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ALIGNING BUSINESS STRATEGY WITH BUSINESS ANALYTICS TO CREATE VALUE FOR THE FIRM

Master's thesis 2019

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ABSTRACT

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The purpose of this qualitative study was to determine how contemporary companies can align their business analytics (strategy) with their business strategy to create value and what kinds of aspects need to be considered for the value creation to be possible from the alignment within those companies.

The study was conducted in Helsinki, Finland during the year 2019 and the interviews took place during the autumn. The study utilized primary data that was gathered through a series of 7 in-depth semi-structured interviews with either managers or experts / analysts in contemporary organizations operating in Finland.

The results implicate that a ‘right way’ of aligning business analytics (strategy) and business strategy in contemporary companies does not exist and that the ability to align the two concepts rather involve accounting for several different aspects and realities that all carry their own weight towards fulfilling the alignment within the specific case company in question. In other words, each company is its own case and the importance of the alignment of the concepts also depended on the size, age and business area of the organization in question.

TIIVISTELMÄ

Tekijä	Sebastian Rainbird
Opinnäytteen nimi	Liiketoimintastrategian kohdistaminen liiketoiminta-analytiikan kanssa arvon luomiseksi yritykselle
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Tämän laadullisen tutkimuksen tarkoitus on määritellä, kuinka nykyajan yritykset voivat kohdistaa käyttämänsä liiketoiminta-analytiikan (ja/tai siihen liittyvän erillisen strategian) oman liiketoimintastrategiansa kanssa niin, että sen kautta on mahdollista luoda kyseiselle yritykselle arvoa. Tarkoituksena on ymmärtää minkälaiset seikat tähän potentiaaliseen arvon luontiin nykyajan yrityksissä vaikuttavat ja minkä takia.

Tutkimus toteutettiin Helsingissä, Suomessa, vuoden 2019 aikana ja laadulliset haastattelut toteutettiin syksyn 2019 aikana. Tutkimuksessa käytetty primaarinen aineisto koostui 7 perusteellisesta semistrukturoidusta haastattelutilanteesta muutaman eri yrityksen esimiesasemassa tai asiantuntijaroolissa työskentelevän työntekijän kanssa.

Saatujen tuloksien mukaan yhtä oikeata tapaa kohdistaa liiketoiminta-analytiikkaa (ja/tai siihen liittyvää erillistä strategiaa) liiketoimintastrategian kanssa ei ole olemassa, vaan kyse on enemmänkin usean eri aspektin huomioon ottamisesta arvonluomisen mahdollistamiseksi yrityksessä. Tulokset viittaavat myös siihen, että jokainen yritys on oma kokonaisuutensa eivätkä huomioon otettavat aspektit ole välttämättä samat eri yrityksien välillä. Lisäksi, konseptien kohdistamiseen vaikuttaa myös kyseessä olevan yrityksen koko, ikä ja liiketoiminta-alue.

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Table of Contents:

Table of Figures:

List of Tables:

List of symbols and abbreviations:

BA	=	Business Analytics
BASM	=	Business-Analytics Success Model
BDA	=	Big Data Analytics
BI	=	Business Intelligence
BPER	=	Business Process Performance
BV	=	Business Value
FP	=	Firm Performance
IT	=	Information Technology
KPI	=	Key Performance Indicator

1 Introduction

1.1 Background of the study

Business environments around the world are changing at a fast pace and that change is for the major part being driven by different kinds of technological advancements. Contemporary companies need to be able to become increasingly more agile in the way they work and are able to answer their clients changing needs and wants. A company’s ability to survive in the marketplace is dependent on how well it can re-invent itself and the way it works. (Aydiner & al., 2019) The adoption and use of business intelligence and business analytics help contemporary companies overcome these challenges in their immediate business environments.

These advancements in technology have forced decision-makers to face an information overload in terms of trying to process all the relevant information regarding an upcoming business decision. The information overload is particularly hard to handle because of the limited information processing capability of the decision-makers. In addition to the advancement of business analytics, business intelligence related technology has also become more powerful and cheaper to purchase. Therefore, it is easier and cheaper than ever before for companies to gather data, and the problem now is how to generate meaningful actionable insights from all that gathered data. (Klatt & al., 2011)

The previously mentioned information overload can present itself in the form of extensive data sets or big data. Information technology and business analytics capabilities within companies present different kinds of techniques to better manage all the information and focus on supporting decision-making processes. Essentially firms want to circumvent potential problems in decision-making caused by the information overload and not being able to process all the information available (Aydiner & al., 2019).

According to Vidgen & al. (2017) people and companies live in “an age of data deluge.” In other words, data is being stored from just about everything we say, do or buy. This is a big part of the reason why big data and analytics have become buzzwords in contemporary companies. Different kinds of analytics methods are being used to predict, describe and even prescribe decision-making in data-driven companies. Alternatively, predictive analytics can also be used to predict medical conditions or simple product selection preferences from customers, as examples. Due to the increase in the amount of stored data, its characteristics are also changing according to Zikopoulos & al. (2012):

- (1) Volume – Increasing amount of data collected (e.g. through the internet of things),
- (2) Velocity – The pace at which data is generated is increasing. (e.g. sensor technology),
- (3) Veracity – A variety of different forms of data can be utilized in the future. (e.g. structured vs. unstructured, text, social media and video). (Vidgen & al., 2017)

The terms ‘business analytics’, ‘business intelligence’, ‘data’ / ‘big data’ and ‘information technology’ are an integral part of this study. This is because all the terms are interlinked and typically affected by one and / or the other. Therefore, it is important to distinguish the differences between the terms in the context of this study.

Business analytics according Seddon & al. (2017) is defined by the act of “using data to make sounder, more evidence-based business decisions.” Business intelligence refers to information technology related tools that make business analytics possible (e.g. statistical and quantitative tools, data warehouses and / or visualization tools) (Seddon & al., 2017), and according to Davenport & Harris (2007) business intelligence “is an umbrella term for an enterprise-wide set of systems, applications, and governance processes that enable sophisticated analytics, by allowing data, content, and analyses to flow to those who need it, when they need it.” Additionally, Davenport (2006) describes the differences between business analytics and business intelligence by stating that: “Business analytics focuses on developing new insights and understanding of business performance whereas business intelligence traditionally focuses on using a consistent set of metrics to both measure past performance and guide business planning.”

Information technology consists of business intelligence (umbrella term for an enterprise-wide set of systems) and other things and is regarded as a broader term in comparison to the others. The role of information technology in a company context traditionally is cost reduction, productivity and efficiency improvement (Suryanarayanan & al., 2018). In comparison to business analytics, these two terms complement each and other because the goal of analytics is to change the way businesses think and use data, improve decision-making processes on an operational and strategic level as well as challenging the pre-existing biases that managers bring to the decision-making processes based on their previous experiences (Suryanarayanan & al., 2018).

The meaning of big data or data is rather self-explanatory in this context because it stands for the information that is collected by the company that is then utilized to make those better-informed decisions using business analytics that in turn, are enabled by information technology and the business intelligence under it.

The bottom line is that business analytics should be thought of as problem solving, and it is important to note that generally it is the people who are responsible for generating insights from data provided to them. No amount of computing power can take care of the creative work related to human problem solving and generating insights from data. This also means that the people who are behind the creative work related to insight generation from data are also supported and hindered by their individual knowledge, limitations and cognitive abilities (Seddon & al., 2017).

Companies employing enough analytics capabilities (e.g. analytics adoption, analytics culture and analytics alignment with business) in order to be able increase business value through business analytics is an important area of study to consider and explore. For example, Shanks & Bekmamedova (2012) argue that increased business value and more efficient firm performance can be achieved through operational and dynamic business analytics capabilities (Suryanarayanan & al., 2018).

According to the comparative case study on business analytics and value by Suryanarayanan & al. (2018), information technology investments in companies have started being held in higher regard by people during the past two decades, considerably more than they were earlier. Over two decades ago information technology investments were used to be considered as part of a company’s internal organizational structure, business processes and workplace practices. During the past two decades however, information technology investments have become more valuable because they extend their reach to external factors or actors within the business environment of an organization. In other words, information technology should be linked to complementary organizational resources (like subcontracting for example) or the company's clients information technology systems directly. Furthermore, a study by Bharadwaj (2000) stated that companies should be doing a more than just invest in information technology, they should be attempting to create company-wide information technology capability. However, the problem with this is that it is not clear how to create this capability (Suryanarayanan & al., 2018). Even though information technology capability and business analytics capability are not the same thing, they still are linked together and fulfil each and other. Figure 1 below portrays the perceived order in which business value is created through information technology / business analytics investments (Kohli & Grover, 2008).

Figure 1:Value creation process for IT or BA investment projects in companies. (Kohli & Grover, 2008)

Performance measurement or business performance has been and still is an important part of strategic management research. The amount of aspects to consider when measuring business performance is dependent on the company in question, but at the very least the measurements should consist of financial indicators that measure if the company is reaching its preset economic goals. In addition, business performance measurement can also include technological aspects that are not directly related to the company's financial indicators. For example, a company can also measure its technological efficiency when it comes to information technology investments or business analytics investments and their conversion to value for the business. (Suryanarayanan & al., 2018) In other words, analytics or information technology investments can increase firm performance by making the business processes around them more efficient or alternatively making them cheaper to maintain through new technology. With that said, it is important to note that in most cases measuring these investments is challenging, which can make pushing them through less enticing for contemporary business leaders and managers. Additionally, because the measured business value is likely to be moderated by other factors (e.g. creating the needed capability to use newly adopted analytics tools or software in order to generate actionable insights), converting this into business value is often perceived to being riskier and harder to justify in comparison to simpler investments (e.g. employing / hiring new resources).

Even though the conversion of analytics / information technology investments to business value is considered being risky and challenging, according to Suryanarayanan & al. (2018) increased firm performance is achieved when management is committed towards the intended investment. In addition to management commitment, also previous experience, user satisfaction and the company's internal political stability also play their own role in being able to convert an information technology or analytics capability investment into business value. More accurately, the value conversion process is described to consist of shared learning, collaborative relationships and a combination of information technology decision-making and competence. Furthermore, according to Kohli & Grover (2008) the value creation process works in the way portrayed in Figure 1. Consequently, the research suggests that companies should first focus on determining the capabilities required, after which, they should determine what is required to build upon those capabilities (Suryanarayanan & al., 2018).

While looking into big data in management academic literature Mazzei & Noble (2017) made the same discovery as George & al. (2014); a large part of academic research focuses on how big data will affect and change academic research instead of looking into how it is disrupting the processes of corporate managers and strategists. In other words, the management field in academic literature has not paid much attention to the practical and academic implications of big data in management literature, despite it having gone mainstream in organizations over the past two decades (Mazzei & Noble, 2017).

According to McAfee & Brynjolfsson (2012) the fact that big data is perceived as a simple performance enhancement to pre-existing organizational processes is dangerous and undermines its potential impact on contemporary organizations (e.g. through digitization) (Mazzei & Noble, 2017). It is paramount that big data is considered as more than a mere performance enhancement – adding analytics (big data analytics) to the mix instantaneously increases the potential power of the concept in general.

1.2 Research gap and research questions

The goal and the research gap for the selected literature was to find out what aspects have been studied in regard of business analytics value creation and how or if it has been deliberately linked to overall business strategy. Secondly, it also aimed at pinpointing benchmarks from prior research by scholars regarding the area in general. Finally, emphasizing on finding previously used frameworks and models regarding the measurement of business analytics capability / information technology capability value to the firm.

The following core and supporting research questions were formulated to be the basis for this study.

Core research question:

1. How to align business strategy with analytics (strategy) to create value for the firm?

Supporting research questions:

1. How to decrease the conceptual distance between company strategic goals and business analytics?
2. Why is it challenging to create firm value through business analytics in the terms of decision-making processes?

1.3 Scope of the study

The scope of the thesis is to benchmark and outline the status of research on value creation through business analytics and business strategy alignment and evaluate and validify the aspects researched by academics through qualitative interviews aimed at practitioners.

The thesis aimed to generate food for thought for practitioners and provide examples of theoretical models regarding firm value creation through business analytics and the alignment between business strategy and business analytics. These are generally aimed at companies that are working towards becoming data-driven and utilize business analytics more in every aspect of their operations and strategic planning.

The thesis also discusses business analytics as a concept as well as, attempt to identify the most typical challenges in terms of creating value with business analytics, and its implementation to be a part of an organization’s decision-making processes from a managerial perspective.

1.4 Structure of the thesis

This thesis consists of an introductory section that aims to clarify the background, research gap, scope and structure regarding the chosen subject and research questions. The literature review section will base its concentration on studying and comparing existing texts and academic frameworks on the subject. Which were then linked to the research design and methods section as well as the discussion and conclusions sections that will discuss the empirical findings regarding a set of semi-structured qualitative interviews aimed at carefully selected practitioners.

The discussion section will study and contemplate the results of the qualitative interviews conducted. The conclusions section will attempt to summarize the key points made during the research and empirical processes, as well as provide the reader with key managerial implications that also act as answers to the initial research questions outlined as part of the introduction.

2 Business analytics alignment with business strategy to create value

2.1 The concept and role of business analytics

Lavalle & al. (2011) identified a collection of three levels of analytic capability within contemporary companies (see Figure 2). In order for a company to be able to move towards the third and final prescribing ‘Transformed’-stage, Shanks & Bekmamedova (2012) imply that an organizations dynamic capability and its ability to extend, modify and create

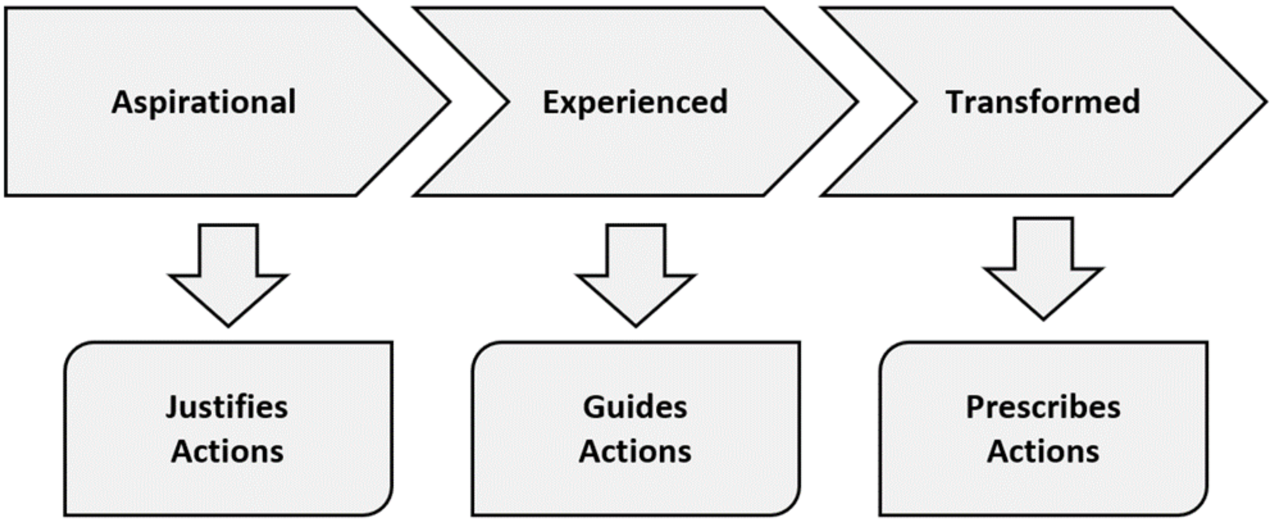

Figure 2: The levels of analytic capabilities in companies (Lavalle & al., 2011)

resources can lead to improved business value and competitive advantage, if adopted into the organization’s processes and culture over a period of time (Vidgen & al., 2017).

According to LaValle & al. (2011) well-performing organizations use analytics to support their decisions-making processes more in comparison to organizations that are not performing as well. Moreover, insights that are generated from business analytics in well-performing organizations are used to guide everyday operations as well as long term strategy formulation (Sharma & al., 2014). This is generally not the case in companies that don’t perform as well in the use of analytics to support its decision-making processes.

Sharma & al. (2014) also make a point regarding insight generation. Even though, contemporary companies have a myriad of different kinds of tools to help them manage their data and use it for reporting, insights from business analytics are not created by simply applying the tool to a dataset, instead insights are created when tools are used on data and the entire process, data selection and the outcome thereof is discussed between managers and analysts. It is also important to note that the insight generation process described previously, already exists within a company’s decision-making processes and is susceptible to the managers pre-existing thoughts and perceptions on the subjects that are being decided on. In other words, insight generation from business analytics involves several people from the different functions of the organization, and these groups of people have been put together for a common purpose based on an outcome that is a result of a previously made managerial decision. Furthermore, these managerial decisions regarding group composition can either help or hinder the insight generation process because the decisions regarding group formation are extremely important (Sharma & al., 2014).

Lycett (2013) describes the insight generation process as a: “IT-driven sense-making process in which data is used to understand a phenomenon that the data represents.” Furthermore, he named this process as ‘datafication’. To clarify his perception of the process further, the generated insights are converted into stories by analysts and managers that aim to make sense of the selected phenomenon that is the subject of the decision-making process at that given moment. After explaining the phenomenon, the teams engage in forming a set of actions, insights and solutions that then make the phenomenon and the related decision-making or solution a reality (Sharma & al., 2014).

In conclusion to understanding the impact of business analytics to organizations, it is important to realize that the method how organizations utilize and implement technologies directly affects their ability to create insights and capture value. Especially managers need pay attention when it comes to changing their decision-making processes when they are employed by companies that are in the process of becoming data-driven (Sharma & al., 2014).

Prior research also suggests that the information technology function (IT) in an organization influences value generation positively as well as plays a part in business-critical strategic-level decision-making (Drnevitch & Croson, 2013). To support the previous statement, Mazzei & Noble (2017) argue that in some cases the relationship between data and strategy and the way they influence each other has changed over the recent years. In other words, the information technology function is becoming increasingly important because it is generally the function that proclaims ownership of the tools that make data analysis a reality. With that said, the presence of the information technology (IT) function in business-critical situations is there to stay, but the perception on how strategies are formulated can be subject to change in the future (see Figure 3).

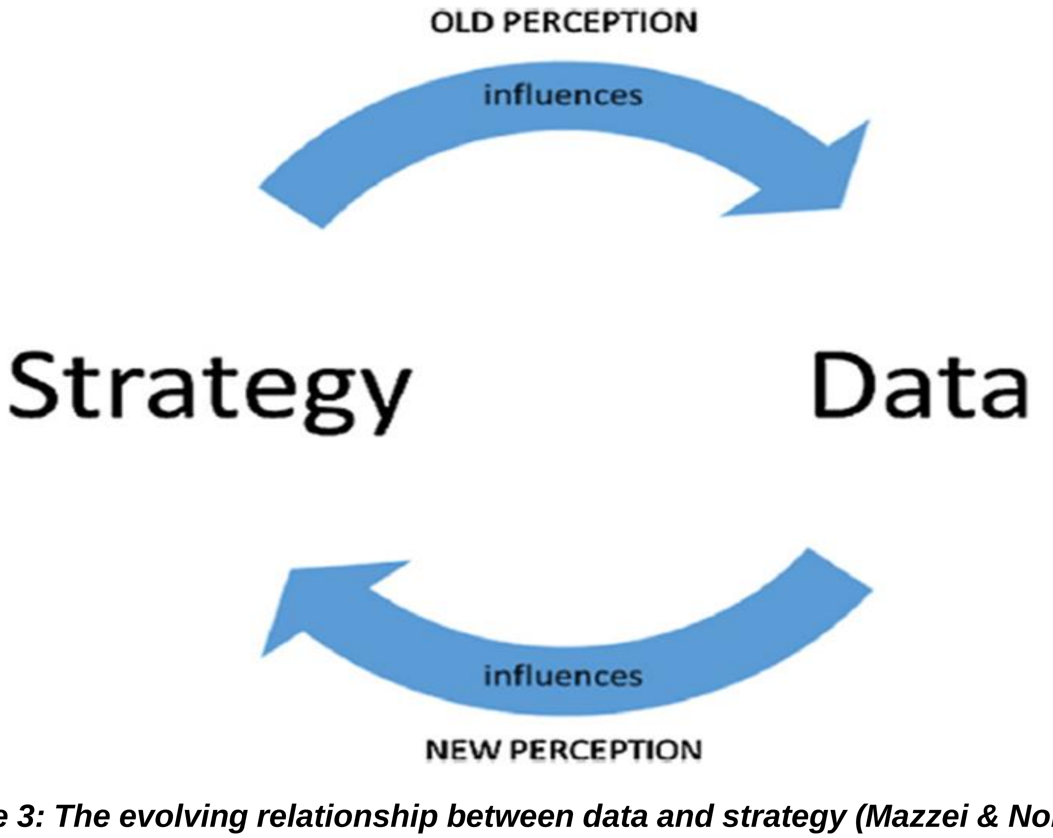

Figure 3: The evolving relationship between data and strategy (Mazzei & Noble, 2017)

As shown in Figure 3, the old perception was that strategy influenced data and determined what kinds of data are being gathered and analyzed, whereas the new perception works the other way around – the data gathered and analyzed influences the formulation of corporate strategy.

Interest in analytics' application in strategic planning is growing among both practitioners and scholars. Klatt & al. (2011) found that analytical planning style is positively associated with better performance. While better-performing firms did not differ in formal reporting or intuitive assessments in the strategic planning process, they differed significantly concerning the application of comprehensive, rational data analysis (Klatt & al., 2011).

Chae & al. (2014) pointed out that business analytics uses data extensively, for example statistical and quantitative analysis techniques, explanatory and predictive models using mathematical and computer-based algorithms to gain insight about business operations. Moreover, business analytics helps organizations build up a fact-based management system (Bayrak, 2015; Holsapple, Lee-Post & Pakath, 2014), which is explained as a set of business and technical activities with a collection of tools for manipulating, mining, and analyzing environments (Sharda & al., 2016; Sun, Strang & Firmin, 2017).

The continuous cycle from data acquisition and processing towards business processes is among the most critical chains that convert data from different sources into consolidated information that can be used to draw actionable insights (Delen, 2015). Therefore, data acquisition and processing related information systems applications are generally included as part of the business analytics adoption models, such as information propagation, data warehousing, data capturing, and document management systems. Furthermore, this is also the link that intertwines / moderates the relationship between business analytics and the information technology functions in contemporary companies.

According to several academics (e.g. Barton & Court, 2012; Davenport & Harris, 2007), big data and analytics have the potential to drastically change the way organizations do business. Furthermore, big data analytics capability is undoubtedly one of the most important aspects to focus and build on when considering an organization that bases its core business within the big data environment (Davenport, 2006), or is attempting to achieve sustainable competitive advantage, through the process of becoming wholly data-driven.

2.2 Business analytics in terms of value creation

In order to properly understand how companies derive value from business analytics, it is important to understand how their resource orchestration and allocation processes work. Some of the guidelines regarding deriving value from business analytics are undoubtedly similar between companies, however it is ultimately dependent on the company attempting to do so. This also means that for a company that is on the path of transforming into a data-driven organization, it is imperative that it evaluates its resource allocation and orchestration processes as part of the change and ensures that they support the desired outcome (e.g. becoming a wholly data-driven organization).

A company's ability to generate insights from business analytics is important, but so is the ability of converting the insights into decisions – without the formulation of decisions, no measurable value can be created for the firm. More accurately, the quality of decision-making in companies has been affected by the scarcity of time, adequate knowledge and training accompanied by complicated circumstances.

According to Mazzei & Noble (2017) big data and analytics have recently had significant impacts on organization strategy formation. Even though, data and analytics have been used in organizations from the 1950's, the disruption started happening over the past two decades due to the increased availability and cost reduction of computing power and storage devices and / or methods (Acito & Khatri, 2014).

According to Evans (2013), companies currently witnessing a change in practice that has started to pull apart some of the theories that have been developed over the past 40 years in the field of strategic management. Changes in typical value chains and competitive forces are a good example of the disruptive power of big data analytics (Evans, 2013). Moreover, according to Mazzei & Noble (2017), the final goal for organizations engaging in big data analytics should be the creation of a sustainable competitive advantage through complex data flows and ecosystems – and being able to maintain the position through real time data processing and cutting-edge analytics capabilities.

On a small-scale, big data analytic technologies are currently known to be used to improve the performance of business processes that already exist, and organizational leaders perceive analytics as a capability and data as a resource (Wernerfelt, 1984) – which both, especially when paired together, lead to organizational success, performance enhancement or even sustained competitive advantages. Additionally, data access is perceived as an enabler for more efficient value chain problem-solving, because it allows executives to back-up their problem-solving capabilities with data and analytics – which in turn enables drawing meaningful conclusions from the data to support the decision-making process associated with solving the problem at hand (Mazzei & Noble, 2017).

According to Davenport & al. (2012), some visionary business leaders and executives exist who have concentrated on making their organizations focus on developing data resources that enable the creation of new business models that merge both ways of strategic thinking – old and new. These business leaders and executives have made data a focal part of their organizational strategy and put more emphasis on data flows over data stocks (Davenport & al., 2012). Having emphasis on data flows over data stocks throughout the organization is a prime example of a wholly data-driven organization.

Organizational strategies receive additional attention especially in the cases in which the organization operates within the big data environment. This is because new business opportunities, micro (e.g. customer preferences) and macro (e.g. economic trends) can be determined with little or less effort in comparison to other environments (Constantinou & Kallinikos, 2014; George & al., 2014). Furthermore, Davenport & al. (2012) states that organizations that can identify the constant change in the macro and microenvironments, and can act swiftly to those changes, will end up having advantages over their competitors (Akter & al., 2016).

Even though there are studies stating that business analytics capabilities and applications provide better business value and lead to organizational performance (Bayrak, 2016; Tan & al., 2016), there are also studies that focus directly on the impact of business analytics in terms of decision-making performance without considering its impact on business processes (Cosic & al., 2015; Gunasekaran & al., 2017; Ramanathan & al., 2017; Sun & al., 2017). Some of those studies imply that performance indicators of business processes should be harmonized with the firms' objectives (Bisogno & al., 2016) and that firms can achieve significant performance gains if business analytics is adopted to align with business processes and the objectives of firms (Ramanathan & al., 2017).

Value creation through business analytics, big data and information technology combined is a complex concept and is not understood completely by practitioners or scholars due to it being such a new phenomenon. Therefore, it is important to consider the different research models, statements, arguments, studies and theoretical frameworks before drawing any conclusions on the subject matter. With that said, it is also important to consider each company as its own case, when it comes to attempting to derive value from business analytics.

2.3 The challenges associated with business analytics

Management challenges regarding business analytics capability development and adoption is an important subject to study. Creating business value from business analytics or information technology capabilities, or improvement thereof is challenging unless all variables are being considered. Especially if or when a company is attempting to measure direct financial impact from these kinds of initiatives.

The hype and disruptive ability of big data and analytics has presented organizations with challenges (Mazzei & Noble, 2017). Particularly, the collection, analysis and storage of data are important aspects for companies to consider as they attempt to capture value from big data and analytics. Additionally, understanding and implementing the technical requirements for the capabilities that enable insight generation is a necessity for value capturing from big data and analytics to become a reality within the organization. Furthermore, Mazzei & Noble (2017) agree with Morabito (2015) who states that the disruptive potential of big data and analytics requires organizations to consider it on a strategic level alongside other strategic level decisions taking place within the organization. This is because big data analytics is a complex, diverse and large concept that requires its own visions and strategy for returns on investment to take place.

Similarly to Sharma & al. (2014) and Mazzei & Noble (2017) also emphasize the many questions that contemporary managers are currently facing or will face soon in regard of big data analytics; how should the data be gathered, codified and stored, how should it be interpreted and analyzed, and perhaps most importantly, how can generated insights be converted into measurable value for the organization. Being able to answer these questions, will help organizations immensely in capturing value from big data and analytics initiatives, and will also contribute to the amount of understanding how that value can be captured and measured throughout all these different initiatives (Mazzei & Noble, 2017).

Vidgen & al. (2017) conducted a Dephi study complemented by a couple case companies in order to be able to determine how organizations create value from data and what kinds of challenges they faced in terms of building on their business analytics capabilities. The case studies confirmed the findings of the Delphi study and the outcome was a collection of key challenge areas (see Figure 4).

Thirty-one Delphi items grouped by research construct.

Category	Rank/average	Item	Rank
Value (3)	1 (6.0)	Using analytics for improved decision making	2
		Measuring customer value impact	7
		Establishing a business case	9
People (3)	2 (9.3)	Building data skills in the organization	5
		Analytics skills shortage	8
		Technical skills shortage	15
Technology (2)	3 (13.0)	Restrictions of existing IT platforms	6
		Managing data volumes	20
Data (7)	4 (13.3)	Managing data quality	1
		Availability of data	4
		Getting access to data sources	10
		Managing and integrating data structures	17
		Managing data security and privacy	18
		Data visualization	19
		Defining what 'big' data is	24
Process (4)	5 (20.0)	Producing credible analytics	11
		Managing data processes	14
		Manipulating data	26
		Performance management	29
Organization (12)	6 (20.9)	Creating a big data and analytics strategy	3
		Building a corporate data culture	12
		Making time available for analytics	13
		Overcoming resistance to change	16
		Agreeing data ownership	21
		Managing costs of analytics	22
		Defining the scope of analytics projects	23
		Securing investment	25
		Legislative and regulatory compliance	27
		Using the data ethically	28
		Safeguarding reputation	30
		Working with academia	31

Figure 4: Thirty-one Delphi items grouped by research construct. (Vidgen & al., 2017)

Some of the most important issues identified in the Delphi study that were confirmed by the case studies were the following; firms need a well-defined analytics and data strategy if they are to pursue business value from such initiatives, firms need to change their internal culture when first attempting to become data-driven and the right people need to be employed in the right positions to make this change happen, firms need to be able to think of ethics related to the use of data and information when using it to pursue competitive advantage. Finally, the quality of data should be thought of as an enabler in terms of being able to generate value from business analytics; if the data is inaccurate the insights that can be drawn from it are also utterly useless, if this is not the case it is more likely that the collected and analyzed data can be converted into valuable and actionable insights for the use of the organization. Despite the extensive information provided by the Delphi study conducted by Vidgen & al. (2017), it is important to take into consideration the fact that answers to questions change depending on to whom and to which part of the organization you present the question to. For clarification, the sample for the Delphi study consisted of 36 practitioners, 23 consultants and 13 academics (72 complete responses) (Vidgen & al., 2017). These numbers were not clarified in further detail, so it is not possible to draw a conclusion about the sample groups further. It could have been informative to know how many of the practitioners represented the different functions of the organization they worked in and how many of them were employed in managerial positions.

Changing an organizational culture towards becoming data-driven is comprised of more than just variables that are related to potential technical issues regarding the new information or analytics technology. According to Vidgen & al. (2017) firms seeking a competitive advantage through a data-driven analytics culture should primarily focus on their business analytics departments and the related capabilities within that function. Enough business analysts, data scientists and IT personnel are needed for solving the analytics challenges in collaborative teams (Vidgen & al., 2017). Kiron & Shockley (2012) reinforce Vidgen & al.'s (2017) notions regarding the development of a data-driven culture within an organization and continue to suggest that contemporary companies need to develop data-oriented management systems in order to be able to utilize the growing amount of data available for them. Furthermore, they also state that the gathered data should be used to gain a competitive advantage along with an increase in business value, not just one or the other (Kiron & Shockley, 2012).

Vidgen & al. (2017) identify a specific issue regarding an organizations ability of becoming data-driven from the managerial perspective, that is supported by the Delphi study they conducted as part of the research (see Figure 4 for Delphi study findings). The clear data strategy, which was already mentioned earlier, also enables other potential key issues to be solved. For example, 'overcoming resistance to change' and 'building a corporate data culture' are key issues that need solving. This is because for change to happen, the ideas need to be sold to the employees who then act as 'champions for change' to speed the process of change within the organization (basics of any change management program) (Vidgen & al., 2017).

For an organization to become data-driven, in addition to having a clear data strategy, the organization also needs to employ the right people with the right skillsets to drive and affect the organization’s cultural change towards a wholly data-driven future. Because these skillsets can be hard to come by it is likely that additional training for existing staff is needed (Vidgen & al., 2017). Additionally, even though the use of data and business analytics is a potential source of competitive advantage for an organization, it is important to keep in mind the ethics related to the data that is being gathered. Especially from the customer point-of-view the difference between added value and an ethical issue is small.

Davenport (2006), Davenport & Harris (2007) and Davenport & al. (2010) present creating a business analytics competency center in an organization as a potential solution if the organization in question does not employ enough trained people with an analytical skillset. However, evidence suggests the contrary and states that central business units like the one suggested by Davenport & al. (on many occasions) does not link up with other business units very well. Since, the insight generation process is characterized by the collaboration between the personnel belonging to different business units, Sharma & al. (2014) suggest that a central competency unit cannot address the potential issues regarding insight generation that were discussed earlier. For further clarification, Sharma & al.’s (2014) suggestion is backed up by the perception of how a data-driven organization works. Data needs to be available for everyone throughout the organization (dataflow), especially when decisions or problems are being assessed.

The ability to convert decisions to value also incorporate two identifiable uncertainties, that no doubt is common with all organizations everywhere – implementation uncertainty and uncertainty related to strategic action success. Even though it is safe to assume that the quality of decisions can be improved through business analytics, it should also be noted that it is not certain if the acceptance related to those decisions can. Furthermore, prior research posits that in many cases the key personnel who oversee an organization’s resources are not included in the processes of insight-generation and decision-making (Shanks & al., 2010; Shanks & Sharma, 2011). This leads to the situation in which managers who have not taken part in the decision are left with the responsibility to ensure that implementation carried out adequately. Even though, the personnel participating in the insight-generation and decision-making processes consists of cross functional groups for different parts of the organization, the personnel who oversee the resources are generally not part of these groups. Because of this, it is unclear how business analytics can affect an organizations resource orchestration capability (Sharma & al., 2014).

Strategic actions are taken by organizations in the desire of positive results. These results are often not the ones the organizations initially expected due to external uncertainty that cannot be controlled by the organizations themselves (Clemons & Row, 1991). Therefore, it is also unclear if business analytics supported decisions could potentially be affected by the same kind of uncontrollable uncertainty (Sharma & al., 2014). With that said, it is safe to state that potential decision uncertainty depends on the issue or decision that is being assessed and should be evaluated thoroughly before proceeding further.

According to a study conducted by Baldwin (2015), a striking 80% of organizations fail at integrating their data with their business processes, which is supported by the fact that 65% of those organizations perceive their data management capabilities or practices as weak. The same study also highlighted the fact that 67% of the organizations did not have a way to measure the success of the big data and analytics investments they had made (Baldwin, 2015).

Organizations attempts to enhance their performance though big data analytics has also presented them with related challenges. One of the reasons for these challenges is the fact that organizations have not been able to make a directly correlating connection between analytics capabilities and firm performance. Even though the subject has been a buzzword for organizations for some time now, the aggressive growth those organizations are generating from the use of analytics is slowly levelling out (Kiron & al., 2014). Some scholars take the subject even further by calling organization made investments into analytics capability a “myth” (Manyika & al., 2011). The problem here is the fact that the direct link to firm performance is missing and that analytics capability investments are extremely hard to justify because they are so difficult to measure. Therefore, it is imperative to have predetermined goals and models for measuring success in place when engaging with these kinds of investments (Akter & al. 2016).

2.4 Business analytics in terms of organizational performance

An organization's process of becoming data-driven is not a simple endeavor and needs to be systematically built towards by management. Vidgen & al. (2017) suggest that business analytics capability acts as a mediator when it comes to the data an organization generates and collects. Therefore, it also affects the effectiveness of leveraging value from better guided decisions and actions based on the data that is collected and analyzed. Leavitt's (1965) diamond model of the organization is adapted and used as the research framework by Vidgen & al. (2017) in order to better conceptualize the process for an organization to becoming data driven (see Figure 5).

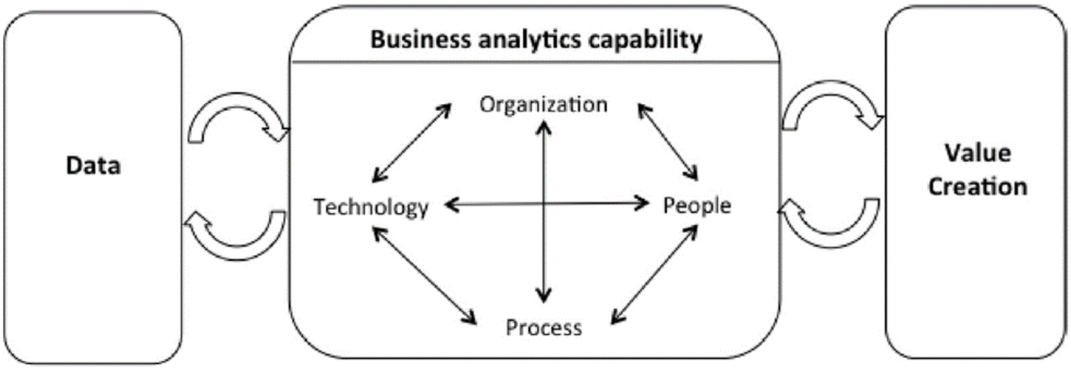

Figure 5: Leavitt's (1965) diamond model (adapted by Vidgen & al., 2017)

Furthermore, according to Mithas & al., (2013) and Gillon & al., (2014) six routes exist that lead to value through an organization's business analytics capability (see Figure 6). The first words of these six paths (in Figure 6) to business value through business analytics form the acronym 'ADROIT'. The abbreviation lists the most focal ways how business value can be derived from business analytics according to Mithas & al. (2013).

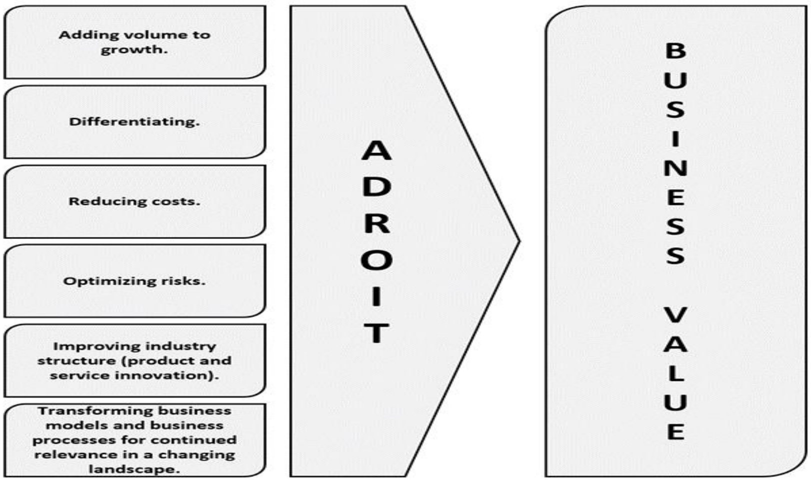

Figure 6: The six paths to business value via business analytics (Mithas & al., 2013; Gillon & al., 2014)

Seddon & al. (2017) created a two-part model (Process Model Panel A and the Variance Model Panel B, see Figures 7 and 8) for looking into how business analytics contributes to the business value of the firm. Additionally, the second part of the model (Variance Model Panel B, Figure 8) incorporates a long-term and a short-term model that look at the issue from different perspectives. The model was designed to be applicable to any company that might be looking into business analytics and is in hope of achieving additional value and / or a competitive advantage in the marketplace. The model is based on previous research on the subject matter and took into consideration the key insights from sixteen different pre-existing models that were analyzed by the researchers (Seddon & al., 2017).

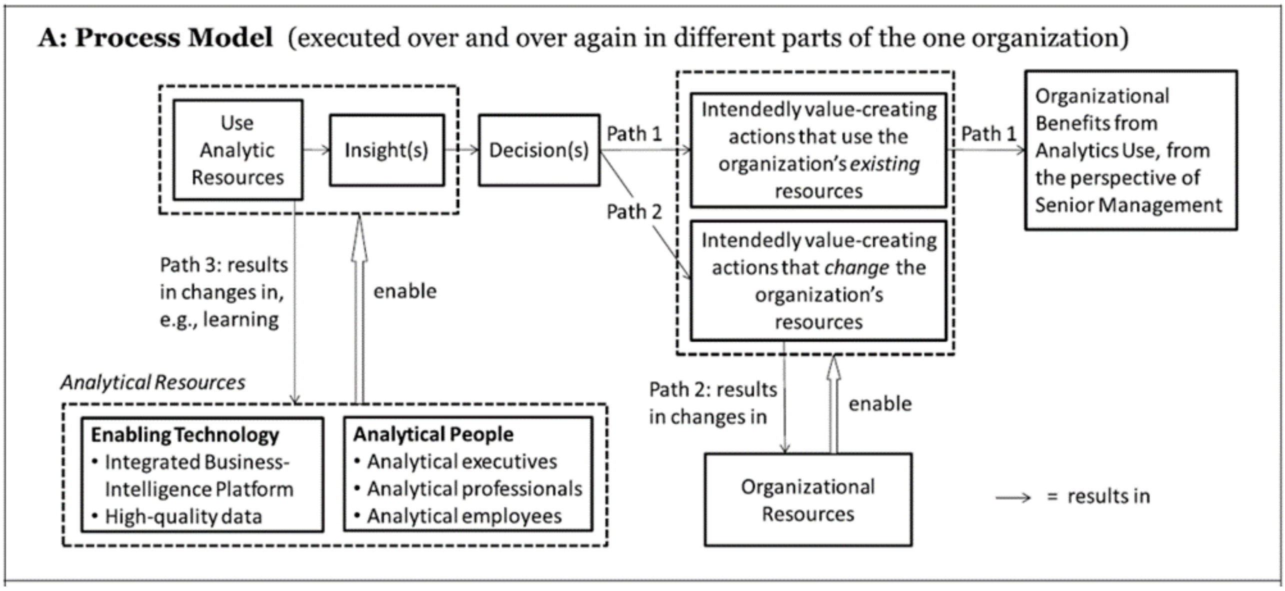

Figure 7: Process Model (Panel A) of the 'BASM' by Seddon & al. (2017)

The process model of the BASM states that, using the analytic resources by the employees in the different functions of the organization creates insights, that can be then converted into decisions, which again can be refined to value-creating actions that ultimately generate profit and/or benefits for the organization (Path 1, Panel A, Figure 7) (Seddon & al., 2017). Being able to determine what success looks like in this sort of use of analytic resources should be considered extremely important, because otherwise nobody would know or be able to measure if the process was worth the cost of using those resources in the first place.

Alternatively, some situations in which the organization's analytical resources are used by employees in different functions of the organization to create insights that are then converted into decisions and value-creating actions can result in changes within organizational resources instead of generating profit and / or benefits for the organization (Path 2, Panel A, Figure 7) (Seddon & al., 2017).

Finally, using analytics resources within an organization by employees in different functions can result into direct changes in those analytical resources that were being used before creating insights (Path 3, Panel A, Figure 7) (Seddon & al., 2017). These changes could include (but are not limited to) improvements in the Business-Intelligence platform, better quality data or perhaps taking a new piece of analytics technology into use in the form of new software.

For more clarification on how Seddon & al. (2017) view the model they created can be seen through them highlighting the importance of human activity as part of the process. In other words, the first three steps (use of analytics resources, insight generation and decision-making) of the process model are referred to being ‘intensely human activities’ by Seddon & al. (2017), which is why they continue to argue that decision making is an obligatory part of the process and without it there can be no profit or organizational benefits from the use of business analytics. Furthermore Seddon & al. (2017) make three important statements regarding the fact that the model should always be used and re-used by as many people in the organization as possible:

- “Many people throughout the organization may have access to business analytics tools.”
- “All the people using the tools may have useful insights.”
- “One million ‘ten-dollar’ insights are worth as much as one ‘ten-million dollar’ insight.”

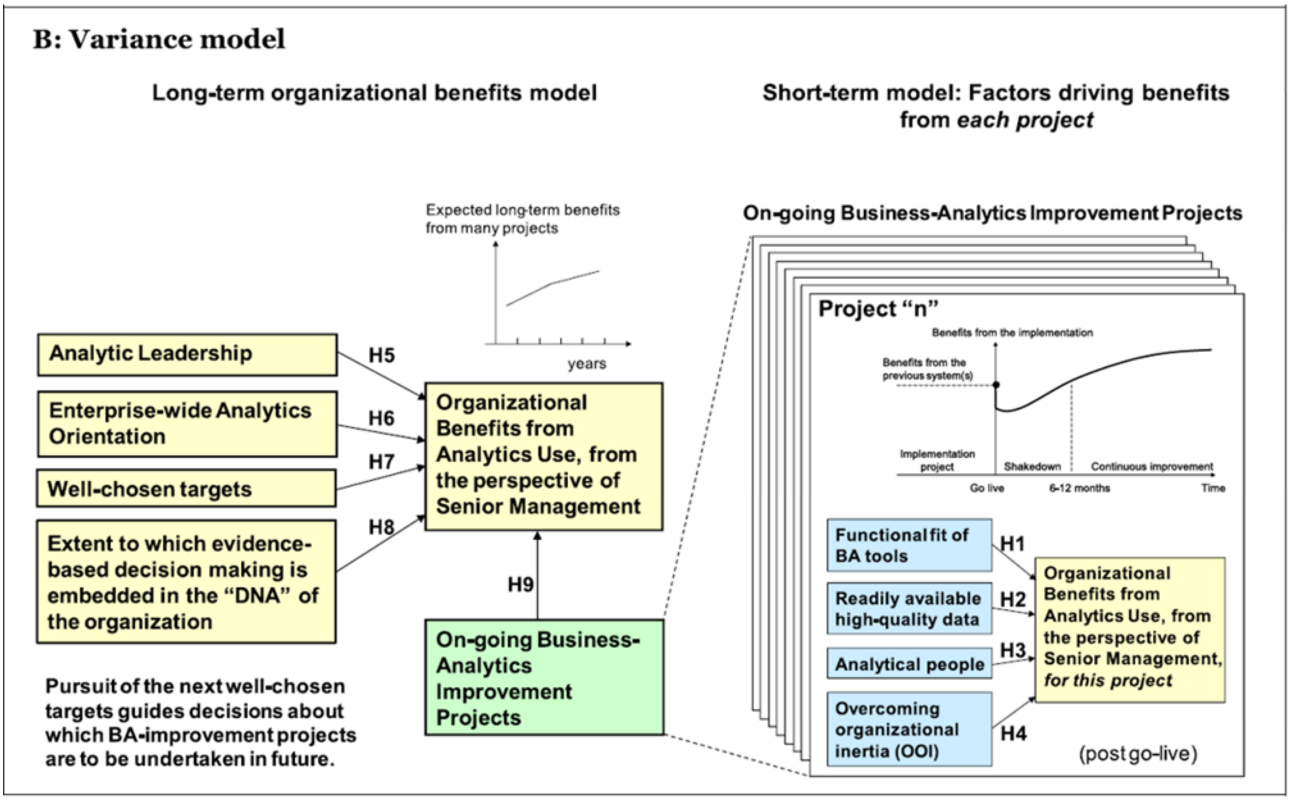

Figure 8: Variance Model (Panel B) of the 'BASM' by Seddon & al. (2017)

The variance model (Panel B, Figure 8) presents an alternative explanation to how organizations use business analytics to create business value. It also considers the things an organization's managers can do to help their organization realize that greater business value. In other words, it argues that an important mechanism through which firms draw increased benefits from business analytics is through ongoing business analytics improvement projects (Seddon & al., 2017).

The left side of Figure 8 argues that in the long term, it is analytics leadership, the adoption of an enterprise-wide analytics orientation, the selection of well-chosen targets, the extent to which evidence-based decision making is embedded in the 'DNA' of the organization and execution of multiple business analytics improvement projects (possibly over many years) that drive benefits from business analytics. The right side of the model in Figure 8 claims that, the greater the extent of functional fit, ready availability of high-quality data, analytical people and success in overcoming organizational inertia resulting from a business analytics improvement project, the greater the organization's success in generating benefits from that project (Seddon & al., 2017). Each of these hypotheses are explained and justified in the following paragraphs in further detail.

Analytic leadership is ‘the extent to which people in any organizational unit take leadership of initiatives or projects to increase use of business analytics for organizational gain’. Moreover, Davenport & al. (2010) state that: ‘If we had to choose a single factor to determine how analytical an organization will be, it would be leadership. Leaders have a strong influence on culture and can mobilize people, money and time to help push for more analytical decision-making’ (Seddon & al., 2017).

Enterprise-wide analytics orientation is ‘the extent to which the organization has adopted an enterprise-wide orientation to the use of business analytics. Additionally, Davenport & al. (2010) argue forcefully that an enterprise-wide view of the role of business analytics is critical to business analytics success. ‘To develop an enterprise-wide view of analytics, a company must do more than integrate data, combine analysts or build a corpore IT platform. It must eradicate all of the limited, piecemeal perspectives harbored by managers with their own agendas, need, and fears – and replace them with a single, holistic view of the company’. (Davenport & al., 2010).

The definition of well-chosen targets is ‘the extent to which targets for new analytics initiatives are selected carefully based on the combination of their business potential and whether the necessary resources, including data, are available (Davenport & al., 2010)’. Furthermore, Watson & Wixom (2007) similarly draw attention to the need for well-chosen targets when they say that business intelligence is more successful if ‘There is alignment between the business and its business intelligence strategies’, and ‘There is effective business intelligence governance’. Similarly, Sabherwal & Becerra-Fernandez (2011) argue that business intelligence governance processes, e.g. articulation of business intelligence principles and creation of a business intelligence steering committee, are important drivers of benefits of from business intelligence.

The extent to which evidence-based decision-making is embedded in the DNA of the organization is an attempt to assess the extent to which evidence-based decision-making is embedded in the core values and processes of the organization. In other words, assessing the ‘information orientation’ of the company (Kettinger & al., 2011). Furthermore, the implication of these statements is that as organizations become more analytical (i.e. as evidence-based decision-making becomes more and more deeply embedded in their DNA), they will realize increasingly more benefits from their use of business analytics. In terms of barriers to the use of business analytics, Accenture's global survey of 8000 'directors and senior managers' reported that 'corporate culture still presents a major barrier' to the wider use of customer 'analytics and fact-based decision-making' (Accenture, 2011).

Ongoing business analytics improvement projects is 'a measure of the number and extent of investment in business analytics improvement projects. Such projects include both the implementation of new business intelligence software (that delivers new analytics functionality) and initiatives that apply existing functionality to new areas of decision-making' (Seddon & al., 2017). In other words, the insight – that business analytics improvement projects are likely to be a primary driver of new analytics resources that, in turn, deliver new benefits – is argued (Seddon & al., 2017).

Functional fit is 'the extent to which the functionality provided by the business analytics platform matches the functionality of the organizations needs to access and analyze data effectively and efficiently' (Seddon & al., 2017). In other words, the better the functionality of the analytics platform supports the organization's need to analyze data – the easier and more likely it is for the organization to be able to derive increased benefits out of that need.

Readily available high-quality data is 'the extent to which relevant and accurate data are readily available for analytics use, from internal and external resources of the organization' (Seddon & al., 2017). Furthermore, according to Davenport & al. (2010), data are 'the prerequisite for everything analytical', and 'You can't be analytical without data and you can't be really good at analytics without really good data'. In other words, this hypothesis highlights the importance of the gathered data and the fact that it needs to relevant and accurate for analytics to help converting it into actionable insights and decision-making.

The definition of analytical people is 'the extent to which there are people within the organizational unit with an analytic mindset who help drive business value from business analytics (Seddon & al., 2017). F. ex., analytical champions, professionals, semi-professionals and amateurs (Davenport & al., 2010). Furthermore, according to Davenport & Harris (2007), 'It is people who make analytics work and who are the scarce ingredient in analytic competition', not the organization's access to, for example, high-powered data-mining tools. Since human resources are an integral part of any organization, it also applies to business analytics in those organizations. Moreover, business analytics is often considered as “automation” that often leads to resources becoming obsolete within an organization – this notion is true to some extent, but according to research it does not apply to organizational human resources due to analytics being such a human resource capital intensive process when it comes to formulating actionable insights for value generation.

Overcoming organizational inertia (OOI) is ‘the extent to which members of the organization have been motived to learn, use and accept the new system’ (Seddon & al., 2017). Seddon & al. (2010) also argue that ‘no matter how good the technical system, unless people in the organization are motived to use the system and have sufficient knowledge on how to use the system effectively (Purvis et al., 2001), the organization is unlikely to gain the benefits it otherwise might from the new system’. For further clarification, organizational inertia often also translates into resistance to change in an organizational setting. Just like analytical people in the previous paragraph, this also is linked to an organizations human resource capital. As an example, employees that have analytical mindsets could be less resistant to changes in terms of new business analytics improvement projects, whereas employees that do not understand the concept might show more resistance towards it.

After empirically testing the process and variance models, Seddon et al. (2017) concluded that the process model (Panel A, Figure 7) is very strong; however, the structure and the choice of factors for the variance model (Panel B, Figure 8) may need more work. In particular, the quality of the business analytics platform is not a factor in the variance model, yet it is a frequently mentioned factor in prior research, also organization size and industry may also be useful controls to add to any quantitative test of the model (Seddon & al., 2017). Despite the fact that the authors see room for improvement in terms of the model’s variance panel, it should be noted that the model as a whole performs well (especially when considering it has not been tailored to suit any specific company or business area) in determining on how and through what aspects organizations derive benefits from business analytics.

Suryanarayanan & al. (2018) conducted a comparative case study regarding business analytics and business value. As part of the study they engage in attempting to outline the resources needed to generate business value from business analytics. They also created a theoretical framework to illustrate the relationships between resources and their link to business performance (see Figure 9 below).

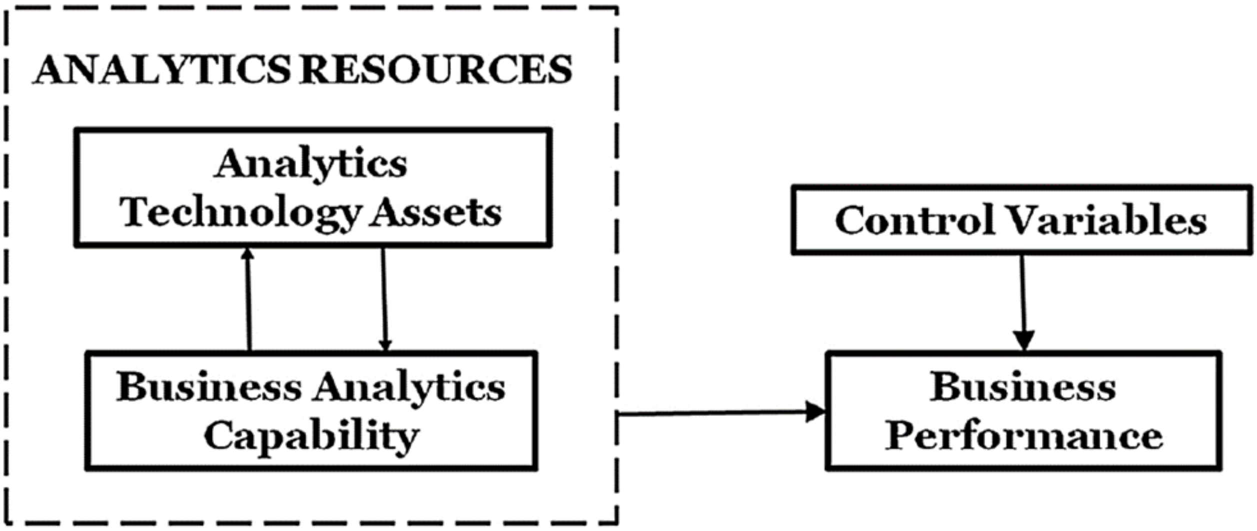

Figure 9: Theoretical framework for BV from BA (Suryanarayanan & al., 2018)

Furthermore, studies regarding business value through IT investments – the assets or resources needed have generally been related to IT infrastructure, commercial aspects or strategic purpose (Aral & Weill, 2007). When it comes to business value through business analytics, the resources are different. According to Shanks & Sharma (2011) the tangible resources for business analytics are: BA technological infrastructure, data sources and analytics software tools. The bottom-line regarding business analytics resources in an organization is the fact that the IT capabilities and function play an important part when it comes to attending the needs of the analytics division (if one exists) (Suryanarayanan & al., 2018).

Other academics also pitch in with several complementary aspects to consider when it comes to business value through business analytics:

- “Seamless integration of business analytics systems with other organization information systems when it comes to business analytics technology assets.” (Kohavi & al., 2002)
- “Conversion of data into information through reporting and visualization systems.” (Watson, 2002)

- “The use of advanced statistical analysis tools to discover patterns, predict trends, and optimize business processes.” (Negash, 2004)

According to the case studies conducted at real organizations by Suryanarayanan & al. (2018), business analytics related business value can be categorized into two different asset categories; operational and strategic. Furthermore, both categories can be applied (simultaneously or not) to any business analytics improvement projects depending on what is being improved through the project in question. Moreover, the best way to distinguish whether an asset belongs to the operational or the strategic category would be determining is it better suited for “running the business” (operational) or “changing the business” (strategic) (Suryanarayanan & al., 2018). The case study also disclosed that the operational category is more often human resource intensive, whereas the strategic category is more often involved by the usage of information technology and / or business analytics technology assets in addition to human resources (Suryanarayanan & al., 2018). Additionally Sharma & al. (2014) highlights an organizations ability to orchestrate its assets in terms of being able to ensure that business analytics is getting the support it needs to be able to contribute towards operation and strategic decision-making processes.

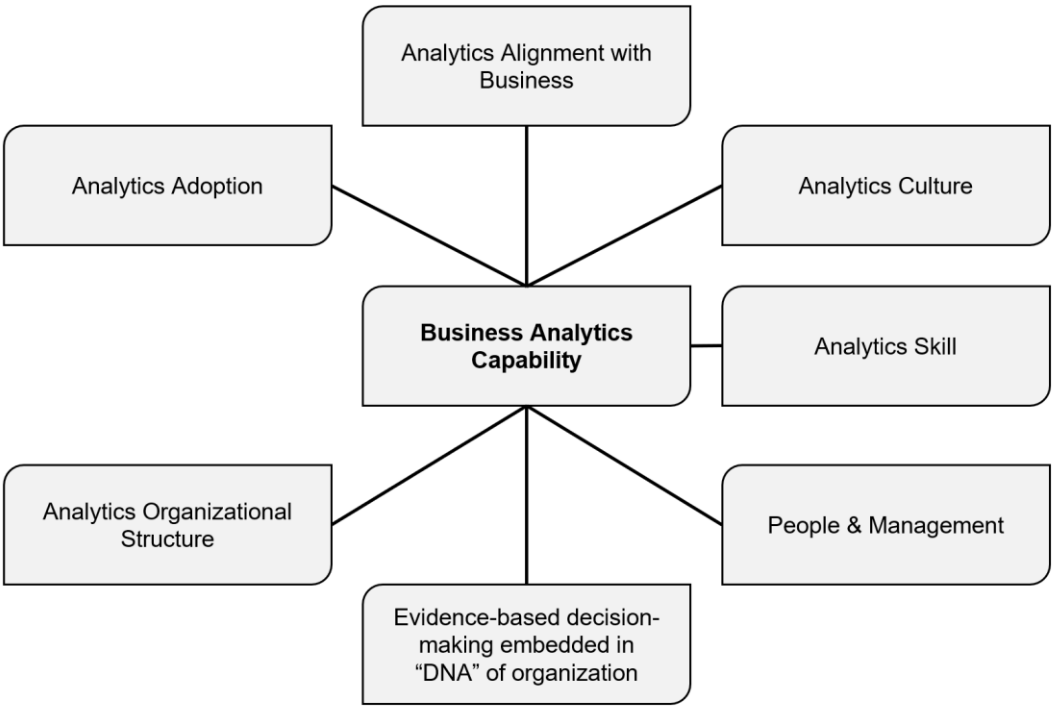

Figure 10: Elements of Business Analytics Capability (Suryanarayanan & al., 2018)

According to the case study materials from Suryanarayanan & al. (2018) business analytics capability consists of at least the seven aspects mentioned in Figure 10. The following paragraph will explain the different aspects of Figure 10 in further detail.

Analytics adoption stands for the amount of analytics use and its prioritization in the organization's different functions (Suryanarayanan & al., 2018). In a generic situation analytics adoption starts with setting up efficiency goals, then moving on to establishing growth objectives, and finally being able to solve difficult business challenges with support from analytics. The further a company moves in this pipeline regarding analytics adoption, the deeper and widespread the analytics adoption within the organization becomes. **Analytics alignment with business** fulfills analytics adoption by standing for the teams of people that are responsible for setting up goals and objectives for analytics adoption to progress in the organization (Suryanarayanan & al., 2018). The teams of people typically come from different areas of the organization to broaden the amount of perspectives involved when the goals and objectives are being discussed.

Analytics culture consists of the organizational values and behaviors regarding business analytics and its use, which ultimately acts as an enabler for business analytics within the organization (Suryanarayanan & al., 2018). In addition to this, analytics culture also consists of the ability to use analyzed data to guide decision-making, the organization's management support to business analytics and the employee's ability to receive and use analytics-based information (Suryanarayanan & al., 2018). Analytics culture is also considered in being the aspect that differs between organizations and ultimately is considered the source of a competitive advantage should an organization achieve it through business analytics in the first place.

Analytics skill and people management revolves around making analytics-based work meaningful (Suryanarayanan & al., 2018). If it is done properly it ensures that analysts retain their interest towards the work, they do and continue providing the organization with the needed information so that they can stay ahead on their analytics journey. **Evidence-based decision-making embedded in "DNA" of organization** describes the extent to which evidence-based decision-making is included into the values and processes of the organization (Suryanarayanan & al., 2018). These values and processes in turn act as an enabler for the use of business analytics because they reduce the barrier for employees to start using analytics to support their work activities and decision-making. **Analytics organizational structure** stands for the parties or the business functions involved in analytics endeavors in an organization (Suryanarayanan & al., 2018). Several academics (f.ex. Seddon & al., 2017) have pointed out in their research that involving people from as many parts of the organization as possible is more likely to help maximizing value generation from analytics in comparison to a situation on the contrary.

From the perspective of business analytics and the fact that business performance is a well-researched subject in academics and practice, a myriad of different performance measures exist that can be used to measure firm performance with a twist into the use of business analytics. According to Suryanarayanan & al. (2018), Davenport & Harris (2007) and Aral & Weill (2007) adequate performance measurements that can be used to measure firm performance from a business analytics viewpoint include (but are not limited to):

- “Net margin and Return on Investment” (Firm profitability)
- “An organizations ability to make above-average profits within a given industry sector” (Competitive Advantage)
- “Revenues from new and modified products” (Innovation)

Additionally, depending on the type of analytics initiative undertaken by the organization, the measurements of success are subject to change accordingly. Finally, the research by Suryanarayanan & al. (2018) is in line with other previous researchers’ conclusions in terms of a positive relationship between strategic investments into an organization’s information technology assets to generate an increase in firm value.

According to Aydiner & al. (2018) and INFORMS (2019), the adoption of business analytics tools and applications by an organization is done in three consecutive steps (1. – 3., see Figure 11). As it can be seen from Figure 11, a “fourth step” is also drawn in and consists of data acquisition and processing, this should not be considered as a step of its own, but rather an enabler for steps 1. – 3. and an organizations adoption of business analytics. The reason for step 4. existing in the illustration is that it acts as a baseline from everything else – without data acquisition there can be no data processing, and without data processing there can be no insights to prescribe decision-making within the organization. Finally, it is also important to notice that these two aspects (data acquisition and processing) are only useful when they coexist and work together to provide the best possible outcome (Aydiner & al., 2018).

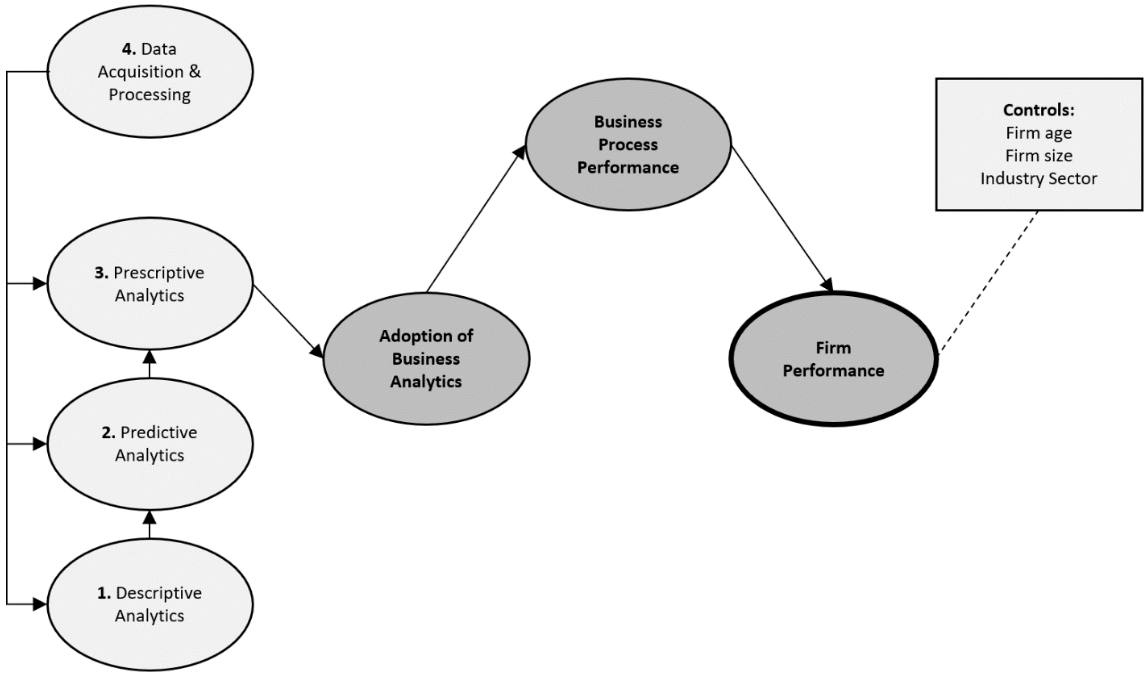

Figure 11: The relationships between BA adoption, BPER and FP (drawn based on Aydiner & al., 2018)

Based on the empirical evidence presented by Aydiner & al. (2018) several conclusions regarding the relationships between adoption of business analytics, business process performance and firm performance can be drawn. First and foremost, a direct link exists between adoption of business analytics and business process performance, as well as business process performance and firm performance in a company (Aydiner & al., 2018). Second, the direct link between business analytics adoption and business process performance confirms that an integration between firm processes and business analytics technologies and algorithms exists (Tan & al., 2016). Third, the direct link between business process performance and firm performance validates the existence of a deep connection between a business process and its output (Gu & Jung, 2013). Finally, despite the fact that a direct link between business analytics adoption and firm performance may sound completely normal, it does not exist. As long as some business process performance is gained through the adoption of business analytics the increase in firm performance is achieved through an improvement in business process performance rather than directly from adopting business analytics within the firm (Aydiner & al., 2018).

To explain the previously drawn conclusions further, three statements should be added. First, big data related technologies (4) that are considered as static assets are turned into dynamic ones in Figure 11 through descriptive (1), predictive (2) or prescriptive (3) analytics (Vidgen & al., 2017). This will result in the organization gaining the ability to better create, extend and modify their resource base (Vidgen & al., 2017). For example, further developing an existing analytics software tool (that handles and presents raw data) into something simpler to use. This would ultimately result in a larger group of people within the company being able to use the tool and to help them take care of their work tasks and make related processes more efficient. Second, an increase in the capabilities of an existing business process results in improved performance of that process as well as firm performance as a whole (Gu & Jung, 2013). Third, process level performance increases are the mediators between business analytics adoption and increase firm performance (Ramanathan & al., 2017). For example, adopting new business analytics applications can increase the rate at which tasks can be handled and decrease the number of mistakes involved in a business process. Due to this, the operational performance is increased which also contributes an in increase in firm performance (Klatt & al., 2011).

Finally, during the testing of their model in practice, it was found that firm size affects the amount of firm performance they show from business analytics adoption. In other words, the bigger the firm, the more resources available, and the greater the increase in firm performance (Aydiner & al., 2018).

2.5 Business analytics and its alignment with business strategy

In order for contemporary companies to develop a robust big data strategy, business leaders and managers need avoid a conflict between the aspirations and authenticity of the intended big data strategy. For further clarification, aspirations focus on outlining motivations and goals for big data investments, as well as attempt to look at the marketplace as a whole and place the organization into that landscape to determine its role and position in it – whereas, authenticity is considered an internal reality-check to determine what kinds of resources and capabilities the organizations currently employs. These resources and capabilities can include; the organizations physical and financial resources to invest in potentially lacking capabilities, organizational knowledge, digital capabilities and its current pool of human capitol. Reflecting to what was said in the introductory section, it was suggested that companies should first focus on determining the what the required capabilities were, and then, determine what is required to build those capabilities (Suryanarayanan & al., 2018). In other words, literature suggests that business leaders should prioritize authenticity over aspirations when attempting to develop a robust big data strategy.

Figure 12 below conceptualizes Vidgen & al.'s (2017) empirical findings in the way the different aspects and organizational functions are interlinked in terms of becoming data-driven and utilizing business analytics for additional value for the firm.

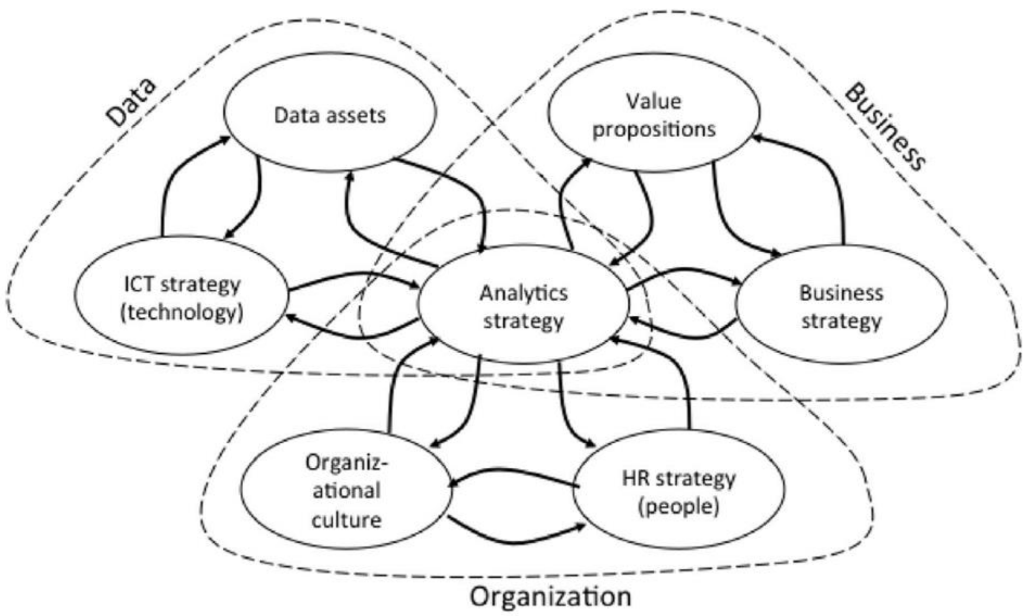

Figure 12: Business analytics as a coevolving ecosystem (Vidgen & al., 2017)

In order to further describe Figure 12 and the three core areas it incorporates, the areas should first be identified as data, business and the organization. All of the core areas have their own strategies regarding the function of the business or company they represent, and those strategies should all be aligned with each other for the organization to be able to become data driven (Vidgen & al., 2017). Data resources require constant evaluations regarding the availability of data, data source access, data quality management and the ability to handle potential restrictions caused by outdated information technology platforms (Vidgen & al., 2017). The organizational resources are linked to people and the organization's internal culture and their combined ability to support the organizations process of becoming data driven. These resources also handle the potential training of existing employees to increase the skill levels in business analytics within the firm, if there is a shortage in the amount thereof. Finally, the business and management resources are responsible for overseeing the transformation, creating a business case for it – so that it can be sold to the rest of the organization, and simultaneously ensured that the strategies from all the core areas are aligned with each other (Vidgen & al., 2017).

Acito & Khatri (2014) present a framework consisting of several different concepts when it comes to the structure of business analytics in organizations (see Figure 13).

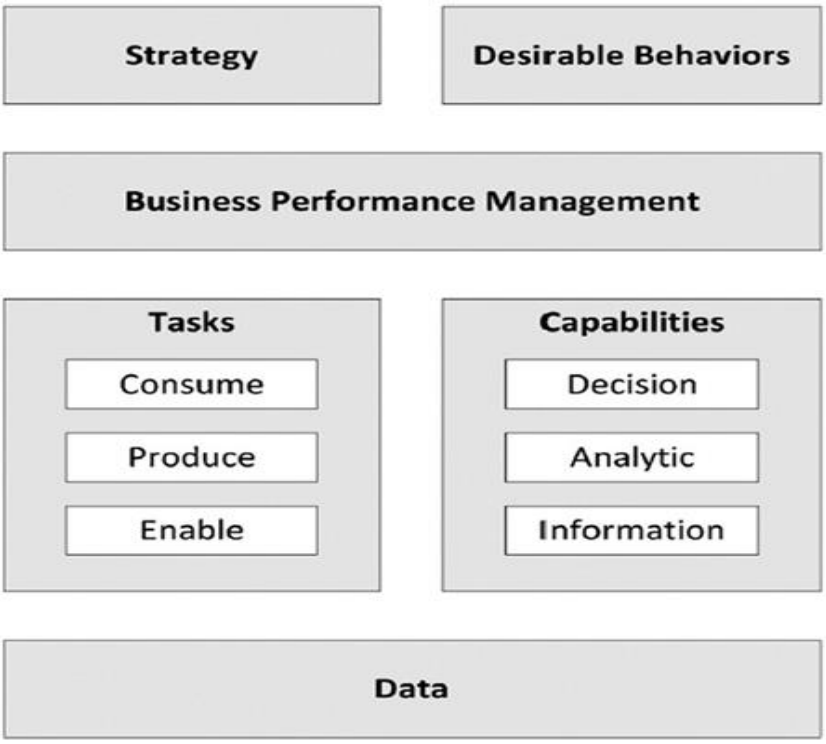

Figure 13: Structural Framework for Business Analytics (Acito & Khatri, 2014)

Davenport & al. (2010) argue that without a strategic context, an organization cannot decide what data to focus on or even what it is trying to achieve with the analytics initiatives it is engaging in. In other words, the strategy part of the model stands for the business case of the analytics initiative in question. Questions like – What is defined as success, what are the organizational benefits, how does it fit the overall strategy of the company, and how is support throughout the entire organization gained to ensure the change required by the initiative happens as planned – need answers and justifications.

Desirable Behaviors are the perceptions within the organization that support the analytics initiative, the beliefs or culture that are embedded into the organization's mission statement, and the behavior within the organization that creates value (Weill & Ross, 2004). For example, an organizations decision to outsource or centralize analytics initiatives can depend on how well its culture supports analytics initiative success (Davenport & al., 2010). In other words, for analytics initiatives to succeed in organizations, it is paramount that desirable behaviors exist alongside those initiatives.

Business Performance Management aims to answer question that asks how analytics initiative performance can be measured or what kinds aspects define analytics initiative performance. After all, it will be nearly impossible to reach an outcome of any kind if you do not have a faint idea what it might look like, or what kinds of features it might incorporate for the organization. (Acito & Khatri, 2014)

Tasks portray the things people in the organization can do with business analytics, whereas capabilities outline the requirements that are needed for those tasks to be able to happen. In other words, capabilities in this model can be thought of as enablers for tasks. For example, for someone to be able to consume, produce or enable insights based on business analytics within the organization, the infrastructure to support decision making from data needs to be in place (e.g. dashboards and / or reports). Analytics capabilities consist of all the methods and tools the organization can employ to use and analyze data (e.g. separate tools for descriptive, predictive and prescriptive analytics). Lastly, information capabilities refer to the organizations ability to integrate, share, organize and describe the information and the needed skillsets to use it. (Acito & Khatri, 2014)

Data is the basis for analytics initiatives and insights; therefore, it is portrayed at the bottom of the model so that it acts as an enabler for the rest of the model. After all, the bottom line is that analytics initiatives cannot happen if data is not gathered or it does not exist.

Big data and analytics over the past years have generated a lot of interest within organizations to engage in attempting to enhance their performance in various ways, however this has only worked out for some of the organizations and not others. Akter & al. (2016) conducted a study that that focuses on shedding light on the high significance of the moderating impact of analytics capability within organizations, and its relationship with business strategy alignment and firm performance. They agree with several other scholars on the importance of being able to align an organizations analytics strategy and capabilities with the rest of its business strategies. And they also the share the notion implied by Kallinikos (2007) who argues that information, data and knowledge in an organizational context are mixed and dependent of each other. He also continues to state that hierarchical organizational resources can be used to achieve benefits for the organization via their synergistic ties. This perception is backed-up by earlier research, according to which sustainable competitive advantage can be achieved for an organization through the utilization of different kinds of resources that can also be characterized as resources that complement and co-specialize each other (see definitions below):

- Complementary resources are in question when the value of one resource is enhanced by the presence of other resources (Powell & Dent-Micallef, 1997).
- Co-Specialized resources are defined as resources that have little or no value without other resources (Clemons & Row, 1991).

For big data analytics to influence firm performance Akter & al. (2016) propose the utilization of an entanglement conceptualization model that supports the notion that different big data analytics capabilities incorporate both co-specialization and complementary resource characteristics. In other words, big data analytics is less likely to influence firm performance positively if all dimensions are not present when its effects are being considered (see Figure 14). (Akter & al., 2016)

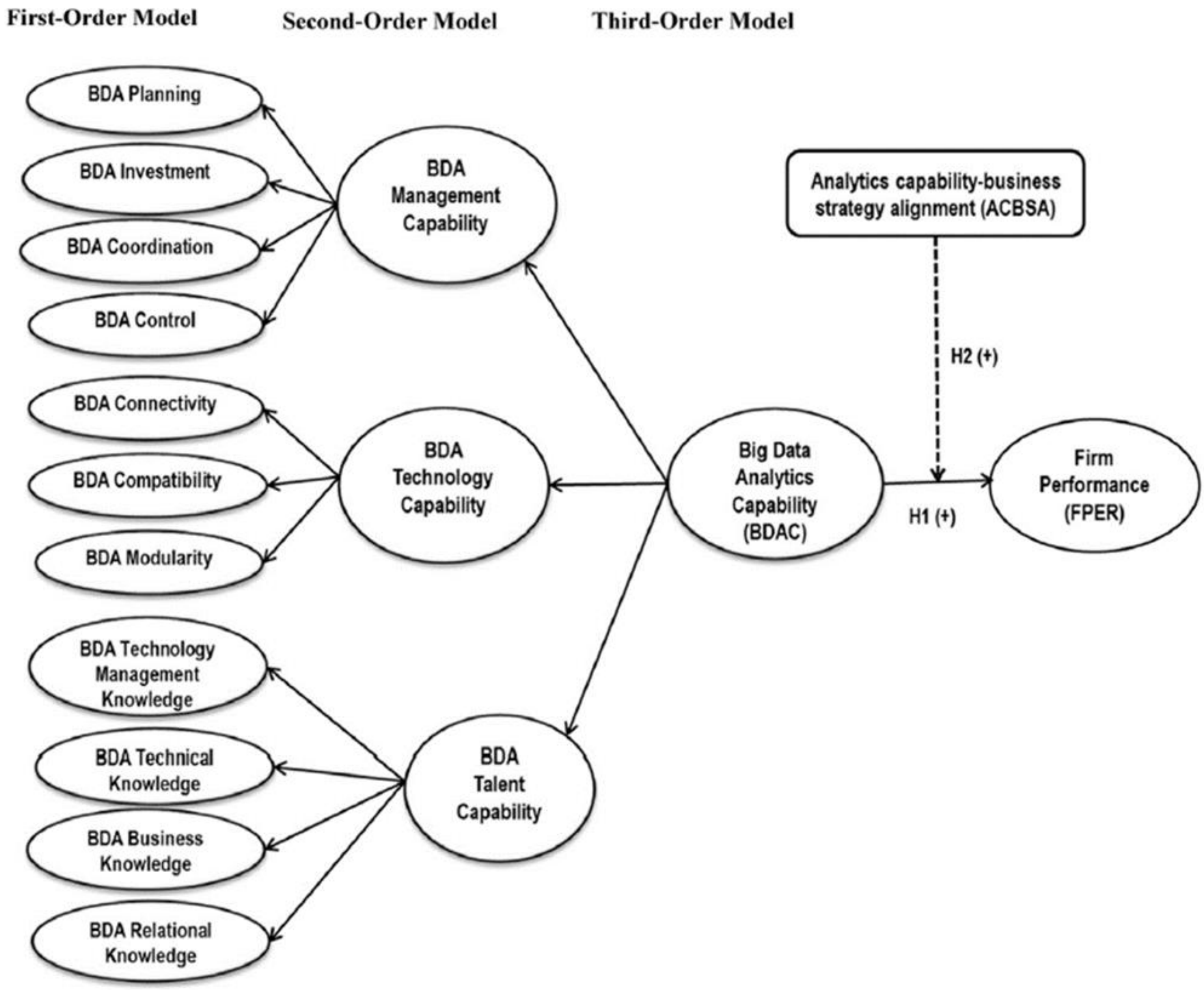

Figure 14: Big data analytics (BDA) capability research model and related dimensions. (Akter & al., 2016)

The model identifies three primary dimensions and eleven subdimensions that all affect an organizations big data analytics capability. Moreover, the big data analytics capability then affects firm performance and is enhanced further if the organization has its analytics capabilities well aligned with its existing business strategies. (Akter & al., 2016)

The alignment between business strategy and analytics capability that was highlighted in the model is dependent on the organization's leadership. In other words, organizational leaders are in the position to align analytics capabilities with the functional objectives and goals of the organization (Akter & al., 2016). Moreover, according to McAfee & Brynjolfsson (2012), synergy between different organizational functions and alignment between business strategies and analytic capabilities contributes to increased firm performance. A direct quote by McAfee & Brynjolfsson (2012) describes the abovementioned setting in further detail:

- “Companies success in the big data era is not simply because they have more or better data, but because they have leadership teams that set clear goals, define what success looks like, and ask the right questions. Big data’s power does not erase the need for vision or human insight.” (McAfee & Brynjolfsson, 2012)

Analytics capability business strategy alignment incorporates strategic organizational capabilities that can be used to match resources according to changing market opportunities. One of the most important ways big data analytics can contribute to increased firm performance is by aiding the organizations align their capabilities with their strategic plans. (Akter &al., 2016)

The empirical research conducted by Akter & al. (2016) supports the multidimensional model they created (see Figure 14). More accurately, the findings imply that the higher the order model in question, the bigger the impact on firm performance. Therefore, Akter & al. (2016) prove that analytics capability – business strategy alignment moderates the relationship between firm performance and big data analytics capability, and that big data analytics capability is a great point for starting to solve big data related challenges in any organization. The same research results also highlight the significance of the ‘entanglement view’ that stands for different capabilities reinforcing each other for greater effect on firm performance. (Akter & al., 2016)

All in all, Akter & al.’s (2016) multidimensional model contributes to both academic and managerial implications by considering the role of the resource-based view and entanglement view when it comes to big data analytics overall impact on firm performance, and by presenting managers with a collection of dimensions that are all important when it comes to creating and maintaining a big data analytics climate in an organization. Finally, the study also underlines the importance of having analytics initiatives and strategic plans within the organization aligned which was initially the core research question this study set out to answer. (Akter & al., 2016)

2.6 The similarities and differences between academic models

In order to conclude the literature section for the study, a comparison between the different models and ideas presented is in order. Based on the different findings in previous research the following similarities and differences were recognized between the different models presented (See Table 1 below).

Similarities:	Differences:
Performance enhancement and value creation potential exists in business analytics and its alignment with business strategy.	The aspects that need to be considered in order for value to be created or business process performance to be enhanced can vary depending on the firm or context being explored.
A company's amount of analytics capability affects the amount of potential value creation available to it.	The challenges associated with business analytics depend on the company and initiative in question. Some similarities may exist between companies, but all of them do not.
A firm's resources (and their allocation) play an important part in the ability to derive value from business analytics and the related alignment.	Incorporating a separate analytics strategy is not necessarily a requirement but can yield potential benefits especially if considering larger organizations.
Using business analytics to justify, guide and prescribe actions is the method how value is generated (descriptive, predictive and prescriptive analytics).	
The amount of benefits available through business analytics and its alignment to business strategy scales with the size of the organization.	

Table 1: Similarities and differences between academic models

As it can be determined from the table above, some variance between the presented models exist depending on what aspect of business analytics is being studied and what kinds of companies are involved in the studies to test hypotheses made by them. Therefore the different models presented in the literature section for this thesis should be thought of critically and tested how well they suit the company context if put into practical use.

2.7 Summary of previous research

Supporting research question: Why is it challenging to create firm value through business analytics in the terms of decision-making processes?

In order to be able to draw conclusions from the academic perspective regarding the supporting research question mentioned above, a thorough aggregation of the academic content related to the question was conducted. The potential challenges to create firm value from business analytics in decision-making processes can be many, but they mostly revolved around the same subject areas using slightly different terms in comparison to each other.

Fully data-driven companies are perceived to have the ability to not just describe or support their decision-making processes, but also predict or even prescribe them with aid of analytics according to previous research (Vidgen & al., 2017). The fact that analytics technology has become cheaper over the past decades has resulted in companies having the ability to store just about any piece of information without having to worry too much about how much it costs, as long as they have had their analytics platforms, data warehouses and cloud storage in good order. This is the root cause for the first challenge mentioned in previous research. The fact that companies store too much data has led to them being in situations where they do not know how to utilize it or what it means. The uncertainty created by this in turn leads to expensive mistakes being made through decision-making processes because the data that was used to back-up the decision was not understood correctly (Aydiner & al., 2019).

The second challenge mentioned in previous research was a big one and can, and most likely is the root cause for many smaller challenges – the employees that work with insight generation based on data and business analytics have their own limitations when it comes to their individual knowledge, personal experiences or cognitive abilities (Seddon & al., 2017). These limitations can be characterized as myriad of different potential challenges such as; prejudices or being biased about the data or analytics used, not being able to have an open enough mind to generate completely new insights, not understanding the logic or the data to be able to draw reliable conclusions, to mention a few. Additionally these limitations also sprout additional challenges related to value generation from business analytics and decision-making processes. Particularly being able to overcome resistance to change, building a corporate data culture and being able to sell the change to all the employees in the company to increase the commitment towards it (Vidgen & al., 2017).

This leads us to our third challenge – the ability to convert the insights created through data and business analytics into actionable decisions regarding the organization making those insights. The fact is that no value can be generated through insight generation from business analytics if the organization is unable to turn those insights in to actionable decisions. According to previous research, the root cause for not being able to create actionable decisions is the fact that decision-making processes in companies suffer from complicated circumstances (fast changing business environment), scarcity of time, adequate knowledge and training related to data, business analytics and insight generation. To support the conclusions made previously several academics (Sharma & al., 2014 and Mazzei & Noble, 2017) argue that the managers in contemporary companies are expected to be able to answering the following questions regarding big data analytics; how to gather the data, how to codify and store it, how interpret and analyze it, how can it be turned into insights and actionable decisions to generate measurable value for the organization.

The Delphi study conducted by Vidgen & al. (2017) outlines several key issues or challenges related to value generation from business analytics that support or add to the challenges mentioned earlier:

- The need for a well-defined analytics and data strategy.
- The need to change internal culture when first attempting to become data driven.
- The need to have the right people employed in the right positions to increase the commitment towards to change.
- The need to be able to consider the ethics behind the usage of data when using it to pursue competitive advantage.
- The need to have access to good quality data and analytics tools.

The fourth and final challenge based on what McAfee & Brynjolfsson (2012) argued is the leadership in contemporary companies. In other words, the reason for succeeding in terms of data and analytics use is not only due to having more or good quality data, but more importantly having the leadership to drive and support the change, define clear goals for it and determining what the success looks like in terms of using data and business analytics to generate actionable insights and create business value.

Supporting research question: How to decrease the conceptual distance between company strategic goals and business analytics?

The scarcity of direct research related to the existence of conceptual distance between strategic goals and business analytics affected the amount of information available from academic sources. The subject was mentioned indirectly in some journal articles which made drawing a collection of academic conclusions possible.

According to several academics' (Bisogno & al., 2016) contemporary companies should strive to align their performance indicators and business processes with their underlying business strategies because this enables them to reach preset strategic goals that are often based on pre-defined financial targets (e.g. revenue or cash flow). Achieving those targets is directly related to measurable value generation that ultimately is part of the very fundamentals of doing business (Ramanathan & al., 2017).

According to Vidgen & al. (2017) and Davenport & al. (2010) a contemporary organization's process of becoming data-driven features some of the same aspects that were already discussed as part of the answer to previous supporting research question in section 3.1. These aspects revolved around having a clear data strategy, employing the right people with the correct skills to drive the cultural change within the organization and eradicating the differences in perspectives among the employees of the organization in terms of what it means to be data driven. More importantly, these differences in perception need to be replaced with an aligned holistic view of the company and what it is attempting to achieve.

In conclusion, the best ways to decrease the conceptual distance between strategic goals and business analytics is through solving the challenges that were listed as parts of the answer to the research question (see Table 4). Them being (e.g.):

- Eliminating the variance in perceptions among employees regarding strategic goals and business analytics.

- Clearly defining the intended outcomes of strategic goals and business analytics, while making sure they are understood throughout the organization through the utilization of effective methods of communication.
- Ensuring that management commitment is on an adequate level in order for the decrease in conceptual distance to take place.
- Streamlining collected data and used analytics tools to be easy to adopt and provide only the necessary information needed to support decision-making.
- Provide training on-demand to the employees that struggle with the concepts to eradicate negative experiences early on that might result in prejudices or bias at a later time.

Core research question: How to align business strategy with analytics (strategy) to create value for the firm?

Even though the amount of direct academic research on the alignment of business strategy with business analytics (strategy) to create value to the firm was limited, a lot of research was available from the business analytics and its value creation standpoint. The research related to business analytics and its value creation potential often included parts about its alignment with business strategy. With this and the help of the chosen supporting research questions, final conclusions on the core research question could be made.

In order to begin highlighting the importance of business strategy alignment with analytics (strategy) to create value Mazzei & Noble (2017) provide a compelling argument regarding the subject. According to them, the relationship between data and strategy and the way in which they influence each other has changed over the recent years – instead of strategy just influencing the data of an organization, the data now also influences the strategy through insight generation based on data and business analytics. Because the two concepts interact with each other in contemporary companies, it is safe to say that they should be closely aligned to be able to do just that.

Vidgen & al. (2017) also argue that the alignment between business strategy and analytics (strategy) is important – in their framework depicting business analytics as coevolving ecosystem (Figure 12), they emphasize the importance of the alignment of strategies between the data, business and organizational functions within a company. Even though this argument was made from the point of view of the organization becoming data driven, it supports the core research question for this study as well because it clearly identifies and emphasizes the importance of having an organizations data strategy aligned with its business and organizational strategies. And business analytics cannot exist without data.

According to Akter & al. (2016) the big data analytics (BDA) capability of an organization affects its overall business performance. The performance increase is enhanced further if the organization has its analytics capabilities well-aligned with its existing business strategies. Furthermore, the alignment between business strategy and analytics is highly dependent of the organization's leadership and management, because they are in the position to align functional goals and objectives with analytics capabilities which in turn – enables the organization to create value from analytics.

For organizations to be able to build strong big data / analytics strategies literature suggests that they need to be able to avoid the conflict between the related aspirations and authenticity. In other words, aspirations regarding big data strategies can end up being misleading from a leadership perspective because they focus on outlining goals and motivations for it, whereas authenticity is not because it mainly involves conducting a reality check of what kinds of capabilities and resources the organization already has available to it as is. These capabilities and resources can be physical or financial, related to human capitol, organizational knowledge or the organization's digital capabilities. In addition, they can used to determine which capabilities are lacking and need additional investment. Suryanarayanan & al.'s (2018) argument supports this notion by saying that companies should focus on identifying the required capabilities and only then determine the requirements needed to build them. Before engaging in building a big data / analytics strategy or thinking about aligning it with business strategy, additional though should be put into questions like:

- What is defined as success? (Clear goals)
- What are the organizational benefits? (Accurate description of intended outcome?)
- How does it fit the overall strategy of the company? (Alignment between strategy, data and analytics)

- How is support throughout the entire organization gained to ensure the change required by the initiative happens as planned? (how to increase the commitment among employees to drive the change)

Apart from highlighting the importance of the alignment between business strategy and analytics (strategy) to create value, none of the academic articles provided a ready plan on how to go about it. Instead, they mostly outlined questions that needed answers (such as the ones above) before engaging in such endeavors. Therefore, it is safe to say that according to previous research there is no right way of aligning the strategies with each other, however if taken into consideration, the aspects and concepts mentioned in the supporting research questions and related conclusions will help contemporary companies align their business strategies with their analytics (strategies) and contribute to value creation and their path of becoming data driven.

3 Research methodology

3.1 Research approach and design

In this research the aim is to objectively look at and draw conclusions on how to align business strategy with analytics (strategy) to create value for the firm based on the material that was collected from selected interviewees working in a few different industries.

In terms of research methodology related theory, Yin (2003) mentions five types of research strategies (‘Strategy’ column, Figure 15) in terms of case study research and the three key areas that should be thought of when deciding which research method to utilize. The five

Strategy	Form of Research Question	Requires Control of Behavioral Events?	Focuses on Contemporary Events?
Experiment	how, why?	Yes	Yes
Survey	who, what, where, how many, how much?	No	Yes
Archival analysis	who, what, where, how many, how much?	No	Yes/No
History	how, why?	No	No
Case study	how, why?	No	Yes

Figure 15: Relevant Situations for Different Research Strategies (Yin, 2003)

different research strategies were; experimental, survey, archival analysis, history and case study. Yin (2003) then moves on to describe what form of questions each strategy type answers (‘Form of Research Question’ column, Figure 15); survey and archival analysis strategy types answer the questions who, what, where, how many and how much whereas; experimental, history and case study strategy types answer the questions how and why. The case study research type strategy was selected based on Yin’s (2003) descriptions and the nature of the research in question.

After defining the relevant for of question, Yin (2003) asks each research strategy type two different questions related to the research area and its setting (Figure 15, two last columns). These two questions were the following; does the researcher have control over behavioral events regarding the research area and; does the research question focus on contemporary or historical events. By asking about control in regard of behavioral events Yin (2003) refers to the type or characteristics of the research. E.g. if the research is related to something that happened in the past and the researcher needs to rely on artifacts or historical documents as a source of evidence, the researcher has no control over behavioral events regarding the research subject. The answers regarding control over behavioral events and basis on historical or contemporary events are the following. There was no control over behavioral events from the researcher’s point of view during the interviews because the research questions we’re based on contemporary events or events that had taken place in the near past (within a couple years). In other words, the researcher had to rely on the interview answers as a source of evidence regarding the subject matter, and since the research subject was based on contemporary events and the data was collected by interviewing people, the researcher had no control over behavioral events either (Yin, 2003):

> *“In general, case studies are the preferred strategy when “how” or “why” questions are posed, when the investigator has little control over events, and when the focus is on a contemporary phenomenon within some real-life context.” (Yin, 2003)*

After determining the research strategy type, further specifications were made regarding the case study strategy. As case studies can be single or multiple / comparative, a decision between selecting one of the previous was in order. Because the researcher wanted to include a wider perspective that includes several different business areas instead of just one into the research scope and comparison, the multiple / comparative case study method was selected.

Suryanarayanan & al. (2018) ads to Yin’s (2003) perceptions for research conducted through the case study method saying that, case studies offer a deeper potential in understanding of contemporary phenomenon within organizational settings. Additionally, the case study research strategy is well suited to understand the nature and complexity of the phenomenon’s in question. Furthermore, it is also an appropriate methodology where studies are scarce, providing an opportunity to gain further valuable insights. Business value studies in business analytics are scarce at this moment, and the mechanism by which analytics contributes to business performance is also not clear (Suryanarayanan & al., 2018).

3.2 Semi-structured interview design and data collection

The approach to gathering the material needed was conducted in the form of a qualitative semi-structured questionnaire (See Appendix 1 and 2) with which the writer then interviewed, recorded and literated the conversations that took place on several occasions. This enabled the extraction of current and personal experience-based information on the subject matter from the chosen interviewees through interview sessions that lasted between 45 minutes to 1 hour per interviewee.

The questionnaire was tested during the first two interview sessions and the interviewees were asked what they thought about the interview situations. Based on the feedback of the first two interviewees the questionnaire was revised a couple times, with the intention of streamlining the interview process. In other words, the interview situation and conversation methods were changed into supporting more structured format – allowing for less conversation around the question in comparison to first two interview situations. The change was made because the amount of open conversation around each interview question made the literation process more challenging than it initially should have been.

3.3 Defining the chosen case companies and the reasons for their selection

The case company selection was initially conducted through reaching out to the pre-existing networks of the researcher. After listing the most interesting potential case company business areas in relation to research subject from the existing networks, a selection of preferred case companies was formulated. After this, the potential interviewee candidates working in those companies were contacted and asked who the best possible interview candidates would be (in their organization) for the research subject. Based on the feedback from asking this question the named potential candidates were then contacted in hope of setting up a time and place for the interviews.

The initial plan was to get 2-3 people from each organization, with a preference that the selected people would be representing different functions and roles (manager / expert) within that organization. This was then planned to be repeated 2-3 times to ensure a larger variety in terms business areas included in the study. In reality, it was proved to be challenging to organize all the intended interviews due to the busy schedules of interviewee candidates.

The final outcome of the case company and interview selection was that a collection of seven (7) interviews were conducted based on a semi-structured questionnaire. Out of those seven (7) interviewees two (2) pairs worked at the same organization. Two (2) interviewees worked for a financial services company and another two (2) for an IT-Consulting company. The rest of the interviews represented their own cases. One (1) interviewee in information technology and transportation services, one (1) in construction and maintenance of electricity / communication infrastructure and finally, one (1) in retail / wholesale. A table featuring interviewee and case company information can be found below (see Table 2):

Company (A) / Interviewee (1) / Order (#):	Position in organization:	Business area of organization:	Organization founded:	Organization employees:
A1 (#3)	Manager	Financial services	2001	~30000
A2 (#5)	Analyst / Manager	Financial services	2001	~30000
B1 (#6)	Analyst & Consultant	IT-Consulting	1999	~300
B2 (#7)	Analyst & Internal process development	IT-Consulting	1999	~300
C1 (#4)	Data Analyst	IT & Transportation services	2015	~100
D1 (#1)	IT Manager	Construction & maintenance of electricity / communication infrastructure	2005	~1000
E1 (#2)	Manager	Retail / Wholesale	2004	~1000

Table 2: Interviewee and case company information

The interviewees and the case companies are not mentioned by name in this study to avoid risking publishing sensitive information regarding the interviewees or the organizations they represent. This was one of the prerequisites agreed upon in the beginning when the interview locations, dates and times were being set up.

3.4 Reliability and validity

During the process of interviewing the different candidates, a couple questions included in the semi-structured interview template resulted in the need to explain the meaning of the question further. The explanation in these cases was for the most part done by rephrasing the question to provide the interviewee a better starting point to begin answering the question. Apart from occasionally having to provide a rephrased question or some additional information about the question in general, the conversations had based on the interview template managed to provide adequate answers to the questions.

The questions that proved to be the hardest to comprehend upon asking them the first time in the interview situations were questions C) and E) (See Appendix 1 and 2). The reason why question C) was hard to understand was undoubtedly the fact the interviewee’s generally thought of business analytics (strategy) alignment with business strategy from a practical point of view that supports the notion that analytics strategy does not incorporate a strategy of its own, but belongs under a contemporary company's business strategy as one of its components. Therefore, in a few cases the possibility of having an entirely separate business analytics related strategy as a possibility had to be clarified to in interviewee's separately. The reason for question E) being hard to comprehend at first was the fact that it was based on a fully hypothetical situation to which the interviewee's either had direct personal experience or not. The question was easier to understand and answer in situations where the interviewees had previous practical experience on the subject.

Some interview answers were more in-depth than others, and one of the largest differences in answer depth was related to the business area of the organization the interviewee represented. For further clarification, companies that operated in IT-heavy business areas were generally better equipped to provide more in-depth answers to the interview questions in comparison to companies that did not.

4 Results

4.1 The definition of business analytics

The interviews began with asking the interviewees to determine what business analytics meant to them personally based on their experiences. The reason behind the question was to be able to determine and compare how the interviewees saw business analytics as a concept. It was also an important question to ask, to make sure that all the interviewees viewed the concept somewhat similarly.

The interviewees conceptualized business analytics to include the use of analytical tools to measure different kinds of business impacts, making decisions based the findings of using those analytics tools and support decision-making processes in general through the evaluation of gathered data based on the daily business operations of the organization. It was also characterized as the act of using recorded data from historical events to create actionable plans for the future as well as predicting market trends. In addition to supporting decision-making processes, its purpose was to support company strategy and the formulation thereof. More accurately, being able to visualize and concretely improve a company's strategy and selection of KPI's to increase the sense of purpose and strategic goals of the organization among the company's employees. Further examples of these characterizations could be the existence and use of different kinds of technologies, organizational processes and applications or the use of data to mold the mindsets of employees to become increasingly supportive towards the use of analytics tools in an organizational context. With that said, the ability of using data situationally and understanding the implications of that data to be able to generate meaningful insights that can be turned into actions was a focal part of what business analytics was all about.

Business analytics and the related IT applications are also often linked to problematic pieces of software or analytics tools that have a tendency of being slow, processing for long periods of time and sometimes not working at all. Notions like these are a good example of the prejudices or biases formed based on previous experiences employees might have accumulated during their careers in different organizations. These same prejudices and biases are also some of the challenges that need to be overcome when business analytics is being discussed and adapted in contemporary organizations.

After discussing the definition of business analytics with the interviewees, they were asked to provide a few concrete examples on how business analytics is present within their job descriptions. The purpose of asking for concrete examples was to ensure that the answers regarding the definition of business analytics and the concrete examples provided were in-line in comparison to each other.

The examples given by the interviewees were many and supported the conclusion that as many definitions exist as there are people. The examples were mainly in-line with the definitions disclosed in the first interview question that asked what business analytics meant to the interviewees personally.

Business analytics was present in the case organizations according to the interviewees in the following ways; transformation of data into streamlined informative visualizations, dashboards or datasets to help decision-makers with their decisions, creating reports tailored for the use of business units within the organization, monitoring data related to user amounts, downloads and usage retention rates for mobile applications, time and resource allocation from a consultant perspective to better track personal billing rates and time usage with the aim to improve personal efficiency and time use, keeping track of service order counts and their deadlines from client companies, optimizing sales processes and tender design based on historical data to ensure a more profitable outcome in the future, recognizing underlying vulnerabilities in existing company systems or software, planning of future sales campaigns and their resource requirements based on data collected from past campaigns, tracking marketing initiatives such as website traffic and cursor locations and using data or analytics justify decisions in business meetings.

4.2 Analytics strategy and business strategy alignment in the case organizations

This portion of the interview was comprised of a realization which stated that not much direct academic research was found on the alignment between analytics strategy and business strategy, because this alignment is highly company-specific and there seemed to be no one right answer on how the alignment should be built. That said, also the fact that in some cases analytics was considered being a part of business strategy instead of featuring its own strategy, had a role to play on why the amount of research found was scarce.

Interviewee's were asked about their thoughts on the two concepts, the alignment between them and if that alignment existed in their organizations. The purpose for the question was to find out what the interviewees thought about the concepts, if analytics strategy was being considered as a separate concept in organizations or was it considered an element of the company's overall business strategy.

The answers received from the interviewee's featured some variety between each other. For example, in some cases the alignment was argued to exist and being strong enough to drive the transformation of the business towards becoming increasingly data-driven, whereas in another it was deemed completely nonexistent due to the relatively small size of the company and the lack of staff in its analytics department. The fact that the alignment was nonexistent according to the interviewee (C1, see table 2) did not mean it was not important, in fact the interviewee (C1, see table 2) emphasized its importance and continued to state that it is likelier to be missing when considering smaller organizations in general. In other words, bigger organizations are more likely to have recognized and aligned both concepts and are either considering them as separate entities or one entity, in which business strategy incorporates developing a purpose and utilization for business analytics in the form a separate strategy or as a part of the business strategy itself. A good example of this was provided by one of the interviewees (A2, see table 2) who stated that his company consists of numerous business units that concentrate on different areas of doing business and that in his particular business unit the alignment and the concepts are very present, but in some others it was missing completely. He (A2, see table 2) also continued to state that in general, the older the business unit of the organization, the less likely it is for it to have adopted the alignment between analytics strategy and business strategy.

Another interviewee (B1, see table 2) presented the possibility that analytics could have a strategy of its own if the case company's core business had something to do with data science and sophisticated forecasting of future events or machine learning models. However, even if this was the case, and if a separate analytics strategy would be beneficial, it should still be a concept that supports overall business strategy. The interviewee (B1, see table 2) then continued to describe the case-specific nature of business analytics and that its use can vary a lot depending on what the company does as its core competence to generate revenue. In the terms of a typical company that uses business analytics to support its day-to-day activities and business strategy formulation, a separate analytics strategy is not a necessity.

Another interviewee (D1, see table 2) pointed out that, if the case company's business operations feature a lot of process-like activities and data is being collected, the alignment of the concepts is likely of being beneficial for the company. However, if the core competences are more project-like (as in every case is different) and there are several ways for those daily activities and getting to the desired end results, it is more difficult for a company to benefit from the alignment. As an example, a service business has a tendency of being very process-oriented if viewed holistically, but it also features a lot of underlying aspects that are parts of those processes when looked at in-depth. The presence of the alignment between the concepts can also be viewed as an underlying way of doing things instead of being implemented by leadership to be an existing part of the business strategy. In other words, company experts and analysts can enable the existence of the alignment just by being aware of the concepts and recognizing them while they work (D1, see table 2).

The last interviewee (B2, see table 2) thought that thinking of two separate strategies (analytics and strategy) felt a little bit funny, yet it isn't too far from the truth. This led to a similar opinion popping up in comparison to several of the other interviewees – the fact that analytics should be considered as part of business strategy and not as its own strategy. He (B2, see table 2) also continued to state that many companies still make operative and strategic decisions based on gut-feelings, which is not necessarily a bad thing assuming the made decision is justifiable (either by data, employee experience or both).

The second question regarding the subject was about the importance of having a separate analytics strategy in place to complement existing business strategy. Based on, what has been discussed thus far, the majority of the interviewee's thought that instead of being separate entities, business analytics should be a part of business strategy to be able to support it as well as it possibly can.

The third interviewee (A1, see table 2) supported the notion stated in the previous paragraph saying that two separate strategies are not needed and that they should complement each and other in the form a single business strategy. As an example, a strategy could consist of elements that aim to increase business momentum (business strategy) while cutting structural cost (analytics strategy) for the business. An example like this sounds particularly good as both aspects contribute positively to the company's bottom line. The fourth interviewee (C1, see table 2) thought on the contrary in the beginning but had a change of heart the further the discussion proceeded. Having a separate analytics strategy and business strategy is important to have, but they should be linked and complement each other. He (C1, see table 2) then moved on to give an example where problem-solvers need a definition of the intended outcome in the form of a strategy in order to develop a solution that solves the problem and simultaneously supports the intended outcome and the business strategy of the company. In other words, business strategy comes first, and analytics strategy follows complementing the business strategy. A visually portrayed framework that features some case examples could be beneficial in terms of an analytics strategy. The ability to see how analytics is being used in the organization with a couple use cases can help define its purpose and increase the general understanding among employees. Many companies also have a separate department that oversees providing the needed data and analytics to other departments. If a separate analytics department exists, its operations should be guided by business strategy so that it can support it through the different ways it operates and aids the other departments with data and analytics within the organization. Attempting to make the use of analytics and data as transparent as possible in the company internally can contribute to the pace at which different departments want to change their operating model towards a more data-driven one at that. Additionally, having a separate analytics strategy (even if it was tied under business strategy) could also help with the company's internal transformation of becoming data driven. The reason behind this is the fact that having clear guidelines on how data and analytics is to be used within the company will help employees wrap their minds around the new data and analytics-based way of thinking.

At one (B1, see table 2) of the companies a significant shift in the amount of analytics use and strategy has taken place over the course of the last 2,5 years. The company created a process and a model to support that process with the goal of emphasizing the importance of the use and improvement of internal analytics tools and the tracking of personal time use per customer to track (e.g.) customer billing rates better. Even though the company has been incorporating strictly analytics improvements and an analytics strategy of sorts, emphasis is still on the importance of business strategy and its ability to guide the use of existing analytics capabilities within the company.

The two last (B1 & B2, see table 2) interviewees shared the notion of analytics being part of business strategy for the most part. However, the first interviewee (D1, see table 2) questions if a separate analytics strategy is needed to help companies decide what pieces of data to store. The last interviewee (B2, see table 2) in turn makes his case by stating that he would not separate the concepts to have their own strategies but would instead utilize business analytics to support and steer the formulation of business strategy within companies. He then justifies his statement by saying that making short-term strategic plans in companies these days can be very challenging because changes in market situations and businesses have a tendency of happening very fast and not much time can be used to make those plans because of those changes.

4.3 Value or competitive advantage generation through business analytics in case companies

The questions in this part of the interview were related to how value or competitive advantage was generated through business analytics in the case companies. The purpose of the first question was to find out whether the case companies were attempting to gain competitive advantages or value generation through the use of business analytics and how they were doing it.

According to one (A1, see table 2) of the interviewee’s tracking the core business related key performance indicators (KPI’s) is important for any company. For example, when working with mobile applications that are considered on being a free value-adding service to the company’s existing customers tracking data relative to usage, downloads, retention and churn rates help determine how much the value-adding services are being used and how they can be improved in the future, or if they should be cut completely due to the lack of usage. Furthermore, following company performance via KPI’s makes it easier to concentrate on other activities (such as working towards developing competitive advantage) because you are constantly aware of how the company is doing.

A good example of the lack of structure and understanding within the company in terms of using business analytics was received from one (C1, see table 2) of the interviewees. Even though, the needed analytics capabilities were in place, decisions were still made based on gut feelings. The perception of being data driven was different among the different people in the organization which made the utilization of business analytics for decision making hard in the company. Furthermore, the different views resulted in the creation of analytics-based metrics or KPI’s being tailored towards personal preferences, which again increased the risk of misunderstanding the situation when the different people had a different way of viewing those KPI’s. In other words, the company lacked a strategy or a purpose that would guide the people with using the existing analytics capabilities in different situations. Because the problem was directly linked to the use of analytics, it can be argued that the lacking strategy was in fact the analytics strategy, but the fact is that even if it is so, it also means business strategy is lacking because the two should be closely linked and support one and other.

Examples of how companies can use business analytics to create value or competitive advantage are many and also depends on what the company in question does as its core competence. Value generation could be achieved through predicting future market trends and being able to cater to the needs associated with them better by reflecting on a past situation. Seasonal sales campaigns could be an example of situation like this (E1, see table 2). That said, in some cases value through business analytics can be generated by streamlining existing business processes that result in cost savings through less time being spent on the process itself. As an example, thinking of a service business that bases its core competence on repairing and maintaining infrastructure (D1, see table 2). The streamlined process could simply mean that the same person moving around a geographical area attending to faulty infrastructure is capable of fixing more faults with the same time he or she uses to move around that geographical area on a daily basis (D1, see table 2). In other words, in this case the streamlining of the process is equal to more efficient route planning between fault locations within the geographical area.

Competitive advantage could be gained through the creation and monetization of new services or ways to do business for the company that have been recognized using business analytics as a tool (B2, see table 2). Strictly from a consultative point of view, the monetization or creation of new services could be an entire business analytics solution (as an example) offered to the company's clients with the purpose of providing them with business value and competitive advantage in their respective business areas in exchange for adopting the offered business analytics solution (B2, see table 2). All in all, generating competitive advantage over business value can be difficult and depends on how business analytics is being utilized in the case company's business area. For example, if the case company strictly operates in retail or wholesale (D1, see table 2), creating a competitive advantage based on just sales data can be difficult especially if the competition is high within that particular market.

Assuming the company in question has access to an adequate amount of data it gains the ability to utilize it for different kinds of activities, which could end up becoming sources for value generation or competitive advantage if refined. Further examples on how to drive value out of analytics could also include the ability to recognize the most profitable activities from the company's product or service offering / portfolio (D1, see table 2). This example becomes more current when the business operations are many and differ between existing clients. Furthermore, these recognized less profitable business processes can be renegotiated with clients with the goal of attempting to make them more profitable in the future. In other words, the proactive recognition of potential problems in terms of business process profitability can and should be done by all companies' despite of where their core competences might lie (B1, see table 2). The only aspect that changes based on the company's core competence or business area is the method how proactive recognition and business process profitability can be tracked through the use of data and analytics.

The second question was aimed at finding out what the case companies were doing with business analytics in terms of improving their business strategy planning and / or tracking. Because analytics can be used to plan for the future, the purpose was to find out if it was being done within the selected case companies.

In one of the companies the strategic planning was not done well for the year 2019 (C1, see table 2). According to the information received, it was formulated by a very small group of people who were under pressure from company investors. This led to the strategic plan not being well-communicated throughout the company. In addition, the strategic plan featured unrealistic targets that contradicted the company's fundamental logic of business operations and the potential to generate revenue. Learning from past mistakes, the strategic planning for the year 2020 was considerably better. They realized that the different analytics ideas were based on the varying backgrounds of the people supplying the ideas and that they ended up overlapping with each and other. This was solved through the standardization of business analytics tools, data, dashboards and reports. Emphasis was put on keeping the standardized analytics structure together. Data-driven decisions were based on standardized analytics tools that were available for everyone. (C1, see table 2)

One of the case companies (B1 & B2, see table 2) used business analytics to strategically plan and track internal systems, software and its external product portfolio through the optimization of products and services while attempting to keep the costs of development in check. Commercialization and monetization of data was considered the key initiative throughout the organization. Continuously monitoring existing products and services enabled the company to optimize resource usage regarding development and maintain sales simultaneously. They also realized that the same tools that were being tailored and provided to the company's customers could be used to track and plan internal resource allocation, time usage and revenue generation internally. (B1 & B2, see table 2)

Increasing the amount of analytics used in strategic planning helps the company recognize aspects of the business that need improving. For example, business processes that could work better and save time instead of being inefficient and be associated with a lot of time wasted. The recognized problem areas can then be communicated to the decision-makers and be further discussed in cooperation with experts to come up more efficient methods or improved processes to implement in the future. (D1, see table 2)

In at least one of the companies the planning of next year was done by looking at KPI's generated by analytics (E1, see table 2). From a retail organization's perspective the improvement of the sales process was a difficult concept to grasp because so much of sales situation relied on the interaction between the salesperson and the potential client. Instead of trying to improve the sales process, the KPI's generated by analytics were efficiently communicated throughout the organization to make sure everyone was working towards achieving their total sales targets (E1, see table 2). In comparison to companies working in different business areas, the way analytics can be utilized to streamline processes and find potential problem areas in them is different. Generally, retail companies use only a fraction of what business analytics has to offer because the additional features are not necessarily needed.

Operating under a fully customer centric strategy has enabled one of the case companies to create a variety of benchmarked numbers, dashboards and analytics tools under each customer separately (B1 & B2, see table 2). This in turn made the customer-based decision-making and leadership possible. The company's over-arching strategy was always applied on every customer separately and then led by reviewing past conversations, customer specific data and the development of the relationship in the light of these details. In other words, analytics plays a focal part in the strategic planning and tracking for the case company. Future plans of expanding to business areas or geographical areas where the company has not operated before present a problem for use of analytics for strategic planning for company. After all, it is difficult to look at analytics data that does not yet exist. (B1 & B2, see table 2)

4.4 Analytics investment opportunities and the willingness to back them up in the case companies

This part of the interview consisted of a statement and a question following the statement. The statement outlined a hypothetical situation for the interviewee implying that analytics investment opportunities cannot easily be measured using financial indicators and that not being able to measure them like this can make them less enticing when compared to an investment that can promise an improvement in cutting costs (for example) from the very get-go. The follow-up question then fulfills the outlined hypothetical situation by asking the interviewee if they would be willing to take the risk with analytics investment opportunities even if they cannot immediately be measured using financial indicators.

Primarily the interviewee's started thinking of risk taking after being asked the question. According to them, the perfect situation for a company would be to be in situation where decisions could be made on accurate data and it would be possible to know beforehand how these analytics investment opportunities would play out. Risk taking is something that needs to be supported by the internal culture and strategy of the organization and it also depends on the size of that company taking the risks. Bigger company's generally have more resources and money at their disposal, so taking smaller risks really isn't a deal breaker for them, whereas small company's might be put out of business even if a small risk results in negative effects. Additionally, start-up companies are a chapter of their own in terms of taking risks, because in those cases the risks are often also personal and cannot be mitigated through having a big pool of resources and money at your back. That said, risk taking is necessary for all organizations if they want to stay current in contemporary fast paced marketplaces and organizations need to take it into account in their strategic / financial planning.

Secondly the interviewees started thinking about the financial planning and budgeting related to taking risks in an organizational context. In personal experience of one of the interviewees, the lack of planning analytics investments into the company budget resulted in decision-makers not willing to decide what kinds of things should be prioritized in the analytics investments the company was making. Thus, taking risks with analytics investment opportunities should only be done after they have been budgeted and their goals well-defined. Due to these considerations, it is fairly safe to assume that analytics initiatives benefit greatly from data-oriented leadership and company management support. Analytics investments are often considered as 'extra' things to do by organizations, especially in cases if they face challenges that need solving somewhere else in their more basic business processes or functions. In these cases, organizations should thoroughly evaluate where to allocate their resources, because the solution to the problem might lie in the added features enabled by business analytics initiatives or not.

The statement implying that the justification and quantification of analytics investment opportunities is difficult because they cannot be accurately measured in the beginning received support from several interviewees. The potential value is generally extracted after the project is close its end and the data related to it has been gathered for a while. Furthermore, analytics investment opportunities generally become trickier if the organization has had no previous history with the use of business analytics in the past. That said, the cultural change requires in these kinds of situations can be big.

To reduce the risks associated with analytics investment opportunities it is important that the opportunity is given an adequate amount of management support, commitment from employees, planning the project and its goals, budgeting and communication throughout the company. If the aforementioned requirements are met, analytics initiatives have a bigger chance to be successful and pay back the investment made by the company in added functionalities, features and improved business processes. Business analytics and data should be thought of as a resource that makes decision-making easier, justifiable, fact-based and faster. On the other hand, thinking of concepts like leading with data or data-driven decision-making, not many risks are directly involved with the concepts themselves or adding to the company's capabilities regarding those concepts. The largest risks that are often associated with analytics investment opportunities are for the major part linked to organizational communication or culture, and for the minor part linked to the technical aspects of the solution, new processes or software. With that said, the potential challenges that can be associated with the analytics investment opportunities need to be clarified before starting the project.

One of the most basic mistakes made by companies in terms of analytics investment opportunities according to the interviewees was the lack of focus and planning needed to successfully finish the project. The most important aspect to consider when engaging in such an opportunity is answering the relevant questions revolving around the purpose why the project is being undertaken. Questions that answer and outline what kinds of challenges are being solved by the project are extremely important. Once answers to those questions have been determined, the goals for project and preferred end result for the project or opportunity can then be determined. At this point, it is still fairly easy to back out of the analytics investment opportunity if the answers to the previous questions result in a situation that implies that the challenge can be solved by other means and that the added value from the project would not be of much use to the organization.

4.5 Conceptual distance between strategic goals and business analytics goals in the case companies

This part of the interview consisted of a main question and a follow-up question regarding the conceptual distance between the strategic goals and business analytics goals in the case companies. In other words, the purpose was to determine whether the two concepts were being considered separately in the case companies and if so, did the interviewees think there was conceptual distance between them based on their experiences. The purpose of the follow-up question was to look at the conceptual distance in further detail and try to engage the interviewees to provide ideas for decreasing it for situations where it was present.

The interviewees provided slightly differing answers to the question whether conceptual distance exists in the case companies. Judging from the answers a conclusion can be drawn that the way conceptual distance between the concepts is being viewed somewhat depends on the interviewee being asked the question, as well as the company and the business area it operates in. In other words, IT-heavy companies and companies that have their IT-services outsourced seem to see less conceptual distance between the concepts whereas smaller sized companies and smaller business units within bigger organizations see more of it. With that said, it seems that the linkage to the presence of conceptual distance between the concepts in addition to the business area of the organization is also dependent on the size and age of the organization or business unit. Smaller companies have generally not put much focus on business analytics because the benefits from it scale with the size of the organization (the bigger the business, the more benefits can be drawn out of business analytics), therefore more conceptual distance between the concepts is present. Furthermore, older companies that have been around for a longer time do not necessarily have much experience with business analytics in the past, which makes it harder for them to adopt now which also results in more conceptual distance.

The example about smaller companies and conceptual distance between business analytics goals and strategic goals was based on the differences in the nature of the two concepts.

Business analytics from an expert point of view can be a very concrete concept, whereas business strategy is not necessarily as concrete (C1, see table 2). Strategic goals for the case company (C1, see table 2) were not accurately defined or set-up in the beginning which resulted in ambiguity when company experts were attempting to understand what should be measured and how. The generic statements which were also the company's (C1, see table 2) business strategy at the time were too unclear to help with clarifying the business analytics goals. After learning from its mistakes the company managed to create a business strategy that helped guide the analytics goals and methods to attain them to the right direction (C1, see table 2).

Another example of a case company that had a longer history and that did not have experience with business analytics experienced some conceptual distance between the concepts (D1, see table 2). Analytics was not used much when it came to the strategic planning of the organization, however it was not completely disregarded either because the company experts were known to include thinking of business analytics related issues while they were solving problems or creating new ways to follow-up on the data the company was gathering from its business operations (D1, see table 2). The reason for the existence of conceptual distance in this example was that because business analytics had not been used in the strategic planning of the organization, the people in the company had a myriad of different mindsets regarding the subject based on their previous personal experiences (D1, see table 2).

The differing mindsets of employees regarding the conceptual distance between business analytics goals and strategic goals was also mentioned to be the reason for the existence of the conceptual distance in another case company (B1 & B2, see table 2). Furthermore, the differing views were related to work tasks and, how they should be prioritized, how many of them could be handled at once and when should they be handled (B1 & B2, see table 2). With that said, it is clear that in this example the problem causing conceptual distance was the work overload among the people in the organization (B1 & B2, see table 2).

The answers and examples received from the interviewees regarding how to decrease the amount of conceptual distance between business analytics goals and strategic goals in organizations were many, because the issue was encouraged to be looked at from several points of view. These points of view being all personal experiences regarding the subject and not just from their current place of employment.

Breaking-down the organization's strategic goals into something that can be directly compared with what a single person or business unit in the organization is doing (C1, see table 2). It becomes exponentially easier to reach strategic goals when you are capable of providing a good idea of how that goal can be attained and what are the things you or a business unit can do to help the organization reach that goal (C1, see table 2). A down-side exists in breaking down the strategic goals into a business unit or personal level. That down-side is the fact that generally speaking people working for the organization do not necessarily want to promise that the personal or business unit goal will be reached due to a carrying amount of uncertainty that is always present when doing business (C1, see table 2). This downside can be mitigated by ensuring that the right people hold the right positions within the organization (C1, see table 2). For example, managing roles that require willingness to take risks and make decisions should be help by people that are not afraid of doing just that (C1, see table 2).

Being able to provide trustworthy analytics tools for the use of the organization's employees also carry their own weight when it comes to changing the mindsets of the employees to become more supportive towards a data-driven method of doing business (D1, see table 2). Moreover, the fact that one can trust the tools without having to doubt them encourages the using those tools. On the contrary, if one has to continuously doubt how the tools work and disagrees with the insights that are being produced, it does the exact opposite – decreases the willingness to use the tools in the future (D1, see table 2). Furthermore, the doubt towards analytics tools is twofold, one reason can be the fact that they do not work correctly (or mistakes have been made in the past) and therefore can result in the wrong conclusions being drawn, and the second can be that person using the tools does not understand the logic behind them enough to be able to trust the end result that they produce (D1, see table 2).

As it was stated on several accounts of the answers to the previous interview question; the fact that people have differing opinions and experiences are the major cause for the existence of conceptual distance between strategic goals and business analytics goals in contemporary companies. Investing into increasing the awareness (changing company culture through communication) and changing the mindsets (eliminating prejudices and bias) of people in terms of business analytics and business strategy in organizations can help decrease the amount of conceptual distance present. With that said, it is also important to keep in mind that committing to making the changes and increasing the success chance of that change can be increased with adequate management support – the managers in the organization should put emphasis to support their employees with the change of their mindsets. Finally, the doubt towards analytics tools that was discussed earlier can also be solved or even eliminated by making investments in analytics awareness and changing the mindsets of the organization's employees.

There seems to be no one 'right way' to decrease the conceptual distance between an organization's strategic goals and business analytics goals according to the interviews, but several different things that receive a varying amount of weight depending the situation, amount of conceptual distance present, size, age and business area of the organization. Therefore, every organization is its own case and should find the right things to decrease the conceptual distance that works for them the best.

4.6 Challenges in combining business analytics with case company decision-making processes

The purpose for this part of the interview was to get an answer to one of the secondary research questions outlined for this study. The interviewees were asked to provide the main challenges they recognized in combining business analytics with an organization's decision-making processes and potential solutions for them.

The answers from interviewees regarding the main challenges revolved around the same subject areas, that were also mentioned in some of the literature collected and examined for the literature review section of this study. The solutions for the main challenges mentioned in the previous paragraph also revolved around the same subject areas, which proves that practice and previous research are more or less in-line with the studies conducted about combining business analytics with an organization's decision-making processes.

The first of these main challenges was not being aware which bits of information to store and measure, which would result in complications related to storing too much data and not knowing how to utilize it efficiently. For the solution to the first challenge, the act of attempting to bring company employees together to enable a continuous dialogue between employees and business units can increase the understanding of how business analytics works and what the best way of using it is throughout the organization. Additionally, having a clear idea how analytics capabilities are being utilized within the organization can also help determining which bits of information are important to store and which bits are unnecessary.

Secondly, understanding the business analytics well enough in decision-making situations was considered a challenge (also referred to as data illiteracy). This can be solved partially with the dialogue mentioned in previous paragraph as well as with actual practice with the use of business analytics as an active part of decision-making. Additionally, the negative effect created by data illiteracy can be reduced through communication, training and increased data flows within the organization.

Third, being able to create streamlined and simple analytics solutions for the use of the organization's employees that do not feature excess information was considered being a challenge. This can be solved through having an adequate amount of dialogue between end users of the tools and people responsible for designing them, having extensive documentation that describes what the tools are supposed to be used for and why and encouraging the people to use those tools to make their working more efficient.

Fourth, decision-makers need to be given enough time to understand and properly evaluate the insights generated with the aid of business analytics. The solution would ideally be a situation where decision-makers have had the chance to learn the basic logic behind business analytics tools that are being used. Because this is often not the case in many organizations, the second-best solution is to ensure the decision-makers have adequate support available to them when they attempt generate insights based on data. Also having an adequate amount of documentation available that provides additional information about the analytical tools being used offers an additional self-help possibility incase support in the from an expert is not available.

Fifth, generally speaking employees do not want to have their work being available to be scrutinized. In other words, employees might have realized what the potential gains could be if they used business analytics capabilities offered to them more, but simultaneously they are afraid of the risks involved. This is something that is not easily solved, however good communication throughout the organization is a good cornerstone to start building on. Changing employee's mindsets to support a data-driven way of thinking by providing valid arguments on the reason why analytics capabilities are being developed within the company. For example, an argument like this could be communicated throughout the organization; the company is developing its analytics capabilities to empower employees with their work and not to keep tabs or scrutinize the way employees choose to work.

Last but not least, the fact that people often view change as a bad thing due to having to modify their own mindsets and ways of doing things is something that hinders the ability to combine business analytics with decision-making processes in organizations. The solution for this lies in the same things as the solution to lack of understanding in business analytics - communication, training and increased data flows within the organization.

4.7 Analytics in well-performing organizations

For this part of the interview a statement from literature was presented to the interviewees. The statement argued that well-performing organizations use analytics to support their decision-making processes more in comparison to organizations that are not. And furthermore, the insights generated by using business analytics are used to guide everyday operations and long-term strategy formulation. After presenting the statement, the interviewees were asked two follow-up questions that focused on finding out their thoughts and personal experiences regarding the statement.

The answers received to the first argument made in the statement and the first question mostly agreed and disagreed simultaneously, except for a couple interviewees who agreed with the statement completely (D1 & E1, see table 2). It is possible for companies to be performing well from a financial standpoint if the market they operate in is new and/or booming. For more established (or saturated) markets the statement is more likely to being true. With that said, it is also possible for an organization to be in a situation where it has not been doing well, which has led to the decision to start investing in improved analytics capabilities, that ended up leading to a solution being found for the poor performance. All in all, the first part of the statement is more of a perfect world example than a realistic argument that applies to all situations – there are situations in which it applies yes, but there are also situations in which does not.

The second argument that was part of the statement implied that insights generated by using business analytics are also used to guide everyday operations and long-term strategy formulation in well-performing organizations. The answers mostly supported this implication however, having good analytics in an organization does not necessarily mean that it is well-performing – it is more likely yes but can also be on the contrary. Analytics capabilities are generally a very good support engine for companies but should under no circumstance be considered as everything that is needed – the human factor carries a lot of weight in terms of how analytics-based insights are being generated, utilized and made actionable. To quote one of the interviewees (B2, see table 2): “Companies are slowly starting to take first steps towards data science and machine learning projects. The point being that machine learning paired with human expertise is the solution, and that relying on human expertise or machine learning alone is likely to result in worse outcomes in comparison to a situation where they are being paired together for the best possible result.”

Personal experiences regarding the statement included (but were not limited to), for example:

- Using analytics to justify action plans for the future regarding the organization’s products and services. (A1, A2 & E1, see table 2)
- Increasing the data flow within the organization to make analytics dashboards available to all company employees (open playing field concept). (C1, see table 2)
- Tracking billing related information to ensure client projects are completed within the allowed timeframe. (B1 & B2, see table 2)
- Upkeeping service-level agreements through active monitoring of agreement-critical business information. (D1, B1 & B2, see table 2)
- Improving old analytics tools and developing new ones to make monitoring business performance more accurate and easier. (D1 & C1, see table 2)

4.8 Insight generation through business analytics in the case companies

Finally, for the last part of the interview a final statement and a follow-up question regarding insight generation through business analytics was presented to the interviewees. The statement also argued that business analytics should be considered being problem solving, which in turn is a process that requires a human presence. The follow-up question aimed at finding how insights were being generated in the case companies from business analytics. The interviewees fully agreed that business analytics should be classified to be a type of problem solving within contemporary organizations. They also thought that the human role in the insight generation process was very important and could not be done without either human or computer alone, but both of them working together. One of the interviewees (C1, see table 2) even stated that: “Using data to support decision-making is more about interpretation of the data provided to the people through analytics tools instead of the tools themselves.”

The answers for the insight generation question were interesting because they featured the same things mentioned also by literature. Cross-functional teams seemed to be buzzword in the literature and when asked the interviewees, they agreed that at least a part of insight generation in their companies was generated through them. Additionally, at least one of the companies represented (A1 & A2, see table 2) had a separate central data team or business unit that specialized in providing the other business units within the same organization the data and insights they needed. The people working in the central data team or business unit were part of the cross-functional teams during insight generation processes. A step-by-step description of how insights can be generated within a contemporary organization with central a data team or business unit, is below (A1 & A2, see table 2):

1. A project manager meets the data analyst with a requirement and defined criteria for data needed.
2. The manager and analyst book a meeting the data team of the organization (cross-functional team is formed). The outcome of the meeting should be knowledge of the data regarding what can and what cannot be done in terms of it.
3. The data team provides the manager and analyst a data dump for their review and books a meeting with them to together generate insights based on the provided data dump.

In most of the case companies (A1, A2, B1, B2, C1 & D1, see table 2), discussions about gathered data or analytics with experts take place on a regular basis and insights generated based on those discussions. Those insights are then evaluated in case they should be sent forward to other business units for a more detailed evaluation. The purpose for the evaluation right after the first discussions take place is to control the amount of insights that need further evaluation from the business units, who also ultimately are in charge of turning those insights into potential action plans. Some slight variations to insight generation does exist depending on the organizational structure of the company in question. For example, an interviewee representing a company that featured a slightly more hierarchical organization structure described their insight generation process in the following way (D1, see table 2):

1. An employee generates an insight regarding a recognized problem and reports it to his or her business unit.
2. The business unit evaluates the insight and the severity of the problem. The business unit sends the insight for further evaluation to the people that are in charge of deciding if a solution needed urgently or not.
3. If the insight is still of high importance at this point, all the people involved in the insight generation process are put together (creation of a cross-functional team) to come up with a potential solution to the problem.

With the cross-functional team being a focal part of insight generation and problem solving, so are the tools that provide the teams the data that can then be used to generate insights. Two interviewees provided a couple descriptive cases how insight generation works in their experience:

“Team- and role-based analytics solutions exist for insight generation. Every company function has its own set of informational dashboards that enable monitoring data and generating insights throughout the organization on a daily basis. These analytics tools are being mostly used to guide personal work activities, but they are also utilized in larger meetings that concentrate on business process development and problem solving. These larger meetings often generate new points of view on existing problems that can then be taken forward and documented for further insight generation.” (B2, see table 2)

“Generating insights through a combination of machine learning / automatic reports paired with cross-functional teams and experts’ opinions on the generated reports to draw insights out of the data or dashboards.” (B1, see table 2)

4.9 Summary of results

Supporting research question: Why is it challenging to create firm value through business analytics in the terms of decision-making processes?

To be able to provide an answer to the supporting research question regarding the challenges in the generation of firm value through business analytics and decision-making processes from a practitioner standpoint, the most focal interview questions and their answers were put together and summarized. The outcome was more or less the same as with the academic portion of the conclusion section (3.1.1.) with the answers revolving around the same subject areas while using slightly differing terms and examples.

The first challenge based on the interviews was the lack of a clear definition of the intended outcome in terms of using data and business analytics to generate value through company decision-making processes. According to the interview answers, the clear definition of the intended outcome should preferably be something that simultaneously is capable of providing a solution to a problem as well as supporting the company’s over-arching strategy while doing so. In other words, lacking a clear definition in terms of the use of business analytics severely hinders its potential performance in an organizational setting.

The second challenge that was drawn from the interview answers was the fact that the perceptions of what it means for an organization to be data-driven were different among the different people working for the organization. If the perceptions regarding the goals are not aligned between the people, it becomes extremely hard to achieve it as a whole because all the employees are working towards a different outcome.

The third challenge mentioned by the interviewees was the need to take risks with data and business analytics organizational capability improvements without having a guarantee what the result of it would end up being. The perfect situation would be characterized as being able to take calculated risks in terms of business analytics capability improvements in the company. However, in most cases this is not possible due to the nature of these kinds of analytics investment opportunities – generally speaking, the data needs time to build up before a determination of its usage potential can be made. Furthermore, to support this a challenge the interviews also provided an example of the inability to budget analytics investments within companies, which led to situations where leaders were unable to make decisions regarding them due to the uncertainty of their costs / outcomes.

The fourth challenge according to the interviews comprised of several parts and was close to the first challenge mentioned. Because the first challenge was about lacking well-defined and clear definitions in relation to data and business analytics, this challenge more or less defined the root causes for them:

- The lack of adequate management support in terms of data and business analytics.
- The lack of commitment from employees to oversee the change.
- Inability to properly plan the relative projects and their intended outcomes.
- Lack of communication to increase commitment towards the change.

The fifth challenge was related to the quality of data and the analytics tools to analyze it. In other words, being able to provide the employees with good quality data and analytics tools carries its own weight when it comes to changing the mindsets of employees to increase their commitment towards the utilization of data and business analytics as part of the organizations decision-making processes.

The sixth challenge was about concentrating on storing the important pieces of information regarding business operation. Quality over quantity in terms of stored data makes it easier to be utilized for different purposes when it comes to business analytics and insight generation. Being able to focus on relevant information without the risk of being overwhelmed with all the data that is being collected and stored. With that said, understanding the data that is being used is key when it comes to making accurate insights and action plans based on those insights. This was referred to as data illiteracy by several interviewees.

Finally, the seventh and last of the challenges mentioned in the interviews was related to resistance to change. Because people generally like to have certain routines in the different things they do, it also applies to changing the ways they work, think and make decisions in a working environment. In other words, employees may have realized the potential benefits of using business analytics to support decision-making, but they are simultaneously afraid of the risks associated with it – they do not want to take the chance of having their work being available to be scrutinized by anyone.

Supporting research question: How to decrease the conceptual distance between company strategic goals and business analytics?

The practice perspective related to the supporting question regarding the existence of conceptual distance between strategic goals and business analytics in contemporary companies was easier to formulate because it was included as a subject for discussion in the qualitative interview template. Even though, the discussions with the interviewees on the subject featured some variance when compared to one and other, they also included some similarities. These similarities were put together to construct an answer to the supporting research question regarding decreasing the conceptual distance between strategic goals and business analytics in contemporary organizations.

Companies that operate in IT-heavy industries or have their IT-services outsources seemed to experience less conceptual distance between the concepts in comparison to other companies. Furthermore, the size of the company played a significant role in terms of the existence of the conceptual distance between the concepts. In other words, smaller companies or business units within bigger companies seemed to experience more conceptual distance than their counterparts. Additionally, it was mentioned that analytics from an expert point of view can be a concrete concept whereas business strategy, especially if not clearly defined, is not – thus, adding to the amount of conceptual distance present.

Suggestions to decrease the conceptual distance between strategic goals and business analytics from the interviewees featured; breaking down strategic goals into something that can be directly compared to what a single person or business unit does within the organization (e.g. providing a clear definition to strategic goals), eliminating the differences in opinion related to how employees perceive strategic goals and business analytics as separate concepts, investing money to increase the awareness and change the company culture and employee mindsets regarding the concepts and their alignment together and finally, ensuring that the managers employed by the organization are adequately committed to oversee the decrease in conceptual distance between the concepts take place.

All in all, most interviewees thought that there is no ‘one right way’ to decrease the conceptual distance between strategic goals and business analytics, but instead decreasing it was possible through a collection of different things (such as the ones mentioned before). In other words, the method to decrease conceptual distance between the concepts from a practitioner point of view depends on the organization, its business area, its age and its size.

Core research question: How to align business strategy with analytics (strategy) to create value for the firm?

The practice perspective on how alignment between business strategy and analytics (strategy) to create value yet again supports previous research in saying that there is ‘no one right’ way of going about, but many different aspects need to be taken into consideration in order for the alignment to be possible.

According to the interview answers, there were described situations where the alignment between business strategy and analytics (strategy) was strong enough to drive the transformation of the organization towards becoming more data driven. However and on the contrary, there were also situations in which the alignment was completely nonexistent due to the size of the company. In other words, the bigger the organization the more likely it seemed to be that they had paid attention and recognized the potential gain in aligning the said strategies together. Moreover, it also seemed that considering the concepts as separate entities and strategies or alternatively considering them belonging under business strategy alone did not make any difference. For example, some interviewees thought that having a separate strategy for business analytics could have been more useful for companies operating in data science, sophisticated forecasting of future events or machine learning models depending on the case. This however did not change the fact that the analytics (strategy) should still be a concept that supports overall business strategy of the organization.

A separate analytics strategy could help organizations change their internal culture in terms of how data and analytics was to be utilized within the company and help employees wrap their minds around the new data and analytics-based mindset – therefore, contributing to the organization's transformation towards becoming data driven and incorporating an alignment between its business strategy and analytics (strategy) to create value.

5 Discussion

Supporting research question: Why is it challenging to create firm value through business analytics in the terms of decision-making processes?

To be able to summarize and compare the challenges presented by previous research versus the ones mentioned by practitioners a table of the key points including both was prepared (see table 3 below). The similarities between the viewpoints were uncanny. The largest gap between the viewpoints was the fact that academics – having extensively studied the subject was able to present shorter more concise ways of describing the challenges, whereas practitioners provided longer answers and arrived at similar conclusions through personal experiences and real-life examples.

Previous research	Practice
Too much data stored, not knowing what to use it for.	Lacking a clear definition of the intended outcome in terms of using data and business analytics to generate value through company decision-making processes.
Limitations in insight generation in terms of individual knowledge, personal experiences and cognitive abilities.	The perceptions of what it means for an organization to be data-driven were different among the different people working for the organization. No alignment in terms of employee perceptions.
Resistance to change in building a corporate data culture.	The need to take risks with data and business analytics organizational capability improvement projects without having a guarantee of their outcome.
Not having the right people employed in the right positions to increase the commitment towards to change.	Inability to budget analytics investments within companies due to uncertainty related to their costs / outcomes.
Inability to convert generated insights based on data and business analytics into actionable decisions.	The lack of adequate management support in terms of data and business analytics and communication to increase commitment towards the change.
Not having leadership that drives and supports change, defines clear goals for it and determines what the success looks like.	Not being able to focus on only relevant information without the risk of being overwhelmed with all the data that is being collected and stored.
Not having access to good quality data and analytics tools.	Employees may have realized the potential benefits of using business analytics to support decision-making, but they are simultaneously afraid of the risks associated with it. Therefore they resist changing the ways they think and work.

Table 3: Comparison of challenges

Contemporary companies are storing too much data and not putting enough emphasis on how it should be utilized. A quantity over quality mentality like this presents companies with various potential risks in terms of their decision-making processes. Limitations in terms of insight generation related to prejudices or bias, individual knowledge, personal experiences, cognitive abilities and the lack clear definitions of what is wanted to be achieved are not receiving enough attention in contemporary companies. In addition, differing perceptions, lack of communication in order to align the aforementioned perceptions and the lack of adequate management support severely hinder the value generation potential of business analytics utilization in organizational decision-making.

Supporting research question: How to decrease the conceptual distance between company strategic goals and business analytics?

The comparison of conclusions in regard to decreasing the amount of conceptual distance between strategic goals and business analytics in contemporary organizations between previous research and practice resulted in them being close in-line with each other. Again, just like with the comparison of challenges for the first supporting research question, academics presented more concise answers, whereas practitioners provided longer answers that ultimately led them to similar end conclusions.

Previous research	Practice
Aligning their performance indicators and business processes with their underlying business strategies.	Providing a clear definition to strategic goals and making them easier to compare from a single workers or business unit's standpoint.
Having a clear data strategy.	Eliminating the differences in opinion related to how employees perceive strategic goals and business analytics as separate concepts.
Employing the right people with the correct skills to drive the cultural change.	Investing money to increase the awareness and change the company culture employee mindsets regarding the concepts and their alignment together.
Eliminating the variance in perceptions among employees regarding strategic goals and business analytics.	Ensuring that the managers employed by the organization are adequately committed to oversee the decrease in conceptual distance between the concepts take place.
Clearly defining the intended outcomes of strategic goals and business analytics, while making sure they are understood throughout the organization through the utilization of effective methods of communication.	
Ensuring that management commitment is on an adequate level in order for the decrease in conceptual distance to take place.	
Streamlining collected data and used analytics tools to be easy to be easy to adopt and provide only the necessary information needed to support decision-making.	
Provide training on-demand to the employees that struggle with the concepts to eradicate negative experiences early on that might result in prejudices or bias at a later time.	

Table 4: Comparison of conclusions

The most effective ways of decreasing the conceptual distance between strategic goals and business analytics in contemporary companies consist of a combination of; having a clear data strategy or providing clear definitions of future strategic goals throughout the organization, eliminating the differences in opinion related to how employees perceive strategic goals and business analytics as separate concepts and aligning them alongside each other, investing money to increase the awareness and change the company culture and employee mindsets or providing training on-demand to the employees that struggle with the concepts to eradicate negative experiences pre-emptively, ensuring that management commitment is on an adequate level and streamlining collected data and used analytics tools to be easy to adopt and learn.

Even though, these are the methods of decreasing the conceptual distance between strategic goals and business analytics – the selection of which ones should be used in what context completely depends on firm being assessed. Like it was stated earlier, the firm's business area, age and size all affect the situation. Therefore, it is important to thoroughly study and plan the courses of action to resolve the problems or challenges which are present in the organization that is being considered.

Core research question: How to align business strategy with analytics (strategy) to create value for the firm?

Previous research and practice clearly agree on the fact that there is no 'right way' of aligning business strategy with analytics (strategy) to create value for the firm. Instead, there are many concepts that need to be taken into consideration and questions that need answers – dependent on the business are, size and age of the organization. The ability to derive value out of the alignment is a reality and scales according to the size of the company. In other words, the core research question was answered through the two supporting research questions. Contemporary companies should attempt in taking in account the challenges associated with value creation though business analytics in terms of decision-making processes (see table 3) and decreasing the conceptual distance strategic goals and business analytics (see table 4).

6 Conclusion

6.1 Summary of the Findings

According to the comparison of previous research and the results of the interviews, the concepts around the core research question (How to align business analytics (strategy) with business strategy to create value for the firm) are in-line with each other. Despite of the differing methods of reasoning between academics and practitioners, the end conclusions both parties arrived at in the end were the same.

There is no ‘right way’ to align business analytics (strategy) with business strategy. Alignment consists of a collection of issues and aspects that need attention from contemporary organizations in order to be possible. Each company is its own case due to the fact that different companies are in different stages of becoming data-driven in addition to which their business area, age and size also impact what alignment related aspects and issues that need attention.

6.2 Managerial implications

The academic models presented in this study can be utilized by contemporary companies to help understand the concept of how to derive value from business analytics (strategy) alignment with business strategy. Additionally, they can also be used to conceptualize ways of value generation from business analytics directly without considering its alignment with business strategy. And finally, some models can also be used to determine the stage in which the companies are in the process of becoming data driven.

The practitioner interview results and templates can be used by contemporary companies to compare their situation with the interviewed case companies to help conceptualize or find the most common issues they might be facing in the future in terms of value creation challenges from business analytics (strategy) alignment with business strategy, or evaluate the effectiveness the solutions that they have implemented in the past to solve the same challenges.

The comparison between previous research and practitioner interviews can be used to pin-point and outline similarities in terms of the challenges in value creation from business analytics use in company decision-making processes, as well as help thinking of ways to reduce the impact of those challenges in the form of decreasing the conceptual distance between analytics goals and strategic goals in those contemporary organizations.

6.3 Theoretical contribution

The largest theoretical contributions of this study were outlining the current status or lack of academic research on the core subject (How to align business analytics (strategy) with business strategy to create value for the firm) and gathering a selection of academic models and comparing their similarities and differences in relation to each other (see table 1). Furthermore, the comparison of previous research and practice also carries weight in terms of theoretical contributions because it proves that both previous research and practice are in-line in terms of the subject matter (see tables 3 & 4).

6.4 Limitations and future studies

The largest limitations for this study were the scarcity of pre-existing research regarding the alignment between business analytics (strategy) and business strategy specifically. The cause of scarcity in research reflects of an underlying problem in limiting the research area. This problem could be avoided by limiting the research into just a couple academic journals instead of attempting to look at all of the previous research that mentions the key words in the selected research questions.

The relatively small amount of case organizations included in the empirical part of the study was also considered a limitation. Spending more time to gather empirical evidence and data from different case companies and their representatives (who preferably work in different roles and business units within those companies) is likely to yield more holistic results for the simple reason that the sample size for the study increases significantly.

To be able to get a more coherent perception of the issue at hand, repeating the study with some alterations to the interview template and a larger selection of case companies and interviewees should be considered a good starting point. Also conducting a new literature review on the subject featuring more effective limits to the research area is likely to yield a larger amount of direct academic research to be utilized by for the study.

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Appendices

Appendix 1: Questionnaire (English, original)

QUALITATIVE QUESTIONNAIRE FOR MASTER'S THESIS
ALIGNING BUSINESS STRATEGY WITH BUSINESS ANALYTICS TO CREATE VALUE FOR THE FIRM

A) Informant profile.

1. What is your organization's field of expertise?
2. What is your role in the organization (manager or analyst / expert)?

B) Defining business analytics.

3. How would you define business analytics?
4. Could you provide a couple concrete examples of how it's being utilized in your organization?

C) Aligning analytics strategy with business strategy in your organization.

Not much research has been conducted on how to align analytics strategy with overall business strategy. Judging from the lack of research on the subject this alignment is highly situational and case specific.

5. What do you think about this alignment as a concept? Does it exist in your organization?
6. Would it be important to have a separate analytics strategy that is directly linked with the business strategy of the organization? Why?

D) Defining corporate strategy formulation in your organization with the aid of business analytics.

7. How does your company attempt to generate value and/or competitive advantage through business analytics?

8. How does your company attempt to improve its strategic planning and/or tracking through business analytics?

E) Defining the willingness to back-up analytics investment opportunities in your organization.

The fact that analytics investment opportunities cannot always be easily measured using financial indicators, can make vouching for or supporting them less enticing in comparison to an investment opportunity that can be measured.

9. Would you be willing to take the risk, even if the financial outcome could not be properly measured? Why or why not?

F) Personal experiences with business analytics.

10. Do you think that there is a lot of conceptual distance between strategic goals and business analytics goals in your organization? If so, why?
11. What comes into mind if you were asked to provide a few ideas on how to decrease this conceptual distance? What would they be?

G) Business analytics and organization decision-making processes.

12. What are the main challenges in combining business analytics with company decision-making processes? How would you solve them?

H) Analytics in well-performing organizations.

According to academics, well-performing organizations use analytics to support their decision-making processes more in comparison to organizations that are not doing so well. Furthermore, insights that are generated through business analytics in well-performing organizations are used to guide everyday operations as well as long terms strategy formulation (LaValle & al., 2011; Sharma & al., 2014).

13. What do you think about this statement?
14. What are your personal experiences regarding the statement?

I) Insight generation through business analytics.

Business analytics should be thought of as problem solving and it is important to note that it is the people who are responsible for generating insights from the data provided to them. No amount of computing power can take care of the creative work that happens during human problem solving.

15. How are insights generated from business analytics in your organization? (e.g. through cross-functional teams formed from different parts of the organization).

Appendix 2: Questionnaire (Finnish, translation)

KVALITATIIVINEN KYSELY PRO-GRADUUN
LIIKETOIMINTASTRATEGIAN KOHDISTAMINEN LIIKETOIMINTA-ANALYTIIKAN KANSSA ARVON LUOMISKESI YRITYKSELLE

A) Haastateltavan profiili.

1. Millä toimialalla organisaatiosi toimii?
2. Mikä on roolisi organisaatiossa (esimies vai asiantuntija)?

B) Liiketoiminta-analytiikan määritteleminen.

3. Miten määrittelisit liiketoiminta-analytiikan?
4. Antaisitko muutaman esimerkin siitä, miten sitä hyödynnetään yrityksessäsi?

C) Analytiikkastrategian kohdistaminen liiketoiminta strategiaan yrityksessäsi.

Tieteellistä tutkimusta ei ole tähän mennessä paljoa tehty liittyen analytiikkastrategian ja liiketoimintastrategian yhteensovittamiseen. Tutkimuksen puutteesta voidaan vetää johtopäätös, että kyseisten asioiden yhteensovittaminen on erittäin tapaus- ja yrityskohtaista.

5. Mitä mieltä olet näiden strategioiden yhteensovittamisesta konseptina? Onko kyseinen konsepti käytössä yrityksessäsi?

6. Onko mielestäsi tärkeää yrityksen näkövinkkelistä, että analytiikkastrategia ja liiketoimintastrategia ovat rinnakkain olemassa ja että niitä aktiivisesti yhteensovitetaan (esim. kun yrityksen strategiaa pohditaan / ideoidaan)? Miksi?

D) Liiketoimintastrategian muodostamisen määritteleminen liiketoiminta analytiikan avulla yrityksessäsi.

7. Miten yrityksesi pyrkii luomaan arvoa / kilpailuetua itselleen hyödyntämällä liiketoiminta-analytiikkaa?
8. Kuinka yrityksesi yrittää parantaa omaa strategiasuunnitteluaan / sen seurantaa liiketoiminta-analytiikan kautta?

E) Analytiikkavalmiuksien parantamisprojekteihin suhtautuminen ja ko. suhtautumisen määrittely yrityksessäsi.
Analytiikkavalmiuksien parantamisprojekteja on usein vaikea mitata taloudellisesta näkökulmasta verrattuna muihin yrityksessä sisäisesti tapahtuviin kehityshankkeisiin / projekteihin.

9. Olisitko valmis ottamaan riskin analytiikkavalmiuksien parantamisprojektin kanssa, vaikka projektin välitöntä hyötyä yritykselle ei pystyttäisiinkään suoraan mittamaan taloudellisesti näkökulmasta? Miksi, miksi et?

F) Omat kokemuksesi liiketoiminta-analytiikasta.

10. Onko yrityksessäsi liiketoimintastrategisten tavoitteiden ja liiketoiminta-analytiikan välillä käsitteellistä etäisyyttä (mietitäänkö asioita strategisessa suunnittelussa / päätöksenteossa molemmista tulokulmista)? Jos käsitteellistä etäisyyttä esiintyy, miksi sitä mielestäsi on?
11. Jos sinua pyydettäisiin keksimään muutama idea aikaisemmassa kysymyksessä mainitun käsitteellisen etäisyyden vähentämiseksi, mitä ne olisivat (liiketoimintastrategia- vs. liiketoiminta-analytiikkatavoitteet)?

G) Liiketoiminta-analytiikka ja sen hyödyntäminen yrityksesi päätöksentekoprosesseissa.

12. Mitkä ovat kokemukseesi perustuen suurimmat haasteet, kun liiketoiminta-analytiikkaa yhdistetään yrityksien päätöksentekoprosesseihin? Millä tavalla ratkaisisit nämä haasteet?

H) Liiketoiminta-analytiikka hyvin toimivissa organisaatioissa.

Tutkijoiden mukaan hyvin toimivat yritykset hyödyntävät liiketoiminta-analytiikkaa enemmän päätöksentekoprosesseissaan verrattuna sellaisiin yrityksiin, jotka eivät toimi yhtä hyvin. Lisäksi hyvin toimivissa yrityksissä analytiikan avulla tehtyjä liiketoimintakohtaisia oivalluksia käytetään jokapäiväisten toimintojen ohjaamiseen sekä pitkän aikavälin liiketoimintastrategian luomiseen ja ideoimiseen (LaValle & al., 2011; Sharma & al., 2014).

13. Mitä mieltä olet tästä toteamuksesta?
14. Minkälaiset henkilökohtaiset kokemukset sinulla on liittyen tähän toteamukseen?

I) Liiketoimintaan liittyvien oivalluksien luonti yrityksessä liiketoiminta-analytiikan avulla.

Liiketoiminta-analytiikkaa tulisi ajatella ongelmanratkaisuna ja on tärkeää noteerata, että liiketoimintakohtaiset oivallukset, joita liiketoiminta-analytiikan avulla luodaan ovat peräisin ihmisiltä, jotka työskentelevät heille toimitetun datan parissa. Mikään määrä tietokoneiden laskentatehoa ei tule poistamaan ihmisten tekemää luovaa työtä ongelmanratkaisun parissa.

15. Miten liiketoiminnallisia oivalluksia yrityksessäsi luodaan liiketoiminta-analytiikan avulla? (Esim. Tiimit, jotka muodostettu henkilöistä ketkä toimivat yrityksen eri funktioissa [asiantuntijat, esimiehet, talous jne.])