data Science. Retrieved 200217 from https://towardsdatascience.com/small-data-and-getting-it-4b3ed795982c.

Brinker, S. & McLellan, L. (2014, July - August). The Rise of the Chief Marketing Technologist. Harvard Business Reviev. Retrieved 200212 from https://hbr.org/2014/07/the-rise-of-the-chief-marketing-technologist.

Bryman, A., & Bell, E. (2017). Företagsekonomiska forskningsmetoder (3.rd ed.).

Brynjolfsson, E., & Mcelheran, K. (2016). The American Economic Review, The American economic review.

Busca, L., & Bertrandias. (2020). A Framework for Digital Marketing Research: Investigating the Four Cultural Eras of Digital Marketing. Journal of Interactive Marketing, 49, 1-19.

Cannon, J.(2019). *B2B marketers look to match B2C in level of customer experience.* Martech. Retrieved 200226 from https://martechtoday.com/b2b-marketers-look-to-match-b2c-in-level-of-customer-experience-236346

Capgemini. (2015). Cracking the Data Conundrum: How Successful Companies Make Big Data Operational. Retrieved 200215 from https://www.capgemini.com/gb-en/resources/cracking-the-data-conundrum-how-successful-companies-make-big-data-operational/

Carillo, K. D. A. (2017). Let's stop trying to be "sexy" – preparing managers for the (big) data-driven business era. Business Process Management Journal, 23(3), 598-622.

Chaine, A. (2019). Technology Impact on Sales Organization. Medium. Retrieved 140520 from https://medium.com/swlh/technology-impact-on-sales-organization-a7b90ad9612e

Conick, H. (2017). The Past, Present and Future of AI in Marketing. Marketing News, Marketing News, Jan 2017.

Cortez, M.R., & Johnston, W. (2017). The future of B2B marketing theory: A historical and prospective analysis. Industrial Marketing Management, 66, 90-102.

Dant, R., & Brown, J. (2008). Bridging the B2C and B2B Research Divide: The Domain of Retailing Literature. Journal of Retailing, 84(4), 371-397.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24-42.

Dayan, M & Ndubisi, N.O. (2019). B2B service innovation and global industrial service management. Industrial Marketing Management.

Dubey, R., Gunasekaran, A., Childe, S., Blome, C., & Papadopoulos, T. (2019). Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture. British Journal of Management, 30(2), 341-361.

Dubois, A., & Gadde, L. (2002). Systematic combining: An abductive approach to case research. Journal of Business Research, 55(7), 553-560.

Dubois, A., & Gadde, L. (2014). “Systematic combining”—A decade later. Journal of Business Research, 67(6), 1277-1284.

El Deeb, A. (2015). What to do with “small” data?. Medium. Retrieved 200313 from https://medium.com/rants-on-machine-learning/what-to-do-with-small-data-d253254d1a89.

Eriksson, P., & Kovalainen, A. (2008). Qualitative Methods in Business Research (Introducing Qualitative Methods). London: SAGE Publications.

Findwise. (n.d.) Retrieved 200404 from https://findwise.com/en

Fitzpatrick, L. (2019). *How Data Analytics Impacts Small Businesses in 2019.* Business.com. Retrieved 200217 from https://www.business.com/articles/the-state-of-data-analytics-in-2019/.

Fleishman, H. (2020). Is Artificial Intelligence A Myth?. Forbes. Retrieved 200519 fromhttps://www.forbes.com/sites/hodfleishman/2020/02/19/is-artificial-intelligence-a-myth/#35bb3b3f3166

Fleming, O., Fountaine, T., Henke, N. & Saleh, T. (2018). Ten red flags signaling your analytics program will fail. McKinsey. Retrieved 200517 from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/ten-red-flags-signaling-your-analytics-program-will-fail

Gale, M., & Aarons, C. (2018). DIGITAL TRANSFORMATION. Leader to Leader, 2018(90), 30-36.

Gallo, A. (2016). A Refresher on Statistical Significance. Harvard Business Review. Retrieved 200424 from https://hbr.org/2016/02/a-refresher-on-statistical-significance

Gartner. (n.d.). Data-Driven Marketing. Gartner. Retrieved 200517 from https://www.gartner.com/en/information-technology/glossary/data-driven-marketing-ddm

Gentner, D., Stelzer, B., Ramosaj, B., & Brecht, L. (2018). Strategic Foresight of Future B2B Customer Opportunities through Machine Learning. Technology Innovation Management Review, 8(10), 5-17.

Gupta, M. & George, J.F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049-1064.

Halinen, A., & Törnroos, J. (2005). Using case methods in the study of contemporary business networks. Journal of Business Research, 58(9), 1285-1297.

Hall, R. (1992). The strategic analysis of intangible resources. Strategic Management Journal, 13(2), 135-144.

Hallikainen, H., Savimäki, E., & Laukkanen, T. (2020). Fostering B2B sales with customer big data analytics. Industrial Marketing Management, 86, 90-98.

Hubspot. (n.d.) Hubspot. Retrieved 200604 from https://www.hubspot.com/marketing-automation-information.
Ishwarappa, J., & Anuradha. (2015). A Brief Introduction on Big Data 5Vs Characteristics and Hadoop Technology. Procedia Computer Science, 48(C), 319-324

Ivančić, L., Vukšić, V., & Spremić, M. (2019). Mastering the Digital Transformation Process: Business Practices and Lessons Learned. Technology Innovation Management Review, 9(2), 36-50.

Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. Industrial Marketing Management, 54(C), 164-175.

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Business Horizons, 63(1), 37-50.

Kesari, G. (2019, November 4). *5 Reasons Why Most Data Science Projects Fail To Get Adopted.* Towards Data Science. Retrieved 200212 from *https://towardsdatascience.com/5-adoption-challenges-that-every-data-science-project-faces-9b9618a7242f*.

Kozlenkova, I., Samaha, Stephen A, & Palmatier, Robert W. (2014). Journal of the Academy of Marketing Science, Journal of the Academy of Marketing Science.

Kumar, V., Chattaraman, V., Neghina, C., Skiera, B., Aksoy, L., Buoye, A., & Henseler, J. (2013). Data-driven services marketing in a connected world. Journal of Service Management, 24(3), 330-352.

Kumar, V., Ramachandran, Divya, & Kumar, Binay. (2020). Influence of new-age technologies on marketing: A research agenda. Journal of Business Research, Journal of Business Research, 1/2020.

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. International Journal of Information Management, 34(3), 387-394

Lau, R., Zhao, J., Chen, G., & Guo, X. (2016). Big data commerce. Information & Management, 53(8), 929-933.

Lee, S., & Kim, S. (2006). A Lag Effect of IT Investment on Firm Performance. Information Resources Management Journal (IRMJ), 19(1), 43-69.

Lilien, G. (2016). The B2B Knowledge Gap. International Journal of Research in Marketing, 33(3), 543-556.

Lin, Y., & Wu, L. (2014). Exploring the role of dynamic capabilities in firm performance under the resource-based view framework. Journal of Business Research, 67(3), 407-413.

Lioukas, C., Reuer, J., & Zollo, M. (2016). Effects of Information Technology Capabilities on Strategic Alliances: Implications for the Resource-Based View. Journal of Management Studies, 53(2), 161-183.

Liu, Y., Foscht, T., Eisingerich, A. B., & Tsai, H. T. (2018). Strategic management of product and brand extensions: Extending corporate brands in B2B vs. B2C markets. Industrial Marketing Management, 71, 147-159.

Margherita, A. (2014). Business process management system and activities. Business Process Management Journal, 20(5), 642-662.

Maxwell, J. A. (2018). Collecting Qualitative Data: A Realist Approach. In Flick, U (Ed.) The SAGE Handbook of Qualitative Data Collection. SAGE Publications Ltd.

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

Medium. (2019).Why domain knowledge is important in Data Science. Medium. Retrieved 200503 from https://medium.com/@anand0427/why-domain-kno wledge-is-important-in-data-science-anand0427-3002c659c0a5

Monauni, M. (2017). Closing the strategy execution gap through business simulations. Development and Learning in Organizations, 31(4), 9-12.

Muluneh, G., & Gedifew, M. (2018). Leading changes through adaptive design. Journal of Organizational Change Management, 31(6), 1249-1270.

Nason, R., & Wiklund, J. (2018). An Assessment of Resource-Based Theorizing on Firm Growth and Suggestions for the Future. Journal of Management, 44(1), 32-60.

Neilson, G. L., Martin, K. L. & Powers, E. (2008). The Secrets to Successful Strategy Execution. Harvard Business Review. Retrieved 200504 from https://hbr.org/2008/06/the-secrets-to-successful-strategy-execution

Panetta, K. (2019). 10 Culture Hacks for Digital Transformation. Gartner. Retrieved 200406 from https://www.gartner.com/smarterwithgartner/10-culture-hacks-for-digital-transformation/.

Paschen, J., Kietzmann, J., & Kietzmann TM., (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. Journal of Business & Industrial Marketing, 34(7), 1410-1419.

Prakash-Maheswari, J. (2018). Breaking the curse of small datasets in Machine Learning: Part 1. Towards Data Science. Retrieved 200426 from https://towardsdatascience.com/breaking-the-curse-of-small-datasets-in-machine-learning-part-1-36f28b0c044d

Provost, F & Fawcett, T. (2013). Data Science for Business. Sebastopol, CA. O'Reilly Media, Inc.

Quinton, S., & Simkin, L. (2017). The Digital Journey: Reflected Learnings and Emerging Challenges. International Journal of Management Reviews, 19(4), 455-472.

Randall, L., & Coakley, L. (2007). Applying adaptive leadership to successful change initiatives in academia. Leadership & Organization Development Journal, 28(4), 325-335.

Reavie, V. (2018). Do You Know The Difference Between Data Analytics And AI Machine Learning?. Medium. Retrieved 200515 from https://www.forbes.com/sites/forbesagencycouncil/2018/08/01/do-you-know-the-difference-between-data-analytics-and-ai-machine-learning/#1ff620225878

Rėklaitis, K., & Pilelienė, L. (2019). Principle differences between B2B and B2C marketing communication processes. Management of Organizations: Systematic Research, 81(1), 73-86.

Resch, K & Enzenhofer, E. (2018). Collecting Data in Other Languages – Strategies for Cross-Language Research in Multilingual Societies. In Flick, U (Ed.) The SAGE Handbook of Qualitative Data Collection. SAGE Publications Ltd.

Sandström, S., Edvardsson, B., Kristensson, P., & Magnusson, P. (2008). Value in use through service experience. Managing Service Quality: An International Journal, 18(2), 112-126.

SAS. (n.d). Big Data, What it is and why it matters. Retrieved 200213 from https://www.sas.com/en_us/insights/big-data/what-is-big-data.html.

Schimel, E. (2020). Don't Trust The Data Alone: Three Reasons B2B Marketers Should Trust Their Intuition. Forbes. Retrieved 200313 from https://www.forbes.com/sites/forbesagencycouncil/2020/01/30/dont-trust-the-data-alone-three-reasons-b2b-marketers-should-trust-their-intuition/#66b26af233fe.

Shan, S., Luo, Y., Zhou, Y., & Wei, Y. (2019). Big data analysis adaptation and enterprises' competitive advantages: The perspective of dynamic capability and resource-based theories. Technology Analysis & Strategic Management, 31(4), 406-420.

Shaughnessy, H. (2018). Creating digital transformation: Strategies and steps. Strategy & Leadership, 46(2), 19-25.

Sirkin, H. L., Keenan, P & Jackson, A. (2005). The Hard Side of Change Management. Harvard Business Review. Retrieved 200519 from https://hbr.org/2005/10/the-hard-side-of-change-management.

Sridhar, S., & Fang, E. (2019). New vistas for marketing strategy: Digital, data-rich, and developing market (D3) environments. Journal of the Academy of Marketing Science, 47(6), 977-985.

Sun, S. J., Hall, D. G., & Cegielski, C. (2019). Organizational intention to adopt big data in the B2B context: An integrated view. Industrial Marketing Management.

Tabesh, P., Mousavidin, E., & Hasani, S. (2019). Implementing big data strategies: A managerial perspective. Business Horizons, 62(3), 347-358.

Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509-533.

Thomson, C. (2019). Top Marketing Trends for 2020. Forbes. Retrieved 140520 from https://www.forbes.com/sites/forbesagencycouncil/2019/10/03/top-marketing-trends-for-2020/#4dc3b6c813d5

Troisi, O., Maione, G., Grimaldi, M., & Loia, F. (2019). Growth hacking: Insights on data-driven decision-making from three firms. Industrial Marketing Management.

Vargo, S.L., Lusch, R.F., Archpru Akaka, M. and He, Y. (2010), "Service-Dominant Logic", Malhotra, N.K. (Ed.) Review of Marketing Research (Review of Marketing Research, Vol. 6), Emerald Group Publishing Limited, Bingley, pp. 125-167.

Wedel, M., & Kannan, P. (2016). Marketing Analytics for Data-Rich Environments. Journal of Marketing, 80(6), 97-121

Wernerfelt, B. (1984). A Resource-based View of the Firm. Strategic Management Journal, 5(2), 171-180

Wiersema, F. (2013). The B2B Agenda: The current state of B2B marketing and a look ahead. Industrial Marketing Management, 42(4), 470-488

Wright, L., Robin, R., Stone, M., & Aravopoulou, D. (2019). Adoption of Big Data Technology for Innovation in B2B Marketing. Journal of Business-to-Business Marketing, 26(3-4), 281-293.

Xu, Z., Frankwick, G., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. Journal of Business Research, 69(5), 1562-1566.

Zott, C. (2003). Dynamic capabilities and the emergence of intraindustry differential firm performance: Insights from a simulation study. Strategic Management Journal, 24(2), 97-125.

Appendix

A. Interview guide 1 - Sales

Background

1. Who are you?
2. What is your current occupation?
3. Could you tell us about your background such as your education and former work experiences?

Internal questions

1. Does the sales department use digital tools today?
    a. How do you use them?
    b. How are the tools used for data analytics?

2. How do you use data today in your department?
    a. How do you gather data?
    b. How do you select what data to gather?
    c. What kind of tools do you use to gather data?

3. What kind of tools do you use to analyse the data?
    a. Do you feel like something is missing with the analytics tools?
    b. What kind of improvements can be done with the tools?

4. How important is digital- and data analytics tools for you in your daily work..
    a. In the sales department?
    b. In the entire company?

5. Has your daily work become easier with help of digital tools? How?
    a. How could data- and analytic tools help or ease your work?

6. Could you please explain how you process the data with your (analytical) tools in each step, from inquiry to finished project?

7. How does sales and IT consultants cooperate together with these tools?

8. How does sales and marketing cooperate together with these tools?

9. Do you have any goals to become more data driven?
    a. What is the goal/s?
    b. If no, why don’t you have a goal?

10. Have you experienced any resistance towards implementation of digital tools in the firm?
    a. How are they resistant?

   b. Why do you think they are against it?

External questions

1. Is the demand for digital tools and data driven solutions increasing among firms?
   a. How do you notice the increased interest?
   b. Is there differences between industries?

2. What kind of digital tools are requested the most by your customers? Can you see ant trends?
   a. Do they often have realistic expectations?
   b. How do you meet those expectations?

3. What goals do the clients have in becoming data driven?

4. Do you have any measurements, such as ROI, to track improvements for your clients' implemented tools?

5. Have you experienced any resistance towards implementation of digital tools with your customers?
   1. How are they resistant?
   2. Why do you think they are resistant?
   3. Are there differences in scepticism/conviction between demographics or professionals etc.? Can you see any trends there?

6. According to our research there are a lot of digital transformation projects that fail, do you find that to be correct?
   a. Why do you think they fail?
   b. What are the reasons/factors for these failures?

7. Can you identify any specific qualities that your clients should have (type of organisation or organisational qualities) to affect a digital transformation positively? Or some kind of successfactors that are important?
   a. What resources are central in order to succeed with a digital transformation?

Lastly:

- The purpose with this thesis is to see how B2B firms successfully can implement data driven processes and data and analytic tools in marketing and sales. Considering the purpose, do you have anything to add that can be of any help for us?

B. Interview guide 2 - Marketing

Background

1. Who are you?
2. What is your current occupation?
3. Could you tell us about your background such as your education and former work experiences?

Internal questions

1. Does the marketing department use digital tools today?
    a. How do you use them?
    b. How are the tools used for data analytics?

2. How do you use data today in your department?
    a. How do you gather data?
    b. How do you select what data to gather?
    c. What kind of tools do you use to gather data?

3. What kind of tools do you use to analyse the data?
    a. Do you feel like something is missing with the analytics tools?
    b. What kind of improvements can be done with the tools?

4. How important is digital- and data analytics tools for you in your daily work.. Hur upplever ni behovet av IT och data-verktyg i ert dagliga arbete?
    a. In the marketing department?
    b. In the entire company?

5. Has your daily work become easier with help of digital tools? How?
    a. How could data- and analytic tools help or ease your work?

6. Could you please explain how you process the data with your (analytical) tools in each step, from inquiry to finished project?

7. How does marketing and IT consultants cooperate together with these tools?

8. How does marketing and sales cooperate together with these tools?

9. Do you have any goals to become more data driven? Har ni ett mål med att bli mer datadrivna internt?
    a. What is the goal/s?
    b. If no, why don't you have a goal?

10. Have you experienced any resistance towards implementation of digital tools in the firm?
    a. How are they resistant?

   b. Why do you think they are against it?

External questions

1. Is the demand for digital tools and data driven solutions increasing among firms?
   a. How do you notice the increased interest?
   b. Is there differences between industries?

2. What kind of digital tools are requested the most by your customers? Can you see any trends?
   a. Do they often have realistic expectations?
   b. How do you meet those expectations?

3. What goals do the clients have in becoming data driven?

4. Do you have any measurements, such as ROI, to track improvements for your clients' implemented tools?

5. Have you experienced any resistance towards implementation of digital tools with your customers?
   a. How are they resistant?
   b. Why do you think they are resistant?
   c. Are there differences in scepticism/conviction between demographics or professionals etc.? Can you see any trends there?

6. According to our research there are a lot of digital transformation projects that fail, do you find that to be correct?
   a. Why do you think they fail?
   b. What are the reasons/factors for these failures?

7. Can you identify any specific qualities that your clients should have (type of organisation or organisational qualities) to affect a digital transformation positively? Or some kind of successfactors that are important?
   a. What resources are central in order to succeed with a digital transformation?

Lastly:

- The purpose with this thesis is to see how B2B firms successfully can implement data driven processes and data and analytic tools in marketing and sales. Considering the purpose, do you have anything to add that you might think can help us?

C. Interview guide 3 - IT (consultants)

Background:

1. Who are you?
2. What is your current occupation?
3. Could you tell us about your background such as your education and former work experiences?

Data analytics

1. What kind of data analytic tools are the most requested today by your customers?
    a. Why do they come to you at Findwise?

2. How do you decide what kind of tools that are needed for each client?
    a. Are there many differences between the clients or does it often concern the same issues?
    b. Are clients often aware of what kind of tools they need or how the tools can improve their business?
    c. Do the clients often have realistic expectations? Har kunden realistiska krav/förväntningar?
    d. How do you meet those expectations?

3. What goals do the clients have in becoming more data driven?

4. Do you have any requirements on your clients before implementation?
    a. What requirements do you have?
    b. What kind of resources do the clients need in order to become more data driven? (such as knowledge, money, time, data, data quality)
    c. How do you use those resources in the transformation process?

5. Have you experienced any resistance towards implementation of digital tools among your clients?
    a. How are they resistant?
    b. Why do you think they are resistant?
    c. Are there differences in scepticism/conviction between demographics or professionals etc.? Can you see any trends there?

6. Do you feel that your digital tools or digital solutions have had a positive impact for your clients?
    a. In what way?

7. Do you have any measurements, such as ROI, to track improvements for your clients' implemented analytics tools?

8. According to our research there are a lot of digital transformation projects that fail, is that correct?
    a. Why do you think they fail? Varför tror ni att det misslyckas?
    b. What are the reasons/factors for these failures?

9. Can you identify any specific qualities that your clients should have (type of organisation or organisational qualities) to affect a digital transformation positively? Or some kind of successfactors that are important?
    a. What resources are central in order to succeed with a digital transformation?

10. What opportunities can you see with digital tools in marketing and sales in the future?

Lastly:

- The purpose with this thesis is to see how B2B firms successfully can implement data driven processes and data and analytic tools in marketing and sales. Considering the purpose, do you have anything to add that can be of any help for us?