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BIG DATA & BUSINESS-IT ALIGNMENT

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Bleiswijk, June 2016

"The most meaningful way to differentiate your company from your competition is to do an outstanding job with information. How you gather, manage, and use information will determine whether you will win or lose"

Bill Gates, Business @ the Speed of Thought: Succeeding in the Digital Economy (1999)

Management summary

The deployment of advanced IT like big data analytics in an organization is an example of value creation. And as to advanced IT, business-IT alignment is a critical factor in creating value and in ensuring success. The purpose of this research was to explore what organizational leaders and policy makers need to do to capture value from big data. It aimed to understand how strategic alignment is developed between de different levels and roles in a big data context and how it facilitates the creation of value from big data projects, which in turn supports the effective and consistent use of this information technology over time. For this the following central research question was raised: *How does big data analytics impact business-IT alignment?*

Based on the literature review this study hypothesized that big data analytics will place additional requirement on business-IT alignment practices and thus will lead to or require higher levels of (perceived) business-IT alignment maturity. To produce more specific insights this study also looked into possible variations per relevant area of application and four coherently interrelating alignment practices which either focus on collaboration and/or which are likely to be present in most companies.

To investigate this four separate ‘intensity’ based cases were selected and an exploratory cross-sectional multiple case study was conducted. The primary method of collecting data were semi-structured interviews, but to create a wider scope of coverage and a more complete overview of the phenomenon under study official company documents like presentations, internal- and external communications and/or annual reports were also collected as well as physical artifacts were observed.

The goal was to investigate the impact big data initiatives have in different contexts and if there were any significant differences between the different areas of application. The findings show that big data analytics is creating an inexplicable link between technology and business and places additional requirements on business-IT alignment practices, requiring them to evolve to more mature levels. The research also showed organizational alignment is a very critical factor in ensuring success in big data projects but it also suggest that that the impact of

big data analytics on business-IT alignment is different when the relevant area of application is the development of new product or service offerings and/or transforming business models, then when the relevant area of application is focused on improving internal processes.

This study also found that the role of the data scientist is less significant or critical than most literature suggest. This study consistently found that in order to create value from big data analytics, organizations establish teams of people which poses complementary analytical, business and IT skills and who can effectively contribute their expertise in collaboration with other people and team members, instead of seeking this diverse skill set in a single person or role. As this usually means involving different stakeholders from various functions at various levels from within business and IT departments, the need for a common language increases, and thus requires different forms of communication in order to establish higher levels of shared understanding between them. While several studies found that shared understanding has an effect on Business-IT alignment (Reich & Benbasat, 1996; Reich & Benbasat, 2000; Chan, 2002; Chan, et al., 2006) most of this research was concentrated around the level of the shared understanding of business and IT executives (Reich & Benbasat, 2000; Chan, 2002). This research found however, that communication and shared understanding in a big data context might be more important on all levels within the organization and even emphasizes the need for communication and shared understanding at a tactical to operational level. It is therefore important that future research takes a wider more granular approach to studying shared understanding on different kind of levels in an organization.

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1 Introduction

The world today is full of data. IBM estimates that every day 2.5 quintillion bytes of data are created, out of which 90% of the data in the world today has been created in the last two years (Ulura, et al., 2012). This data comes from sensors used to gather climate information, diagnostic sensor data generated by products in the field, posts to social media sites, digital pictures and videos uploaded on internet, purchase transaction records, and cell phone conversation (IBM, 2012) “These days companies churn out a burgeoning volume of transactional data, capturing trillions of bytes of information about their customers, suppliers, and operations and millions of networked sensors are being embedded in the physical world in devices such as mobile phones, smart energy meters, automobiles, and industrial machines that sense, create, and communicate data in the age of the Internet of Things” (Manyika, et al., 2011).

Another source of data are social networking sites like Twitter, LinkedIn, Instagram and Facebook which are growing at an incredible pace. At present social media company Facebook has 1.55 billion users, Twitter 320 million users, and LinkedIn 100 million users. Meanwhile, blogging service Tumblr has more than 555 million active blog users on their site and cross-platform messaging service 'WhatsApp has 900 million users most of which are sharing content every day (Statista, 2016). All these sources are examples of a process which Mayer-Schönberger & Cukier (2013) call ‘datafication’ and are producing huge amounts of data in form of posts, comments, sharing of pictures and videos and other activities. Google shares statistics on YouTube usage across the world on their website. The popular video website now has over one billion users — almost one-third of all people on the Internet — and everyday people watch hundreds of millions of hours on YouTube and generate billions of views. It is estimated that 300 hours of video is uploaded every minute on YouTube and over 4 billion YouTube videos are viewed every day (YouTube LLC, 2016). Approximately 2 billion internet users are using social networks and these figures are still expected to grow as mobile device usage and mobile social networks increasingly gain traction.

1.1 Big data as a top challenge

The McKinsey Global Institute report (Manyika et al., 2011) predicted that by 2018, the United States alone will face a shortage of 140,000 to 190,000 people with deep analytical skills, as well as a shortfall of 1.5 million data-savvy managers with the know-how to analyze big data to make effective decisions. All this data cannot be measured in gigabytes any more. These day's petabytes, exabytes, zettabytes and yottabytes are used (Ulura, et al., 2012). "The ability to store, aggregate, and combine data and then use the results to perform deep analyses has become ever more accessible as trends such as Moore's Law in computing, its equivalent in digital storage, and cloud computing continue to lower costs and other technology barriers" (Manyika, et al., 2011). The McKinsey Global Institute estimates that data volume is growing 40% per year, and will grow 44x between 2009 and 2020.

It is from this giant and exponentially growing volume of structured, semi-structured and unstructured data the 'big data' phenomenon has emerged. The basic idea behind the phrase 'big data' is that everything we do is increasingly leaving a digital trace (or data), which we (and others) can use and analyze to become smarter (Marr, 2015). Organizations are more and more starting to realize the importance of using their own, and potentially linked with (commercially) available data from third parties, in order to support decision making and discover new value. The process of transforming this diverse and varied forms of data into information on which competitive advantage can be created is what makes "big data" such an impactful revolution in today's business world (Davenport, et al., 2012; Mayer-Schönberger & Cukier, 2013; Brynjolfsson & McAfee, 2012). Big data is now relevant for leaders and organizations across every sector. As data-driven strategies take hold, they will become an increasingly important point of competitive differentiation (Manyika, et al., 2011; Barton & Cour, 2012).

1.2 Relevance

"Business intelligence and analytics and the related field of big data analytics have become increasingly important in both the academic and the business communities over the past two decades" (Chen, et al., 2012). Digital data is now everywhere—in every sector, in every economy, in every organization. This makes 'big data' is a trending buzzword and a hot research area. The purpose of this research is to explore what leaders of organizations and policy makers need to do to capture its value and accelerate general understanding of key organizational challenges and barriers that emerge with deploying big data analytics.

The deployment of advanced IT in an organization is an example of value creation (Vermerris, et al., 2014). Business-IT alignment is a critical factor in creating value from big data analytics and in ensuring success. Unless the business and technology sides work together so that there is an understanding of the business objectives and the technology capabilities, a big data initiative would not be as successful as it should be (Kiron & Bean, 2013). Both Davenport *et al*. (2012) and Galbraith (2014) argue that in order to capitalize on big data, big data analytics needs to move away from the IT function into core business and relies heavily on data scientists[1] rather than data business analysts.

However, despite years of research the topic of business-IT alignment remains on of the top concerns of executives, scoring consistently among the top 10 issues on IT Executives' agendas for almost 30 years (Luftman & Ben-Zvi, 2010; Luftman, et al., 2015) and business alignment continues to be elusive for the following reasons. First, organizations need to recognize that it is not how *IT* is aligned with the *business*; it is how *IT* and *business* are aligned *with each other* (Tallon & Kraemer, 2003; Coltman, et al., 2015). Second, technology needs to match the pace of business. The accelerating pace of business change on the one hand, and the exploding rate of technology innovation on the other, is making it increasingly difficult for IT leaders to align

[1] A data scientist represents an evolution from the business or data analyst role. The formal training is similar, with a solid foundation typically in computer science and applications, modeling, statistics, analytics and math. What sets the data scientist apart is strong business acumen, coupled with the ability to communicate findings to both business and IT leaders in a way that can influence how an organization approaches a business challenge. Good data scientists will not just address business problems, they will pick the right problems that have the most value to the organization. (IBM Corporation, n.d.)

business and IT strategies (Beers, 2013) and third, business-IT alignment needs new insights because boundaries between business and IT are disappearing as increasing information intensity of value chains are affecting the integration between business and IT and require organizational models that focus on collaboration (Kearns & Lederer, 2003). Some would even go so far that it is time to rethink the role of IT strategy, from that of a functional-level strategy - aligned but essentially always subordinate to business strategy - to one that reflects a fusion between IT strategy and business strategy (Bharadwaj, et al., 2013).

A recurring theme creating value from advanced IT like big data analytics applications has been a lack of business-IT alignment. A key finding in a recent survey of conducted amongst C-level and function heads from Fortune 500 companies showed organizational alignment is a very critical factor in ensuring success in big data projects (Kiron & Bean, 2013).

1.3 Research goal

This research has focused on the business-IT alignment in a big data context and aims to improve and broaden the knowledge and understanding of the concept of business-IT alignment in theory and practice, and to gain deeper insights into the relationship between business-IT alignment and big data analytics. We need to understand how strategic alignment is developed between de different levels and roles in a big data context and how it facilitates the creation of value from big data projects, which in turn supports the effective and consistent use of this information technology over time. The ultimate intent of this study is to gradually build a new theory of how business and IT should be aligned in a big data context.

1.4 Research question

In order to get a better understanding of how big data analytics impact business-IT alignment the following central research question was raised:

How does big data analytics impact business-IT alignment?

To answer the central research question the following sub-questions are formulated which will be used as guides for the theoretical foundations.

What is new about big data and how does big data differ from traditional analytics?

and

What policies or actions facilitate the generation of strategic alignment?

1.5 Structure of this thesis

This thesis is organized as follows. This chapter deals with the introduction and the rationality behind the research question. Chapter two focuses on the theoretical foundations and conceptual model which will be used in guiding this study. Chapter three is concerned with the methodology used in this study. Chapter four shows the empirical findings from the within-case analyses and cross-case analyses, whereas these findings are discusses in chapter five. Finally chapter six will deal with the conclusion. Further pages will contain the references and appendixes.

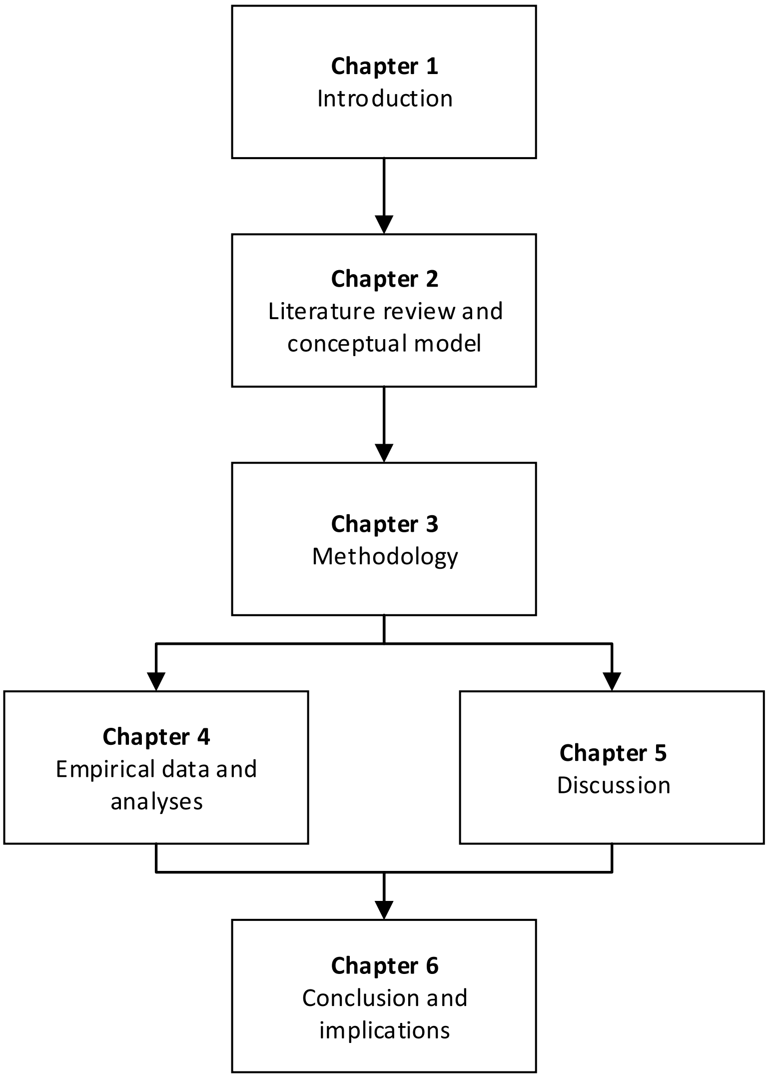

Figure 1 Structure of the thesis

2 Theoretical Foundations

This literature review is not to provide a summary of everything that has been written on the research topic, but will aggregate and review the most relevant and significant research using the research questions as a guide. From this a conceptual framework is developed that groups constructs related to the contextual conditions surrounding.

2.1 Big data

Big Data is a field dedicated to the analysis, processing, and storage of large collections of data that frequently originate from disparate sources (Erl, et al., 2015). What is new about big data and how does big data differ from traditional analytics? Interestingly, for the most part, much of the technology classified as "big data" is not new (Loshin, 2013). Firms and other organizations have been using large databases and analytics for the last couple of decades. For some time already all kinds of (transaction) data has been stored in data warehouses and analyzed with data-mining algorithms to extract insights before the whole big data hype started (Galbraith, 2014).

Data management and warehousing is considered the foundation of business intelligence and (big) data analytics. "Design of data-marts and tools for extraction, transformation, and load (ETL) are essential for converting and integrating enterprise-specific data. Database query, online analytical processing (OLAP), and reporting tools based on intuitive, but simple, graphics are used to explore important data characteristics" (Chen, et al., 2012). Russom (2011) explains that the "techniques have been around for years, many of them appearing in the 1990s. What has changed is that far more users are now analyzing big data instead of merely hoarding it en that a few organizations that have been analyzing this data now do so at a more complex and sophisticated level. Big data in itself is not new, but the effective analytical leveraging of big data is" (Russom, 2011). "In the age of big data … the emphasis in industry has shifted to data analysis and rapid business decision making based on huge volumes of information" (Chen, et al., 2012). It is due to these large volumes, high velocity and high variety of data, that traditional 'Database Management Systems' (DBMS) do not provide sufficient possibilities for analyzing big amounts of data and that these characteristics of big data are the result of the expansion of traditional business analytics centers on large data stores holding highly structured data typically in the form of data warehouses and/or data marts and the move toward dealing with massive collections of relatively unstructured data such as audio, video, clickstream, and text (Holsapple, et al., 2014). Big data is data that exceeds the processing capacity of conventional database systems. The data is too big, moves too fast, or doesn't fit the structures of current database architectures. To gain value from this data, you must choose an alternative way to process it (Dumbill, 2012). Thus big data analytics can be seen as both the successor and enhancer of traditional data analytics. From all these definitions it can be concluded that big data is intrinsically related to data analytics and the discovery of meaning from data (Barker & Ward, 2013).

2.1.1 Understanding the business drivers

The overarching disruptive power of big data demands that organizations engage with it at a strategic level (Morabito, 2015) According to a Bain & Company study (2013) "early adopters of big data analytics have gained a significant lead over the rest of the corporate world. Examining more than 400 large companies, they found that those with the most advanced analytics capabilities are outperforming competitors by wide margins" (Pearson & Wegener, 2013). According to research by Andrew McAfee and Erik Brynjolfsson of MIT companies that inject big data and analytics into their operations show productivity rates and profit ability that are 5% to 6% higher than those of their peers (Brynjolfsson & McAfee, 2012)

Big data analytics can reveal insights from data previously hidden as it was too costly to process. For example, big data analytics can be used to predict issues based on diagnostic sensor data, uncover relationships between social sentiment and sales data such as peer influence among customers, or act as a basis for a recommendation system for books or products customers might be interested in revealed by analyzing shoppers' transactions combined with social and geographical data. According to Pearson & Wegener (2013) "there are four areas where big data analytics can be relevant: improving existing products and services, improving internal processes, building new product or service offerings, and transforming business models". As Russom (2011) explains; "If you really want the lowdown on what's happening in your business, you need large volumes of highly detailed data. If you truly want to see something you have never seen before, it helps to tap into data that's never been before" (Russom, 2011). One of the big drivers of excitement around big data is the expectation that we will be able to identify novel insights. Digital companies such as Amazon have disrupted industries with new data-driven business models (Berner, et al., 2014). "When big data is distilled and analyzed in combination with traditional enterprise data, enterprises can develop a more thorough and insightful understanding of their business, which can lead to better business decisions, enhanced productivity, a stronger competitive position and greater innovation – all of which can have a significant impact on the bottom line" (Dijcks, 2013).

A good example is provided within an economic study on the value of big data undertaken and published by the Center for Economics and Business Research (CEBR) that speaks to the cumulative value of:

- Optimized consumer spending as a result of improved targeted customer marketing
- Improvements to research and analytics within the manufacturing sectors to lead to new product development
- Improvements in strategizing and business planning leading to innovation and new start-up companies
- Predictive analytics for improving supply chain management to optimize stock management, replenishment, and forecasting
- Improving the scope and accuracy of fraud detection (Mohamed, et al., 2012).

Using big data analytics, organizations can extract valuable information and insights out of very big, complex, varied and connected datasets in the sense of supporting knowledge acquisition, insight generation, problem finding, and problem solving to assist decision making (Holsapple, et al., 2014). Business drivers are about agility in utilization and analysis of collections of datasets and streams to create value: increase revenues, decrease costs, improve the customer experience, reduce risks, and increase productivity (Loshin, 2013).

"Big data is hard to miss these days. Industry analysts and media observers hype it as the next big thing for every enterprise, and many companies have been rushing to climb on board" (Pearson & Wegener, 2013). Companies that were born digital, such as Google and Amazon, are already masters of big data. But the potential to gain competitive advantage from it may be even greater for other companies (Brynjolfsson & McAfee, 2012). “Analyzing new and diverse digital data streams can reveal new sources of economic value” (Dijcks, 2013).

2.1.2 Definitions of big data

Big data is still a relatively young concept and although big data is a trending buzzword in both academia and the industry, its meaning is still shrouded by much conceptual vagueness. Owing to a shared origin between academia, industry and the media there is no single unified definition, and various stakeholders provide diverse and often contradictory definitions (Barker & Ward, 2013). The term is used to describe a wide range of concepts: from the technological ability to store, aggregate, and process data, to the cultural shift that is pervasively invading business and society, both drowning in information overload (Mauro, et al., 2014; Mayer-Schönberger & Cukier, 2013) and is used when referring to a variety of different entities including – but not limited to - social phenomenon, information assets, data sets, analytical techniques, storage technologies, processes and infrastructures (Mauro, et al., 2014). The term big data has become ubiquitous. Big data is not a single out-of-the-box product. The term is frequently associated with the specific technology and techniques that enables its utilization, the extent of the dataset size and the complexity of operations needed for its processing. The seemingly ubiquitous use of the term “big data” somewhat simplifies the technical landscape in ways that hide a level of complexity that can confuse potential organizational stakeholders (Loshin, 2013).

The analysis of extensive quantities of data and the need to grasp value out of individual behaviors require processing methods that go beyond the traditional statistical techniques (Mauro, et al., 2014). Both Manyika et al. (2011) and Chen (2012) propose a list of big data analytic methods, that include A/B testing, anomaly detection, graph mining, classification, cluster analysis, data fusion and data integration, machine learning, natural language processing, neural networks, network analysis, pattern recognition, Predictive modelling, regression, sentiment analysis, signal processing, spatial analysis, statistics, supervised and unsupervised learning, simulation, time series analysis and visualization. Manyika et al. (2011) further argue that “big data refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze”. This aligns with Laney (2001) which defines big data is as the representation of the progress of the human cognitive processes, which now usually includes data sets with sizes beyond the ability of current technology, method and theory to capture, manage, and process the data within a tolerable elapsed time. Big data is fundamentally about applying innovative and cost-effective techniques for solving existing and future business problems whose resource requirements (for data management space, computation resources, or immediate, in-memory representation needs) exceed the capabilities of traditional computing environments as currently configured within the enterprise (Loshin, 2013).

Today many IT vendors and solutions providers use the term "big data" as a buzzword for smarter, more insightful data analysis (Davenport, et al., 2012). But there are multiple definitions and perspectives on what 'big data' is. The open source standard for Information Management MiKE 2.0 states that "size is the primary definition of big data, comprising a large, complex and independent collection of data sets, each with the potential to interact" (MIKE 2.0, 2016). This definition that is also supported by Intel which links big data to organizations which are "generating a median of 300 terabytes (TB) of data weekly" (Intel Corporation, 2014). Also Microsoft provides us with a notably short definition description which seems to emphasize volume more than the origins of data. "Big data is the term increasingly used to describe the process of applying serious computing power – the latest in machine learning and artificial intelligence – to seriously massive and often highly complex sets of information" (Microsoft Corporation, 2013) thus also framing the phenomenon of big data in term of volume or exceeding (current) available computational power. This idea is supported by the NIST definition which states that big data is data which: "exceed(s) the capacity or capability of current or conventional methods and systems" (NIST, 2013). But like Manyika *et al.* (2011) already insightfully noted in their remark on why they kept their definition intentionally subjective; "given the constantly advancing nature of computer science this definition is not as valuable as it may initially appear. These definitions suggests that data is "big" relative to the current standard of computation. How big a dataset needs to be in order to be considered big data assumes that "as technology advances over time, the size of datasets that will be perceived as big data will also increase" (Manyika, et al., 2011) Therefor a definition based on volume in relation to computational power and/or the ability of typical database software tools to capture, store, manage, and analyze the data in scope can only be seen as a common anecdotal definition and can only serve as a set of continually moving goalposts and suggests that big data has always existed (Barker & Ward, 2013).

The assertion that big data is data that challenges current practices is not new. But while volume is often the most visible characteristic on which big data is defined, it is not the only characteristic that matters. Russom (2011) argues that is not so much the size or volume of the data what defines big data, but that the sources are more defining. He states that "one of the things that makes big data really big is that it's coming from a greater variety of sources than ever before" (Russom, 2011), which have its impact on current capabilities to extract insights and value from analytic efforts. This aligns with what NIST (2013) describes as an important aspect of big data; the fact that it cannot be handled with standard data management techniques due to the inconsistency and unpredictability of the possible combinations (Ulura, et al., 2012). Also Dijcks (2013) contends that "big data is the derivation of value from traditional relational database driven business decision making, augmented with new sources of unstructured data. Such new sources include blogs, social media, sensor networks, image data and other forms of data which vary in size, structure, format and other factors and thus also emphasizes the inclusion of multiple and varied sources of data used for analytic purposes" (Dijcks, 2013). To make the most of big data, enterprises must evolve their IT infrastructures to handle these new high-volume, high-velocity, high-variety sources of data and integrate them with the preexisting enterprise data to be analyzed (Dijcks, 2013)

While the moment of writing there still is no generally agreed understanding of what exactly make up the concept of big data and what its definition should be, an increasing number of V's has been used to characterize different dimensions and challenges of big data (Hitzler & Janowicz, 2013). While some still refer to big data as analytics performed on just large amounts of data, the most commonly used definition of big data at this moment is defined by Garner's analyst Doug Laney in 2001 which described 'Big data as 'high-volume, -velocity and – variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making''. From this perspective big data is not just about giant data volumes; it's also about an extraordinary diversity of data types, delivered at various speeds and frequencies (Russom, 2011). Big data is about analyzing structured and unstructured data that is increasing in volume, velocity, variety. Scholars and practitioners now seem to break down big data into many dimensions starting with a V, namely Volume, Velocity and Variety.

Volume

The anticipated volume of data that is processed by big data solutions is substantial and ever-growing. The rational for using these big volumes is that some correlations that can never be found if the data is analyzed on separate (smaller) sets. A larger amount of data gives a better output. If these large volumes are defined properly and used accordingly, organizations can get a better view on their business (Ulura, et al., 2012) which can lead to efficiency in different areas like sales, improving the manufactured product or even uncover relationships between social sentiment and sales data. High data volumes impose distinct data storage and processing demands, as well as additional data preparation, curation and management processes. As Jacobs (2009) explains; "what makes most big data big is repeated observations over time and/or space. The Web log records millions of visits a day to a handful of pages; the cellphone database stores time and location every 15 seconds for each of a few million phones; the retailer has thousands of stores, tens of thousands of products, and millions of customers but logs billions and billions of individual transactions in a year" (Jacobs, 2009). The amount of data is at very large scale and can be so huge that modern database management tools (Chen, et al., 2012) are unable to handle it and therefore become unusable. Working with it can become a challenge due to processing limitations (Ulura, et al., 2012) Russom (2011) describes this issue by referring to the humorous but revealing terms he found being used in practice like 'honking big data', 'pain in the neck', and 'we-need-to-buy-more-hardware analytics' (Russom, 2011). Although Moore's law suggests that storing capacity increases over time in an exponential manner (2006) the volume dimension of big data will still require a continuous and expensive research and development effort to keep up with the pace at which data size increases especially with the growing share of byte-hungry data types such as images, sounds and videos (Hilbert, 2011).

Variety

Due to the different origins of the data, data in a big data context comes in multiple forms. Variety refers to the multiple formats and types of data that need to be supported by big data solutions and brings challenges for enterprises in terms of data integration, transformation, processing, and storage (Loshin, 2013). Structured data (traditional text/numeric information) is now joined by unstructured data (audio, video, images, text and human language) and semi structured data, such as XML and RSS feeds (Russom, 2011). In classifying data a distinction can be made between three types; structured data (e.g., relational databases), semi-structured data (e.g., XML documents), and unstructured data (e.g., text documents).

Structured data is homogenous data. It's generated in a consistent data format and data type, is consistent over time and can be analyzed as soon as it is created. Structured data fits cleanly into a predefined structure (Stubbs, 2014). The sources of structured data are divided into two categories. Computer- or machine-generated; data that is created by a machine without human intervention. Examples are sensor data, web log data, point-of-sale data, and financial transaction data. And human-generated; data that is supplied by humans interaction with computers, for example input data from electronic forms, click-stream data from websites, and online gaming-related data (Hurwitz, et al., 2013) Structured data has been analyzed from the 1990's on (Chen, et al., 2012). It is not a new phenomenon. However, the evolution of technology provides new sources of structured data being produced and often in real time and in large volumes.

Most of the new breed encompasses semi-structured and even unstructured data, ranging from text, log files, audio, video, and images posted, e.g., on social networks to sensor data, click streams, e.g., from Internet of Things (Loshin, 2013). Unstructured data is data is heterogeneous in nature. Most of the existing analytic tools work can only work with homogenous data. To extract insights from (semi) unstructured data new tools and techniques are required.

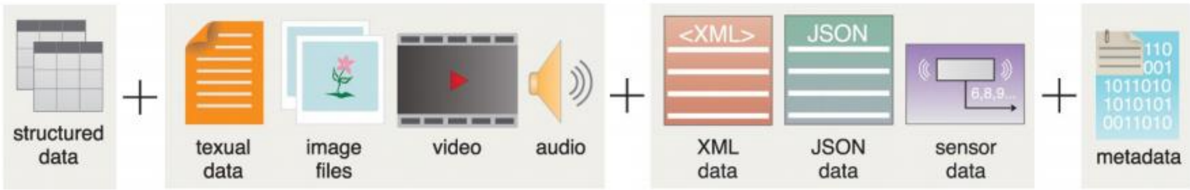

Figure 2 Examples of high-variety big data datasets (Erl, et al., 2015).

Velocity

In big data environments, data can arrive at fast speeds, and enormous datasets can accumulate within very short periods of time. From an enterprise's point of view, the velocity of data translates into the amount of time it takes for the data to be processed once it enters the enterprise's perimeter (Erl, et al., 2015). The speed of their creation and use is often (nearly) real-time (Loshin, 2013). Coping with the fast inflow of data requires the enterprise to design highly elastic and available data processing solutions and corresponding data storage capabilities. As Davenport *et al.* (2012) explain "the increased volume and velocity of data in production settings means that organizations will need to develop continuous processes for gathering, analyzing and interpreting data" (Davenport, et al., 2012).

These dimension of big data show that in addition to traditional analytic approaches, big data uses new techniques that leverage computational resources and approaches. This shift is important as datasets continue to become larger (volume dimension), more diverse (variety dimension), more complex (variety and veracity dimension) and streaming-centric (velocity dimension). According to Ed Dumbill chair at the O'Reilly Strata Conference "big data is data that exceeds the processing capacity of conventional database systems. The data is too big, moves too fast, or doesn't fit the structures of your database architectures. To gain value from this data, you must choose an alternative way to process it" (Dumbill, 2013).

However, there is a challenge with use of V's to define big data. It is essentially a marketing definition to understand the concept's core intent. The definition is not really a definition, but rather a description of the dimension of the data used in big data analytics. People in an organization cannot use the definition to determine whether they are using big data solutions or even if they have problems that need a big data solution (Loshin, 2013).

While previous attempts to define big data emphasize the technological ability to store, aggregate, and process data, other scholars recognize big data not only data challenges current practices but also current paradigms (Barton & Cour, 2012; Brown, et al., 2014; Brynjolfsson & McAfee, 2012; Davenport, et al., 2012). The emergence of big data into the enterprise brings with it a necessary counterpart: agility. Successfully exploiting the value in big data requires experimentation and exploration (Dumbill, 2012). Chen et al. (2012) state that companies need to invest in education that would be "interdisciplinary and cover critical analytical and IT skills, business and domain knowledge, and communication skills required in a complex data-centric business environment". The investment in analytical knowledge should be accompanied by a cultural change that would span across all employees and urge them to "efficiently manage data properly and incorporate them into decision making processes" (Buhl, et al., 2013). Companies are heavily impacted by the rise of big data: the call to arms for acquiring vital skills and technology to be competitive in a data-driven market implies a serious reconsideration of the firm organization and the full realm of business processes (Pearson & Wegener 2013). The transformation of data into competitive advantage (McAfee & Brynjolfsson 2012) is what makes "Big data" such an impactful revolution in today's business world. Big data requires the mastery of specific techniques, awareness of their strengths and limitations, and a spread cultural tendency to informed decision making that in most cases has still to be built (Mauro, et al., 2014). Therefor the definition that will be used for this study is the definition from analyst firm Gartner;

"Big data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation." (Gartner, n.d.)

2.1.3 Impact of big data on business-IT alignment

The extent to which big data is impacting our society and our companies is often depicted through anecdotes and success stories of methods and technology implementations (Mauro, et al., 2014). But as organizations attempt to develop a big data analytics capability, they will encounter barriers and challenges before they really can make use of these new technologies and valuable insights. These questions become much more relevant when one realizes that the expectations for usability of big data clash with existing approaches for business intelligence (BI), reporting and analytics, as well as the end-to-end data integration, data collection (Loshin, 2013).

The leading obstacle to widespread analytics adoption is a lack of understanding of how to use analytics to improve the business (LaValle, et al., 2011). Leaders now discover that succeeding with big data requires a different and more holistic approach; big data analytics needs to be embedded deep into the organization. The adoption barriers that organizations face most now are managerial and cultural rather than related to data and technology. Successfully exploiting the value in big data requires experimentation and exploration (Dumbill, 2012). As Barton & Cour (2012) explain; first, companies must be able to identify, combine, and manage multiple sources of data. Second, they need the capability to build advanced analytics models for predicting and optimizing outcomes. Third, and most critical, management must possess the muscle to transform the organization so that the data and models actually yield better decisions.

"People who work with big data need substantial and creative IT skills" (Davenport, et al., 2012). Before an organization can make decisions based on big data analytics it must get data scientists and analytics experts embedded into decision processes. Capturing data related opportunities to improve revenues, boost productivity, and, sometimes, create entirely new businesses puts new demands on companies—requiring not only new talent and investments in information infrastructure but also significant changes in mind-sets and frontline training (Barton & Cour, 2012). As Pearson & Wegener (2013) also point out; "organizations don't change easily and the value of analytics may not be apparent to everyone".

Big data analytics are again increasing the need integration of information technology in businesses. According to Davenport *et al.* (2012) "big data analytics flip the traditional role and approach of IT on its head. A key implication of big data is that the world and the data that describe it are constantly changing, and organizations that can recognize the changes and react quickly and intelligently will have the upper hand. The new advantages are based on discovery and agility — the ability to mine existing and new data sources continuously for patterns, events and opportunities" (Davenport, et al., 2012). Russom (2011) implicitly confirms this by labeling advanced analytics as "discovery analytics" or "exploratory analytics" "because users are trying to discover new business facts that no one in the enterprise knew before".

For this organizations are going to need a critical mass of 'data scientists' as "their upgraded data management skill set — including programming, mathematical and statistical skills, as well as business acumen and the ability to communicate effectively with decision-makers is a necessity" (Davenport, et al., 2012). Davenport *et al.* (2012) proceed in explaining that big data is changing the technology, skills and processes of the IT function and that is will require a move from analytics from IT into core business and operational functions. It are these aspects that are "prompting organizations to rethink their basic assumptions about the relationship between business and IT and their respective roles" (Davenport, et al., 2012). It requires transforming the organization's culture and capabilities, not in a rush to action, but in a deliberative effort to weave big data into the fabric of daily operations (Barton & Cour, 2012).

Before an organization can make real-time decisions, it must get data scientists and analytics experts embedded into decision processes. Davenport et al. (2012) argue that in order to capitalize on big data, big data analytics needs to move away from the IT function into core business and rely heavily on data scientists and product and process developers rather than data analysts. For this organizations need to change, and in order to undergo change a shared understanding of business domain knowledge and big data analytic applications, technologies and services work needs to be developed that will contribute to business objectives. Before any of these new technologies can be fully incorporated within production business processes, they must win adoption in a broader enterprise setting in ways that add measurable value (Loshin, 2013).

2.2 Business-IT alignment

2.2.1 Business-IT alignment as a top challenge

Alignment between business and IT has been studied intensively. Despite years of cumulative research, business-IT alignment "remains one of the leading areas of concern for business executives and has been constantly and repeatedly ranked as the most important issue facing corporations since the mid-1980s" (Benbya & McKelvey, 2006). The annual CIO surveys conducted by the Society for Information Management (SIM) repeatedly put business-IT alignment among the top three challenges facing IT executives (Luftman, et al., 2015). The latest 2015 SIM survey identifies IT-business alignment as the number one concern over a 11-year period. Despite the prevailing global economic conditions, management concerns such as IT-business alignment appear consistently both globally and locally in the top management concerns (Luftman, et al., 2015).

2.2.2 Business-IT alignment payoffs

Although some studies indicate that rigid and incompatible systems, or failure to establish a common IT architecture can lead to a *paradox* between strategic alignment and IT payoffs (Tallon & Kraemer, 2003) and there are indications that organizations can fall into a *rigidity trap* where tight or inflexible links between business and IT can delay or impede an organization's ability to respond quickly to environmental change (Benbya & McKelvey, 2006), the importance of aligning the objectives and strategies of an organization's IT with those of the broader organization, as an increasing body of academic researchers did find a positive relation between alignment and performance (Chan, et al., 1997; Tallon & Kraemer, 2003; Sabherwal, et al., 2001; Kearns & Lederer, 2003) has been recognized for some time. Business-IT alignment "has been defined using such distinct terms as 'matched with', 'in harmony with', 'complement each other', 'contingent upon', and 'congruent with' or more simply as 'aligned', 'fit', 'support', 'integrated', 'synergy', 'linked', or 'co-aligned'" (Coltman, et al., 2015). While in some literature the creation of IT business value and business-IT alignment are often viewed as separate concepts, researchers argue that a firms inability to realize sufficient value from IT is due in part to an absence of strategic alignment (Henderson & Venkatraman, 1993) And when IT payoffs are indeed a function of strategic alignment, then an absence or deficiency in payoffs from IT may point to a misalignment between the business and IT strategies (Tallon & Kraemer, 2003). The central argument in these studies is that organizations will perform well when key IT resources such as physical IT infrastructure components, technical and managerial IT skills and knowledge assets, are aligned with business strategy and when appropriate structures are used to supervise the deployment and effective management of these resources (Coltman, et al., 2015).

2.2.3 Definition of Business-IT alignment

Where previous views holds that organizational and IS infrastructures should be integrated and aligned Benbya & McKelvey (2006) argue that alignment practices of a more coevolutionary and emergent nature are necessary. Their view "considers business-IT alignment as a series of adjustments at three levels of analysis: individual, operational, and strategic, and suggests several enabling conditions and principles of adaptation and scale-free dynamics which aimed at speeding up the adaptive coevolutionary dynamics among the three levels". This coevolutionary and emergent nature of alignment has rarely been taken into consideration in IS research and Benbya & McKelvey (2006) argue that this is the reason behind why business-IT alignment is so difficult. This research follows the view of Benbya & McKelvey (2006) which regards business-IT alignment as a dynamic and continuous process and therefore adopts the definition of Business-IT alignment as: *"a continuous coevolutionary process that reconciles top-down 'rational designs' and bottom-up 'emergent processes' of consciously and coherently interrelating all components of the Business/IS relationships in order to contribute to an organization's performance over time*"

2.2.4 Models of Business-IT alignment

Research into the form and function of strategic IT alignment is not new. The building blocks for of business-IT alignment emerged little over 25 years ago when Venkatraman and Prescott (1990) identified "a lack of systematic frameworks to conceptualize the logic, scope and patterns of organizational transformation enabled by information technology" (Henderson & Venkatraman, 1990). The argued that at that moment in time the role of information technology in organizations has shifted beyond it's traditional 'back office support' role towards a more integral part of the strategy of organizations and that "emergence of the competitive role has significant implications for organizational transformation. This is because the "mere superimposition of powerful IT capabilities on the existing organizational structure and processes is unlikely to yield superior competitive benefits" (Henderson & Venkatraman, 1990). This is supported by one of the central messages from the recently concluded MIT Research Project, Management in the 1990s (Scott Morton, 1990, cited from Coltman *et al.* 2015) "that successful organizations can be distinguished by their ability to leverage IT capabilities to transform their businesses (structures, processes, and roles) to obtain new and powerful sources of competitive advantages in the marketplace" (Henderson & Venkatraman, 1990). The now classic Strategic Alignment Model (SAM) emerged and looked at the link between business strategy, IT, structure, and management processes (Coltman, et al., 2015). However, these perspective assume that IT follows business strategy. And if misalignment occurs, it is generally attributable to insufficient or misdirected IT investment. This way business-IT alignment is typically defined as a measure of the extent to which IT supports the business strategy.

To gain deeper insights into the relationship between business-IT alignment and the creation of business value Talon *et al.* (2003) introduce a two-dimensional definition based on the notion of IT shortfall (IT fails to support the business strategy) and IT under-utilization (business strategy fails to utilize existing IT resources to the fullest extent possible). "If the definition of IT alignment is revised to reflect both the extent of IT support for business strategy and the extent to which IT is deployed/leveraged in facilitating current and future business strategy, it may be possible to spot instances of misalignment that are because of underutilized IT capabilities" (Coltman, et al., 2015).

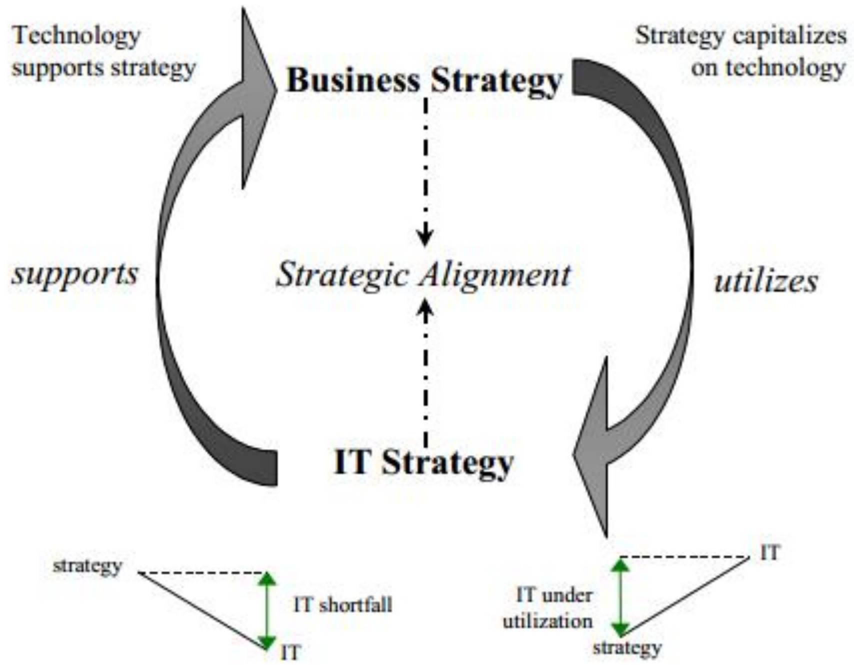

Figure 3 Dimensions of Strategic Alignment *(Tallon & Kraemer, 2003)*

As contemporary organizations are changing the way they utilize IT in combination with products and services (Queiroz & Coltman, 2014) and "organizations digitize their entire businesses and build digital options to capitalize on future opportunities, business processes that execute business strategy are becoming progressively dependent on IT. This would then imply that executing such a digital business strategy is dependent on the ability of firms to leverage IT through business processes, in which case two-way alignment becomes a key mechanism through which IT creates value" (Bharadwaj, et al., 2013).

2.2.5 Dimensions of Business-IT alignment

Based on these early studies a number of dimensions of strategic alignment have emerged. Table 1 provides an overview of empirical studies that looked at dimensions of alignment.

Table 1: Dimension of alignment

Dimension	**Explanation**
Strategic	Strategic alignment refers to the degree to which the business strategy and plans, and the IT strategy and plans, complement each other (Chan & Reich, 2007; Kearns & Lederer, 2003).
Intellectual	Reich and Benbasat (2000) define intellectual alignment in terms of 'the state in which a high quality set of inter-related IT and business plans exist' and refers to the particular methodologies, techniques, and data used in the formulation of strategy (Reich & Benbasat, 1996; Reich & Benbasat, 2000). Business- IT alignment is a reciprocal, two-way relationship (Kearns & Lederer, 2003).
Structural	Chan (2002) defines structural alignment as the degree of "structural fit" between IS and the business and relates to the organizational structure decision-making rights, reporting relationships, (de)centralization of IS services and infrastructure, and deployment of IS personnel.
Social	The social dimension of alignment is defined as "the state in which business and IT executives within an organizational unit understand and are committed to the business and IT mission, understand each other's objectives, and plan (Reich & Benbasat, 1996).
Cultural	Chan (2002) suggests that a strong company culture is a precondition to the type of informal structure that fosters alignment. Tallon (2003) emphasizes the need for a mind-set change that avoiding the 'alignment paradox' which takes flexibility in the form of vigilance and smart management approaches. There has to be top management commitment and a common 'language' between business and IT executives (Chan & Reich, 2007).

2.2.6 Antecedents of alignment and alignment practices

Table 2 below provides an overview of empirical studies that looked at antecedents and alignment practices. In order to select a practical approach to assess alignment in the context of this research, these approaches were analyzed using the taxonomy proposed by Vermerris, Mocker & van Heck (2014). Those factors that cannot be influenced (at the moment of study) on an organizational level by a company (like environmental uncertainty and successful IT history, etc.) were excluded.

Table 2: Antecedents and factors of alignment, cited from (Vermerris, et al., 2014)

Study	**Nature of business-IT alignment**	**Antecedents of alignment**	**Alignment practices**
(Sabherwal & Kirs, 1994)	Alignment between critical success factors and IT capability	Environmental uncertainty Organizational integration IT management sophistication	Shared understanding
(Teo & Ang, 1999)	Critical success factors for IS planning alignment	Top management is committed to the strategic use of IT Information systems (IS) management is knowledgeable about business Top management has confidence in the IS department The IS department provides efficient and reliable services to user departments There is frequent communication between users and IS departments	Management commitment Shared understanding
(Luftman & Brier, 1999)	Alignment of IT plans with business plans	Senior executive support IT involved in strategy development IT understands the business Business-IT partnership Well-prioritized IT projects IT demonstrates leadership	Management commitment Shared understanding Communication IT investment evaluation
(Reich & Benbasat, 2000)	Social dimension of business-IT alignment	Shared domain knowledge Successful IT history Connections between business and IT planning Communication between business and IT executives	Shared understanding Communication
(Cragg, et al., 2002)	Alignment between the contents of business and IT strategies	CEO commitment to IT IT sophistication IT External IT expertise	Management commitment Investment evaluation
(Kearns & Lederer, 2003)	Knowledge sharing between the IT domain and other business domains	The significance of the information component in the value chain.	Communication Shared understanding
(Chan, et al., 2006)	Mission, objectives and plans contained in the business strategy are shared and supported by IS strategy	Shared domain knowledge Planning sophistication Prior IS success Organizational size Environmental uncertainty	Shared understanding IT investment evaluation
(Preston & Karahanna, 2009)	Congruence of the business strategy and IS strategy	Shared understanding	Shared understanding

2.2.7 Conceptual model

Big data analytics is considered advanced IT. Its value creation potential is based on the ability to do an outstanding job with information on which one can compete. Information technology has transformed the way companies act and compete with each other and the increasing strategic importance of information technology and the availability of technologies and systems result in integration between the business and IT (Dewett & Jones, 2001). As increasing information intensity of value chains are affecting the integration between business and IT and require organizational models that focus on collaboration (Teo & King, 1997; Dewett & Jones, 2001) and second, is considered an antecedent of alignment (Kearns & Lederer, 2003). Third, it is not how IT is aligned with the business; it is how IT and business are aligned with each other (Tallon & Kraemer, 2003).

Based on the literature review this study hypothesizes that big data analytics will place additional requirement on business-IT alignment practices and will lead to or require higher levels of (perceived) business-IT alignment maturity. It is however, not clear which dimensions and alignment practices are impacted the most, why that is and if this varies per depending on context. To produce more specific insights this study will also look into possible variations per area of application. Therefor this study distinguishes four areas where big data analytics can be relevant: improving existing products and services, improving internal processes, building new product or service offerings, and transforming business models (Pearson & Wegener, 2013). As business IT alignment is a multifaceted construct, based on the literature review and taxonomy of alignment practices we have chosen four coherently interrelating alignment practices which are likely to be impacted and are present in most companies. The goal was to investigate the impact big data initiatives have in different context and if there were any significant differences in this relation between the different areas of application.

The conceptual model as shown in figure 4 therefore reflects eight components: business-IT alignment (BITA) in the form of three dependent variables. (Comprised of the alignment practices defined in §2) and four independent variables in the form of four areas where big data analytics can be relevant.

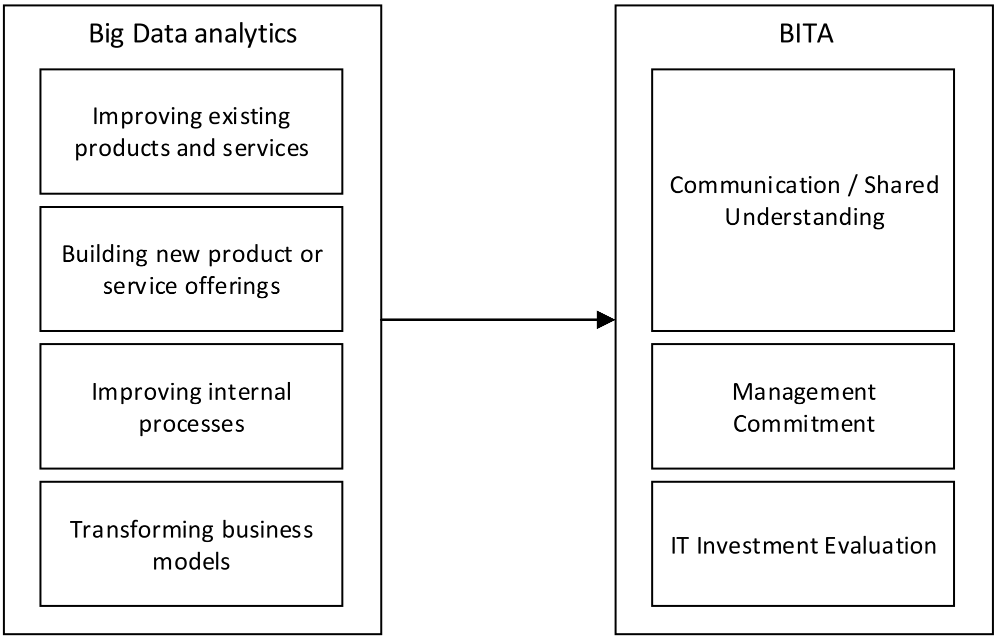

Figure 4 Conceptual model used in this study

3 Methodology

3.1 Research

3.1.1 Research approach

This research has been conducted via exploratory research. Exploratory research is used when problems are in a preliminary stage, and/or when the topic or issue is new and when data is difficult to collect. Exploratory research is flexible and can address research questions of all types (what, why, how) and is often used to generate formal hypotheses.

The purpose of this research was to gain familiarity and/or acquire new insight into the phenomena of business-IT alignment in a big data context. As an explicit problem has not been clearly defined, this study will be conducted via exploratory research and based on the principle of an inductive approach which means that theory will be developed after the data have been collected. An exploratory study is a valuable means of finding out 'what is happening; to seek new insights; to ask questions and to assess phenomena in a new light' (Robson, 2002).

Although this research has a clearly defined purpose, conceptual framework with research question(s) and objectives, it will not emphasize any predetermined theories. The purpose is to leave room for alternative explanations of what is going on as this research is particularly concerned with developing a close understanding of the context in which business-IT alignment is taking place. An inductive approach also permits a more flexible structure to permit changes of research emphasis as the research progresses. Although enough is known to make conceptual distinctions or posit an explanatory relationship, a perceived problem might not actually exist. However this research aims to provide significant insight into the phenomenon of business-IT alignment in a big data context. To do this existing theory has been used to develop a research strategy to collect data and formulate more precise research. If the data collection and analysis is effective, new findings and theories will emerge that neither you nor anyone else has thought about. This does not mean absence of direction but that the focus is initially kept broad and becomes progressively narrower as the research progresses. This methodology is also referred to as a grounded theory approach to qualitative research and is an attempt to uncover theory from the data itself rather than from a predisposed hypothesis.

3.1.2 Research strategy

This research has been conducted using an exploratory cross-sectional multiple case study. Although numerous definitions of case studies exist, Yin (2003) defines a case study as “an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident” Yin (2003) further explains that the case study research strategy is most likely to be appropriate for “how” and “why” research questions because they deal with operational links needing to be traced over time, rather than mere frequencies or incidence (Yin, 2003).

Case research is therefore useful

- when a phenomenon is broad and complex
- where the existing body of knowledge is insufficient to permit the posing of causal questions
- when a holistic, in-depth investigation is needed, and when a phenomenon cannot be studied outside the context in which it occurs (Yin, 2003).

The rationale for the choice of the case study strategy is that it is particularly suitable to gain a rich understanding of the context of the research and the processes being enacted (Saunders, et al., 2009). According to Paré (2004) only a case study can capture such dynamic, changing conditions and that ontologically, positivist case research assumes that IT departments in organizations are understood to have a structure and reality beyond the actions of their members. The focus of positivist research consists of “discovering” the objective reality by crafting measures that will detect those dimensions of reality that interest the researcher. Therefor case studies have been used to study IS phenomena, particularly in system development and implementation. However increasingly, they are also being used to explore a variety of IT management issues and the impacts of IT on organizations (Paré, 2004). The rationale for using multiple cases focuses upon the need to establish whether the findings of the first case occur in other cases and, as a consequence, the need to generalize from these findings (Yin, 2003; Saunders, et al., 2009).

This study follows the methodology and recommendations of Yin (2003) and involves four distinct stages.

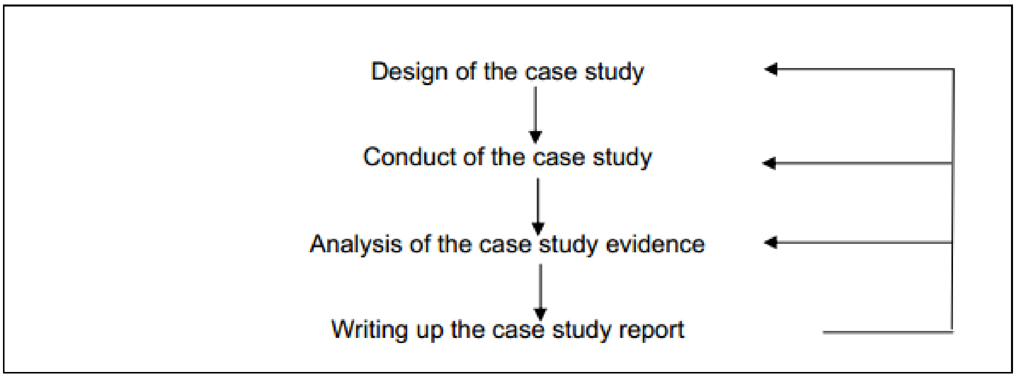

Figure 5 Scientific Approach for Conducting Positivist Case Study Research (Yin, 2003).

Yin (2003) stresses five issues which are of great importance, namely

- the initial definition of research questions (as described in §1.3)
- the a priori specification of constructs or theory (as described in §2.1-2.2)
- the definition of the unit of analysis (as described in §3.2)
- the selection and number of cases (as described in §3.3)
- the use of a case study protocol (as described in §3.4)
- each of these issues will be examined in turn (as described in §3.5)

3.2 Unit of analysis

A clear definition of the unit of analysis helps define the boundaries of a theory, which in turn set the limitations in applying the theory (Paré, 2004). To limit the boundaries of this research it focused on the firm as the unit of analysis in the various stages of the big data life cycle (plan, implementation and use). The level of analysis is therefore not limited to a single, but multiple levels of analysis. The rationale for this is that respondents were then able to give their views and opinions on the full roadmap, from plan, implementation to the use of big data analytics and from strategic to tactical and operational, and the impact it has on current business-IT alignment practices.

3.3 Selection and number of cases

3.3.1 Selection of cases

An important choice in the research design was the decision to include more than one case. The purpose of this research is to examine how the different big data impacts business-IT alignment. More specific management practices have been researched in order to understand how value is created though business-IT alignment and how the different aspects of big data have impacted these practices.

Large organizations exhibit differences in terms of resources and expertise available in comparison to those found in small and medium enterprises (Gutierrez, et al., 2009) Also Chan *et al*. (2006) observed that organizational size affects alignment and explained that in general small and medium-size firms have limited need for explicit alignment mechanisms and that in large organizations the decentralized governance structures make coordination more difficult and therefore need more mechanisms to promote strategic alignment and usually have more resources available to invest in these mechanisms (Chan, et al., 2006). Considering that large organizations tend to have well defined and usually large IT units this study will therefor focus on large companies (1000 FTE's and up) as I expect to encounter more business-IT alignment challenges and the cases to be more information rich.

Furthermore this the study has followed the literal replication logic according to the guidelines of Yin (2003) which means that the conditions of the case lead to predicting the same results. In the selection of the cases in this study we have followed the guidelines from Paré (2004);

- Each unit of analysis must be as specific as possible
- Each case should be a bounded system
- Each unit must be related to the initial research question(s)
- Literature must be used as input

For this research we needed particularly good stories that illuminates the questions under study. Therefor this study considered two specific sampling strategies, 'extreme or deviant case' and 'intensity' based (Paré, 2004). The extreme or deviant case sampling strategy involves selecting one or more cases that are information rich because they are unusual or special in some way, such as outstanding successes or notable failures from which this research will focus and analyze the interaction between business and IT and the social/organizational setting in which the big data application is being implemented. However, extreme and/or deviant cases may be so unusual as to distort the manifestation of the phenomenon of interest. But there were practical considerations as well. Therefor this study has convenience sampled 'intensity' based cases. This sampling strategy involved the same logic as extreme case sampling but with less emphasis on the extremes (Paré, 2004) and will focus on information-rich cases that manifest the phenomenon of interest intensely, but not extremely. "In short, using the logic of intensity sampling, one seeks excellent or rich examples of the phenomenon of interest but not highly unusual cases" (Paré, 2004).

3.3.2 The number of cases

Ideally, researchers should stop adding cases when theoretical saturation is reached (Eisenhardt, 1989). For this research however there were practical considerations which dictated when case collection ended. Therefore this study aspired to select as many information rich 'intensity' based cases as possible to reach a certain degree of certainty on the results, and to maximize what can be learned in the period of time available for the study.

3.4 Data collection

3.4.1 Case study protocol

Prior to the data collection phase a case study protocol has be defined. The protocol was used to structure the multiple case study and, besides the interview instruments, also contained procedures and general rules that have been followed. Besides its representation of the research agenda in pursuing the line of inquiry for the case study it will also enable other researchers to repeat the procedures in order to arrive at the same conclusions (Paré, 2004). For this research the following case study protocol has been defined according to the guideline of Yin (2003).

Table 3: Case study protocol

Case study protocol components	**How they will be used**
Case study overview (objectives, issues, topics being investigated)	Based on the theoretical foundations a conceptual model and methodological choices will be made.
Field procedures (credentials and access to sites, sources of information)	In order to grasp information during data collection in the field the following will be done; 1. To prevent inaccuracies due to poor recall, all interviews will be recorded when the interviewee agrees. 2. Notes will be kept during interviews. 3. An overview of business-IT alignment practices and explanation for communication purposes during interviews will be created. Wherever necessary or valuable visualization will be created as well. 4. An overview of the various aspect of big data applications and its perceived impact on business-IT alignment practices will be created. 5. Data collection activities like gaining access to the subject organizations, and appointment with interviewees will be clearly scheduled and will also provide for unanticipated events.
Interview guide	A list of topics for the interview (appendix 1), and interview protocol (appendix 2) will function as an interview guide during interviews. The specific list of questions and specific issues will depend on factors such as the individual's position in the organization and his/her affiliation with the big data application.
Case study report guide	To corroborate essential facts and evidence presented in the case report, the final version of the case report will be reviewed by key participants and informants in the case.

3.4.2 Methods of collecting data

Exploratory research often relies on secondary research such as reviewing available literature and/or data, or qualitative approaches. For this study I have chosen a formal approach through semi-structured face-to-face in-depth interviews. Semi-structured interviews were used when the researcher knows most of the questions to ask but cannot predict the answers (Paré, 2004). It allowed to obtain all information required, while at the same time it allowed the interviewee the freedom to respond and illustrate concepts. 'The primary goal of interviews is to elicit the respondent's views and experiences in his or her own terms, rather than to collect data that are simply a choice among pre-established response categories' (Kaplan and Maxwell, 1994 as cited by Paré, 2004). To get a complete picture and full narrative per case I have interviewed as many stakeholders as possible on a tactical or operational level (e.g. data scientist, IT engineers, business owner) and/or IT responsible on strategic level (e.g. CIO, Director IT, Program Manager). For reliability purposes this research will also provide an overview of the number of interviewees by job function (see table 4 interviewees per unit of analyses) which has been included in this research.

Table 4: Concept - interviewees per unit of analyses

Case study	**Interviews**	**Information source**
1	1	Manager Business & IT Solutions
	2	Technical Lead Big Data
2	1	Program Manager
	2	Head of Big Data Acceleration Lab
	3	Head of Big Data Retail
3	1	Business Change agent
	2	Project Manager
	3	Manager Data & Analytics
4	1	Lead Business Analyst
	2	Manager Team Data Management

For the selection of interviewees a ‘Snowball or Chain’ (Patton, 2002) sampling strategy has been followed. After the initial identification, in whatever way possible, of a few stakeholders for a particular big data context those interviewees were then used to identify others, and they in turn others.

This research has applied the practice of triangulation (Webb, 1967). Although interviews were the primary method of collecting data this study also collected official company documents like presentations, internal- and external communications and/or annual reports and physical artifacts observed when visiting the company in order to produce stronger evidence, a wider scope of coverage and a more complete overview of the phenomena under study.

3.4.3 Data collection procedure

When the initial contact with the organizations under study had been established the topic list and interview protocol was sent to the company representative who had a high level view of all big data analytics efforts within the company. In most cases an initial contact took place before a meeting was be scheduled in order to discuss and agree on the following topics:

- Quickly explain the research;
- Expectations regarding the different stakeholders;
- Confidentiality;
- Research approach (data collection, data analysis, review of reports and conclusions);
- How to establish contact with interviewees and schedule appointments.

Before the interview was conducted an email with the purpose, time, place and initial interview topics has been send to the interviewee which should have helped the interviewee to prepare information and answers to the topics. At the time of the interview the purpose of the interview had been explained, and the interviewee was asked about his/her permission for recording the interview.

The interviews consisted of open and closed questions and has been conducted according to the interview guide and interview protocol as defined in appendix 1 and appendix 2. The specific list of questions and specific issues depended on factors such as the individual’s position in the organization and his/her affiliation with the big data effort and helped direct and guide the overall interview for the interviewer as well as the interviewee. It's important to mention that this topic list did not limit the interview to give his/her opinion, assessment or view on the specific topic, and allowed the interviewee the freedom to respond and illustrate concepts.

To prevent inaccuracies due to poor recall, all interviews have recorded when the interviewee agrees and all interviews have been fully transcribed according to the recordings. These transcripts have not be incorporated in this study because of the confidential information they might contain.

3.5 Data analysis

The basic goal of qualitative data analysis is understanding through the search for coherence and order. Case studies however, tend to produce large amounts of data that are not readily amenable to mechanical manipulation, analysis, and data reduction (Yin, 2003). Therefor as Paré (2004) suggest the data analysis stage has been broken down into two distinct stages, namely, 'Within-Case Analysis', and 'Cross Case Analysis.' and the measure for impact of business-IT alignment will be discussed.

3.5.1 Within-Case Analysis

As stressed by Eisenhardt (1989), a key step in building theory from case research is within-case analysis. In this phase an 'explanation-building' mode of data analysis has been adapted. Explanation-building is considered a form of pattern-matching in which the analysis of the case study is carried out by building an explanation of the case (Paré, 2004). To make this possible a case description framework has been developed to organize the case study, which in turn was used to establish a logical chain of evidence by finding answers to the how and why business-IT alignment changes associated with big data were executed. This chain of evidence will be built in several steps. The first task was to identify the challenges encountered during the big data implementation process through an in-depth analysis of the contextual conditions surrounding the implementation project. After that for each (anticipated or not anticipated) challenge the actions have been described to cope with the problems encountered. The extent to which each challenge is overcome was explained by:

1. Providing evidence of the effectiveness of each coping tactic
2. Identifying and explaining how certain contextual conditions enhanced the effectiveness of coping tactics
3. Explaining how other conditions prevented the adoption of tactics (Paré, 2004).

3.5.2 Cross Case Analysis

To enhance generalizability and gain a deeper understanding and explanation a cross-case search for patterns have been done. Following the guidelines of Paré (2004) this iterative process started with the development and presentation of an initial set of theoretical propositions based on evidence from the first case. These initial propositions were then used as a vehicle for generalizing to other cases. The emergent findings from the first case were then be systematically compared with findings / evidence from the second case and so on. The central idea was to iterate towards a theory that fits the data, where cases which supported the emergent theory enhanced confidence in its validity, and cases which do not support the theory provide an opportunity to refine and extend the theoretical model (Eisenhardt, 1989).

3.6 Measures

Measuring the impact of big data on business-IT alignment was based on perceptual measures in the form of subjective perceptions acting as a proxy for realized business value. According to Tallon *et al.* (2000) the legitimacy of perceptual measures as a proxy for objective measures of IT business value is still open to debate as there is a possibility that executives (and IS executives in particular) will exaggerate their views on IT impacts as a means of self-promotion and the sheer complexity of modern corporations, both in terms of organization structure and market uncertainty, complicates the task of giving an accurate assessment of the “true” payoff from IT. While there are more objective measure available like IT payoffs like growth, profit, or revenues for the business Tallon *et al.* (2000) provide three answers to this. Fist, different researchers have found that perceptual measures of firm performance correlate strongly with more traditional objective measures. Second, perceptual measures are more and more accepted in literature and practice because executives are direct consumers of IT and more involved in IT investment decisions, thereby having better awareness of the impacts of IT on the business, and exposure to other opinions of professionals. And third, numerous of researches showed that executives' perceptions are key to understanding how IT affects firm performance because of their decision-making authority and strategic focus on the future (Tallon, et al., 2000; Tallon & Kraemer, 2003).

3.7 Operationalization

The specific business-IT alignment practices in scope of this research were operationalized in the following way. On this basis interview questions have been defined, which can be found in appendix 2.

3.7.1 Communication

Communication includes exchange of ideas, knowledge and information among the IT and business managers, enabling both to have a clear understanding of the organization's strategies, business and IT environments (Gutierrez, et al., 2009). The measurement of the communication construct has been done in accordance to the measurement approach of Reich and Benbasat (2000) who used Galbraith's (1977) typology of seven techniques, thought to increase communication between two separate units and defined the construct for which the six most pertinent techniques are listed below:

1. Direct communication (e.g., communication between business and IT executives, such as regular or ad hoc meetings, electronic mail or written memos).
2. Liaison roles (e.g., a named person as liaison between IT and a line function).
3. Temporary task forces (e.g., IT project team, new product development team).
4. Permanent teams/committees (e.g., IT steering committee)
5. Integrating roles (e.g., IT person leads the business quality team).
6. Managerial linking roles (e.g., product management role) (Reich & Benbasat, 2000, p. 88).

The typology was used in this study to formulate interview questions identifying the type and number of these techniques employed.

3.7.2 Shared understanding

Reich and Benbasat (1996) identified two aspects of the social dimension of alignment, namely short-term and long-term alignment. While short-term alignment refers to shared understanding of short term goals, long-term alignment refers to shared understanding of IT vision. These two dimensions were found to be distinct because some organizations had achieved high levels of one while rating low on the other. As this study perspective on business-IT alignment is that of a continuous process and not an end state, short-term alignment was used and defined as the state in which business and IT executives understand and are committed to each other's short term (one to two year) plans and objectives (Reich & Benbasat, 2000). This aspect was operationalized by interviewing business and IT executives, asking them to identify both current business and IT objectives/plans, and measuring the level of understanding that business and IT executives have of the role of big data in the organization, big data as a competitive advantage, big data to increase productivity, and prioritization of big data investments, how to make full use of its capabilities.

3.7.3 Management commitment

There seems to be no single definition for management commitment to IS, however management commitment has been discussed in IS literature as one of the main enablers of alignment (Luftman, et al., 1999; Teo & Ang, 1999) and has been describes as "the attention and dedication of business managers on various levels to IT and vice versa" (Vermerris, et al., 2014). The state in which business and IT executives within an organizational unit understand and are committed to the business and IT mission, objectives, and plans (Reich & Benbasat, 2000). And management needs to be committed to and supportive of IT initiatives in order to understand the strategic potential of IT (Kearns & Sabherwal, 2007). Companies that show support from senior non-IT executives or realize management commitment are able to recognize the value of information technology, define and communicate vision and strategies that include the role of IT, and sponsor IT projects (Luftman, et al., 1999).

Top management can demonstrate their commitment to the strategic use of IT in several ways. First, they can elevate the status of the top IS executive such that he or she reports directly to the CEO. Second, top management can allocate appropriate and adequate resources (e.g., funds, manpower) for the development of strategic IT applications. Third, top management can initiate the setting up of an IS steering committee. The presence of the CEO as a member of the IS steering committee will send a clear message to the rest of the departments regarding the importance of the IS function in the organization. Fourth, top management can play a leadership role in terms of providing directions for strategic IS initiatives rather than a controlling role in determining details of IS planning activities (Teo & Ang, 1999).

3.7.4 IT Investment evaluation

Before deciding to invest in IT, most firms will typically conduct a feasibility study or pre-implementation review to determine, among other things, the likely impact of the investment on the corporation (Tallon, et al., 2000). Evaluating IT investments has been argued and empirically proven as an important enabler of strategic alignment (Henderson & Venkatraman, 1993; Tallon, et al., 2000; Sledgianowski, et al., 2006) Evaluating IT investments at different stages of a project is a mature alignment practice and concerns frequent and formal IT assessments and reviews (Sledgianowski, et al., 2006). “Without an effective evaluation policy or a set of investment guidelines, there is a risk that IT investments will not support the business strategy” (Tallon et al, 2000).

An IT investment might be conditional on a positive cost benefit analysis or a favorable net present value calculation. As corporations use IT for more strategic purposes, there is an even greater need for these investments to undergo routine, systematic and recurring evaluation. As an alternative to using ROI or other objective criteria in evaluating IT investment decisions Tallon et al. (2000) raise the question of whether IT investments that undergo systematic evaluation will realize higher IT payoffs than investments which are more a function of gut feeling, intuition or blind instinct.

This study used IT investment evaluation measures consisting of management practices like frequent and formal IT assessments and reviews (Sledgianowski, et al., 2006) and pre- and post-implementation reviews where pre implementation reviews consist of 1) executive review of large spending proposals and 2) justification before purchase and post implementation reviews consist of 1) formal reviews after implementation and 2) regular reviews by business units.

3.7.5 Communication and shared understanding

Communication and shared understanding have been studied in one single study (Reich & Benbasat, 2000; Campbell, et al., 2005). Where Reich and Benbasat (2000) found that shared understanding positively influences communication between business and IT executives for short-term and long-term business-IT alignment. They argued that shared understanding only had a positive effect on long-term alignment and that communication was not important. However, Campbell *et al.* (2005) argue 'as with much of literature were only concerned with dealings between IT and business executives. They do not consider effects at lower levels of an organization.' and therefore suggest that good communication is a prerequisite to shared domain knowledge and not a result of it. As this study views business-IT alignment as a continuous process and not an end state, and considering the nature of the central research question, this study considers communication and shared understanding not only to be complementary but also be interdependent and interrelated. For example, if big data initiatives require higher levels of shared understanding, it automatically will require higher levels of communication, and if higher levels of communication are required it will be with the sole purpose of increasing shared understanding on big data analytics.

3.8 Validity and reliability

The goal of validity and reliability is to minimize the errors and biases in the study. Reliability refers to the extent to which your data collection techniques or analysis procedures will yield consistent findings. Although exploratory research is not typically generalizable to the population at large, the general way to achieve reliability is to conduct the research so that another investigator could repeat the procedures and arrive at the same conclusions (Paré, 2004). It can be assessed by posing the following three questions (Easterby-Smith, et al., 2008).

1. Will the measures yield the same results on other occasions?
2. Will similar observations be reached by other observers?
3. Is there transparency in how sense was made from the raw data?

To insure high levels of validity and reliability four tests common to social science methodology were used: construct validity, internal validity, external validity, and reliability.

Table 5: Validity and reliability

Criterion	**Guidelines from literature**	**How they will be used**
Internal validity	Explanation-building Pattern-matching	- A logical chain of evidence was established - Empirical patterns from cross-case analysis.
Construct validity	Triangulation Case report reviews Establishing a chain of evidence	- Multiple sources of evidence were used - The case report was reviewed by key participants and informants in the case - Per case a detailed chronological narrative has been developed with cross referencing to different interviews.
Reliability	Case study database Case study protocol	- Field notes have been made during each interview - Every interview has recorded and wordily transcribed - A case narrative per case has been made - A case study protocol can be found in paragraph 3.4.1
External validity	Increasing degrees of freedom Case sampling strategy	- Freedom to respond and illustrate concepts - Multiple interviews per case - Multiple cases will be selected Extreme and/or deviant and intensity case sampling strategy has been used.

4 Empirical data and analyses

This chapter presents three illustrative case studies as a practical approach to the concept of business-IT alignment in a big data context and aims to illustrate how the theory and concepts of the business-IT alignment framework presented in chapter two are impacted in practice. The three case studies were developed by gathering data from interviews and official company documents like presentations, internal- and external communications and/or annual reports of two firms in the energy industry, one from the airport industry and one from the banking industry. Based on an agreement with my interviewees, these firms will be presented anonymously and without any details or identifiable information for confidential considerations.

The gathered materials in the presented case studies comprise the various components and characteristics of the use of big data. The empirical finding for each case will be initiated with a brief description about the organizational context, which will be followed with a brief description of its corporate strategy and attributes. The results will show how these three firms have developed different approaches in an attempt to minimize or bridge between corporate- and IT strategy to achieve strategic alignment.

4.1 Within-Case Study 1

The first company is active in the energy sector with its headquarters in Rotterdam, the Netherlands. Although the company roots go back to the mid-19th century, the company in current form was established in 1995 and is the result of a long history of collaborations and mergers of municipal utilities. The company shares are still held by over 50 Dutch municipalities. In 1995 it was the largest energy company in the Netherlands. In 2000 the company merged with six regional energy companies and in 2003 the last merger and acquisitions took place. The company’s international activities in wind and solar power and biomass are thus expanded and with a focus on local production of renewable energy it also made them a top 5 player in the Belgian business market. They are also active in Germany, France and the UK in the field of renewable energy. Finally, they are active worldwide in trading (renewable) energy products and CO2 emission rights.

In 2011 it acquired a well-known price fighter in the energy market. This acquisition expanded their sustainable supply portfolio with more than 426,000 customers and thus, with approximately 2.1 million customers, strengthened their position as one of the major energy suppliers in the Netherland. Year end 2015 the company employed about 6700 employees and had roughly 4.3 billion in revenue. The company however operates in a highly competitive category with potential disruptive competition coming from unusual sources. An obvious example being the Tesla Powerwall (Ramos, 2015). The energy world is changing and is moving from a centrally organized and conventional energy system to a system that is decentralized and sustainable and customers have an increasing need to have their energy into their own hands.

Its ambition for 2020 is to be the service provider of choice for customers as well as partners. Through co-creation it aims to develop products and services which make it possible to companies and consumers to generate, use, store and exchange their own energy. More than ever it focusses on finding decentralized solutions. Focusing on this transformation new strategic principles have been formulated. The choices it makes have to meet the principles, "relevant to the customer", "contribute to the energy transition', and 'gain momentum'. In their new business model the focus is on three areas of growth: 'Client Sources', 'Smart Sustainable Solutions' and 'Energy as a Service'.

For growth areas 'Smart Sustainable Solutions' and 'Energy as a Service' the IT component has become a core business. By developing smarter systems and the use of data and analytic in all parts of the organisation it aims to accelerate innovation and provide customers with more control over their energy.

These developments create new opportunities and markets. Although these new markets come with opportunities, new competitors also appear in the energy market. To sustain profitability, spur growth or even survive as an independent company it relies on not only on incremental but rather radical product- or business model innovation. With this in mind a new Innovation & Ventures business-unit has been created with a 100 million investment budget to finance the development of new products and services and to participate in start-ups. Within this business unit there is also a big data team was formed to centrally support business unit led big data initiates.[2]

> *"Big Data is getting more and more important and seen as a strategic asset. There is much to win and it and is potentially transformational for our whole organisation"* [Manager Business & IT Solutions]

The company believes it can benefit from big data and sees great strategic potential for organizations that adopt big data and advanced analytics. The company believes the use of big data analytics will lead to enhanced business intelligence insights and represents a key basis competition and will define the difference between winners and losers in their industry and that big data analytics is amongst the most important battlefields for 'classic' energy companies today.

> *"All this data has to be combined in a way it can solve business problems, but also serve as a source for new ideas or insights to create new business or new business models. We need new propositions and all the data we have can really be a strategic weapon to need to capitalize on. I would spend most of my innovation budget on it if it was up to me."* [Manager Business & IT Solutions]

Although the company already had a big Business Intelligence (BI) team, a separate big data team of about 7-9 people from both business and IT was created which acts as a delivery center and provide solutions to business needs. While only 20% of the total innovation budget was allocated for this the company invested heavily in getting their data sorted. As the company had captured mountains of data over several years, all this data was fragmented and scattered in silos of data across the domains within the company. As they now considered data a strategic asset the first step was manage the multiple data sources to get it together into an integrated form that can be used across the company.

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[2] Information obtained from interviews, official company documents like presentations, internal- and external communications and/or annual reports.

> *"The most important part is that you have your 'data lake' in order. Your data integration and the collection of data. It does contain structured and unstructured data. If it was up to me would leave the 'big' part off. I don't consider it very relevant. You need to do something smart with it."* [Manager Business & IT Solutions]

To effectively use this big data the company also invested in big data team which has the right set of capabilities to capitalize on the potential of big data. The last four years the company has been working on developing a capability to turn data into useable insights. The company hires and develops skilled analysts or data scientist who can help support the business in the selecting relevant from irrelevant data and draw the right assumptions. However, the company found that you do not only need people with hard analytical skills, but also lots of supporting staff. On the one hand they needed technically skilled people, but on the other hand you need people who can identify and formulate new business models or sources or revenue and who are enthusiastic supporters of that mission. It is essential that employees feel connected and are committed to create momentum. The company does not think these people match with the typical 'IT profile' or even "business profile".

> *"As an organisation we must learn to anticipate the uncertain and unknown. We used to be long distance skaters were you could plan ahead with a strategy that would win us the match. Now we are playing hockey. You should be able to quickly decide that we must do things different or move into another direction. You need to be very agile and/or be able to reduce uncertainty and ambiguities. This takes a lot of training. Otherwise you won't be champion, but the long distance skater won't ever be a good hockey player. You need different people. And the big data phenomenon only accelerates this"* [Manager Business & IT Solutions]

The company found that this new way of working if not for everyone and you can't retrain people to use these new technologies. A lot of people who did not fit their view on the skills they need go were let go because of this. Most of the former management has been replaced. New people including a much younger management team have been hired, incentives were aligned to support the new way of working and someone with a strong HR background was added to the IT management team and was tasked with developing and maintaining the right skills- and competences.

> *"What we see is that to be succesful in a big data landscape, you need a complete different set of skills and a different mind-set. They also need to have more broad knowledge then the people we have. We don't need people who aren't T-shaped anymore. T-shaped to us means that you are either capable of fulfilling multiple roles or, and that's what we prefer, have both business and IT skills. And management must coach them properly and help them learn. Those are the people we need."* [Manager Business & IT Solutions]

The company found that in order to create value from big data analytics there is a need for the business to fully grasp the possibilities big data brings take the lead. They found that it's very important to start with a sense what problem is you're trying to solve or the outcome you're trying to achieve. It does not work if you start with a mindless exploration of a huge amount of data and hope that eventually you find something in there. Although these open-ended exercises did sometimes produce novel insights they feel it does not help in achieving large-scale results. The finding are either not actionable or able to influence business results in a meaningful way.

> *"Digging for hidden treasures should not be a goal. You can't just store everything you come across. There has to be some sort of business case."* [Technical Lead - Big Data Integration Team]

The data and IT infrastructure is operational and agile enough to facilitate the business.

> *"For us big data is about 'volume' but maybe more important 'velocity'. End of 2013 we started with our smart device for consumers analysis. We then had 30.000 devices, with 35 measure points that resulted in half a million files of 12GB of data per day. You can't manage that in a traditional transactional database. It also placed new and additional requirements on our IT-architecture. We needed to bring the processing to the data instead of the other way around and needed to be able to scale up- or down quickly.*

> *That's one of the reasons we made a partial move to the cloud."* [Technical Lead - Big Data Integration Team]

The business however struggles finding the right way of leveraging their data assets and even to define desirable outcomes based on big data. In other words; to request the insights from the data scientist that can help them transform the way the business operates.

> *"On the IT side we don't need anyone anymore. But there is still a gap in communicating with the business. The business just can't formulate the necessary requirements. As a fix the business now communicates with IT via the data scientist who has better business acumen."* [Technical Lead - Big Data Integration Team]

> *"The business struggles to define outcomes for which we can develop and build big data applications. They don't ask the right questions. Asking the right questions would make it much easier to define a good business case and invest. I think the IT function could be more inquisitive about the business to find their biggest challenges and create awareness on the potential value of big data. This might help establish a common language, a focus on goals and a way of getting started." [Manager Business & IT Solutions]*

Because of this the IT function lacks direction and does not know how to structure the data, which data should be aligned to which functional- and non-functional requirements, or to buy off the shelf software or build a proprietary solution for example.

> *"What is it that you want to do with the data? Let say you want to know where that customer call was about. Well, you could put those mp3 files thought a voice-to-text-converter and then mine that text for specific keywords. But then you can't answer the question if you could listen to her voice and tell if that call ended in a happy or unhappy customer."* [Technical Lead - Big Data Integration Team]

Getting the business to view data as a strategic asset is the most important thing. This mindset will help to figure out how to start develop something the business can act on every single day. But the company has not reach the point where insights from big data analytics are being used in every decision and or transform the operations.

> *"When you look at our big data team we have enough space to focus on innovation. However, I think we should have five or six of those teams to create more awareness and really transform into a data-driven organisation. In some cases this will mean that the power will shift from the business to IT or the data scientist. But I foresee that IT and business will merge together in the future. We are going to be a marketing and IT company"* [Manager Business & IT Solutions]

Big data project or investments are still being evaluated according to existing criteria which means they will be evaluated on the creation of measurable (SMART) benefits. Although the business case for big data has been negative by default IT has been able to gain enough support with top management.

> *"They should quit that way of thinking and trust us more. The team knows what the goal is and if the team says we can't do it within reason or we don't have the skills we know when to pull the brake."* [Technical Lead - Big Data Integration Team]

4.2 Within-Case Study 2

The second company under study is also active in the energy sector and a direct competitor of the first company under study. It has about 2700 employees. Almost 4.5 billion in revenue and supplies 2.5 million consumers and businesses in the Netherlands and Belgium and it part of the international energy group which is active in the generation, trading, sales, transmission and supply of electricity and gas and is one of the largest Dutch producers of conventional and renewable energy. In July 2009 they had to split off the network business. Since then it's only responsible for the electricity and gas networks and troubleshooting it.

The also find that the traditional consumer-facing energy market becoming more demanding at all stages of the value chain. The traditional business model of a fully integrated energy utility is coming under increasing pressure as customers are seeking to make efficient use of energy and want to take advantage of the opportunities offered by the digital revolution. They believe this offers entrepreneurial opportunities which they intend to seize by offering their customers innovative products and services that enable them to make more efficient use of energy and increase their quality of life. Now more than ever before, utilities are being assessed based on how flexible and innovative they are. They believe that in order to survive over the long term in a market undergoing dynamic change such as the energy market they must ensure that have compelling offerings to satisfy customer needs tomorrow and beyond.

To fulfil this promise, they have set themselves the strategic goal to successfully contribute to the sustainable transformation of the European energy system. To defend their market share in this environment, they are extending their field of activity far beyond the traditional supply of electricity and gas and are developing new business models for all customer segments by pooling their know-how in energy supply and information technology. The result is innovative products and solutions tailored to suit personal needs, distinguishing us from other utilities. One of the most important themes in this strategy is the development of new products and services by using data. As do most companies these days they also have an ever-growing amount of data and wants to make better use of it in order to develop their products and services. For instance, for years they have been collecting operating data from turbines from various manufacturers which they used it to optimize the stations. This knowledge is unique in breadth and depth and new methods of analyzing this high volumes and fast flowing data make it possible to use energy more individually and efficiently. As a result, their customers will see how much electricity is used by antiquated, inefficient refrigerators, as well as being alerted to short interruptions in the power supply, which may indicate that a failure is about to occur. They also want to market it to the manufacturers engineering departments and to power plant operators all over the world.

To do this two main themes or light houses have been defined. ‘Digital and Big Data analytics’ and ‘Smart and connected’ (leveraging the Internet of Things and analytics for smart energy management). They believe that leveraging their data will give them the ability to tap into additional revenue opportunities, get incremental improvements in marketing, supply-chain and management decisions, provide client a 360 degree view of their customers and businesses, enabling better and more accurate decisions and is going to define the difference between winners and losers in their industry. They therefor made significant investments in big data. [3] However, the company found that actually mapping out a roadmap to be an analytical competitor or data-driven company is not a simple task.

> *"Our innovation perspective turned out to be both an advantage- and disadvantage. On the one hand we underestimated the technological impact and encountered much more technical challenges then we expected. On the other hand if we had approached it from a business intelligence (BI) or IT engineering perspective we might have limited ourselves."* [Program Manager]

After setting this strategy, investment in assets such as technology, tools, and data sets had to be made to build a basic but substantial supporting infrastructure, while internal support and commitment had to be secured without figuring out *how* it’s going to be used and even *who* was going to use it.

> *"You see all the big challenges. And a lot of cost. It impacts your whole architecture. That's not something that is taken lightly. You should have a really clear picture were*

[3] Information obtained from interviews, official company documents like presentations, internal- and external communications and/or annual reports.

you are heading. Which data are we going to collect? What do we need today but also what might we need tomorrow? What's the impact? These are all hard questions. And some people said we should not do it, and just focus on the way we are doing things now." [Head of Big Data Acceleration Lab]

They soon discovered that getting data wasn't an easy task and found that to get the data together into an integrated form that can be used across the company, is the first challenge. Before they could start innovating processes the company first had to find which types of data they were already capturing and storing the data they need and which types of data they might need to create the necessary insights. For this their whole way of thinking on data architecture needed to be changed. Data silos should now be connected and integrated. And then topics like data integration, data hygiene, data cleansing, and developing data governance around who's responsible for keeping and securing clean, accurate data that gets fed into the big data analytics had to be addresses all subject to the overarching topic of data security and privacy.

"When we just started we hired five data scientist, only to conclude we did not have access to the right data. I now picture it as triangle or pyramid. You need a very large basis of supporting skills." [Head of Big Data Acceleration Lab]

Deciding and searching which internal data to use, and where to look for data outside their organization quickly the brought focus on the human element: the skills needed, people, and roles.

You need much more people capable of making the translation and link with the business. That's something we also learned. A data scientist and a marketing manager working together had a hard time creating value. I haven't seen a data scientist who can do it" [Big Data Lead Retail]

Spelling out the ambition to be a data-driven company is one. Embracing it as a new way of doing business is another. They were still searching to what end and how it was going to improve their business. Where should they focus on?

"When our CEO first announced our new strategy and said we were going to be a data-driven company everyone was asking what that would mean exactly. We were an energy company, not Netflix or Google. 'Data-driven' is very abstract term. That in itself was not enough to create awareness. So we went about it in another way. We organized inspirational sessions, invited start-ups, freelancers, some of the big five consultancies and service providers. All with Big data experience. We tried to find out how everyone looked at big data. Is it a technical issue? Is it a business issue? What challenges do we see and how can we overcome them? That turned out to be quit hard as every stakeholder looked at it from their own perspective. So that did not work."
[Head of Big Data Acceleration Lab]

The current business workforce had been operating in the same way for many years and were not used to doing things differently. That brought up a real change management challenge. But before taking existing people and train them in new methods and new skills management then decided to create an application that would benefit the business affect the whole organisation. Very essential was that it was done in a 'closed loop', meaning by continuously iterating this business case and refining it as they learned, and having senior sponsors participate in validating results hoping the concept of big data would gain momentum and gain interest from the business side. We need business managers to identify and prioritize opportunities.

"We then decided to create a case which would impact every function and every stakeholder and we named it the 'Three A' model. The first 'A' stands for 'acquiring information', which means the data. That turned out to be mostly an IT challenge, were can I find the data I need? This might sound simple, but it is not. The data is spread all over the place, there is no connectivity or integration, data structures are not compatible and/or data is not consistent. We needed to find out if we had the data or that we needed to capture more. And the legal aspects of it all...you name it and we encountered it. When we established access we needed to figure out how to analyze it, the second 'A'. We quickly learned our IT architecture and infrastructure was not up for the task. We needed to partially move to the cloud and needed to select the right tools to be able to analyze anything at all. And do we have the right skills as this variety in

> *data is much more complex? It really was a matter of data science not 'basic analytics'. And after that came the third 'A', make our insights 'actionable'. You have to get these 'beautiful insights' into a closed loop. You have to get the right information at the right person at the right time. Preferably real-time."* [Big Data Lead Retail]

> *"One of the first applications we created was one for our call center. Together with an external start-up we created a predictive model to help us determine who would call us and for what reason after they would receive the bill. For each customer we then created a personalized dataset with all the information we had and based on this we would send them a video hoping to answer these predicted questions two days before sending the bill. The result was that these customers stopped calling. So we established a business proof case. And closed the loop. When does the customer start the video? How long does he watch it? How does he click trough? We could use that data to make incremental improvement. And then people started to get excited. Since we don't have it in our DNA we have to do it this way."* [Program Manager]

> *"Showing what you can do, automate it so it help them in their job helps. These stories will be told and this helps accelerate the transformation. We now established a network of ambassadors to help us with this. We have to make a lot of noise about this!"* [Head of Big Data Acceleration Lab]

A more centralized approach combined with making sure that this "guerilla' big-data experiment could show benefits to the business within six to seven months after they had started helped getting senior sponsorship and broader participation. Receiving an internal award also helped gain momentum. However, they still need a lot more people that can create the connection and link with the business. The need a lot more succesful big data application to scale impact on the company's performance.

> *"I act as a link between the different operating companies for innovation for retail, digital and big data. By setting up several proof of concepts within the big data domain we aim to close the existing gap between the business and the future and try to accelerate the transformation."* [Head of Big Data Acceleration Lab]

4.3 Within-Case Study 3

The third company under study is active in the aviation industry. It employs about 2000 people and one of its principal activities it the operation of a hub airport. Over the years, with 322 direct destinations, this airport has grown to become one of the largest hub airports in Europe. In 2015 over 58.2 million of travelers were served and 1.6 million tonnes of cargo volume was handled. It is also an important marketplace, with the airport sites alone accommodating some 500 companies that together employ around 65,000 people. In 2015 a total of 64.3 million passengers travelled through the group airports, had a total revenue of 1.423 billion, managed 1.9 billion in real estate assets and held 6.4 billion in total fixed assets.

By joining forces with their sector and business partners, the authorities and the local community, it aims to achieve its ambition to further develop the airport as a multimodal hub and position it itself as Europe's first choice of airport of passengers, airlines and logistics services providers. The group has four shareholders. In turn, the group is involved in the activities of international airports in the United States and has engaged in strategic collaboration with one of the biggest airports in South-Korea, have an interest in airports in Australia, Hong Kong and Aruba. These international activities account for a significant part of group's results. In the Netherlands it has interests in three regional airports. Their main airport, as an AirportCity, a dynamic metropolitan area that offers passengers and airlines all the services they need 24 hours a day encompasses three business areas that complement and enhance each other. The first business area is aviation which provides services and facilities to airlines, passengers and handling agents. The business area supports an efficient and high-quality passenger and cargo process. It is responsible for the provision of the check-in and security facilities, the design of the terminal, piers and gates, the development and management of the baggage system, management of the landing area, the maintenance of this infrastructure and the coordination of safety on platforms, roads and grounds and in the buildings. The second business area is Consumer Products & Services which develops and manages the range of products and services. Its primary aim is to enable passengers to travel care-free and comfortably. This business area grants concessions for shops, restaurants, services and entertainment and operates a number of shops and the car parks. It also creates opportunities to advertise at the airport. Their third business area is real estate. This business area develops, manages, operates and invests in property on and around airports in the Netherlands and abroad. The portfolio comprises both operational and commercial real estate that, for the most part, is located on and around the main airport.

Overall, the aviation industry is expected to continue growing. However, the group operates in a dynamic environment. Consumer behavior has changed dramatically over the last few years. Passengers increasingly expect an omnichannel experience, including continuous access to consistent and real-time information. It believes technological developments and digitization will affect future demand for air travel or the way in which airports organize their services. It tries to strengthen its position by remaining alert to new developments and responding with forward-looking strategies. The group regards supply chain innovation, the ongoing digitization and big data as important opportunities. [4]

> *"Developing new revenue streams in our business is hard. But we are more and more becoming a system integrator. A management organization which need to capitalize on the available capacity as efficiently as possible. With a big data center of excellence we started to work on integrating and managing the separate processes more efficiently started developing one big efficient network."* [Business Change Agent]

> *"We are quit used to handling large volumes of data. For us big data is not only about velocity but also about variety. We have radar equipment scanning and plotting the airspace for bird movements. We are now integrating new external sources to that data to refine and improve the predictive model. To track passenger flow we now use our Co2 measurement devices as sensors. When the value go up we can estimate the amount of passengers and based on data collection we can predict future movements, which we then connected to infrared sensors behind counters so we can, through our dashboards, match the amount of people working there."* [Manager Data & Analytics]

[4] Information obtained from interviews, official company documents like presentations, internal- and external communications and/or annual reports.

While the company had access to increasingly enriched data, both in volume, variety and velocity. To be able to create insights that were actionable, they needed to establish ownership for data.

> *"We want to drive decisions based on data. The current data landscape did not fit the way we want to manage it now."* [Business Change Agent]

> *"There used to be a direct relation between the data source and de user of that data. We now working on a single unified source, with unified data logic and data definitions which we plan to make available to several parties and employees in the value chain."* [Project Manager]

Business enablers such as data management, data quality and data governance were established across the organization.

> *"Flight data can be can be interpreted in many different ways. For instance when a plane has landed. For some it was when the wheels touched the ground, others when it was at the gate." We needed to make huge steps there.* [Project Manager]

As a strategic asset, data needed to be managed and owned across the organization. Apart from that they choose to store data in a single 'golden' source so only a single leading instance exists across the enterprise to able to ensure accuracy.

> *"We are integrating and storing data more centrally. We are also adding more external data sources and making all this data available through API's. (Application Programmer Interfaces)"* [Manager Data & Analytics]

To create a point of accountability and ownership for the company's data a 'data board' was established. The data board is now responsible for establishing the organization's data architecture, the required governance structures, policies and guidelines to ensure data quality and management. Although IT needed to update the business on the importance of proper data governance practices, the business is clearly in the lead. The current experience is IT has no trouble keeping up, although the business would like some more input once in a while.

> *"The business is in the lead. But now and then I would like to be challenged by IT."* [Business Change Agent]

> *"We needed to ask the business to better govern their data and/or ask better questions. For instance if you want flight information you got to let us know if you want to include military and/or helicopter flights. We also try and assign owners to the data. We established a data board to organize certain decisions on data."* [Manager Data & Analytics]

The group sees a lot of potential using big data analytics to improve internal processes and the business in clearly in the lead.

> *"Our big data strategy aims unlock an in- and out flow of information on every touchpoint. We want to know where our assets and resources are at all times. And employees and passengers. If we can track passengers in real-time we can manage the processes better with predictive analytics. For instance, we can predict when a customer will not make a flight so we can have it take off as soon as possible."* [Business Change Agent]

> *"We have a lot of assets we can better manage. We have a track & trace program were our goal is to create a grid were we can track all kinds of resources. Basically everything you can put a sensor on."* [Manager Data & Analytics]

> *"We currently have a short-term and long-term forecast. Out short-term is now 24 hour, but for personal we have a 3 hours changeover time. And we want to move from using historical data tot real-time and predictive analytics and the insights available at the front-line which in turn can update us in near-real-time to. This will safe us a lot of briefing and de-briefing."* [Business Change Agent]

The big data initiatives until now are be considered quit succesful. However, while big data-analytics investments might significantly add value and/or increase operating profits the group has raised questions about the magnitude and timing of the returns on such investments as the company's asset based it very large and diverse. The capital expenditures on infrastructure would be enormous. And since broader performance improvements from large-scale investments in data-analytics often don't appear right away, and early efforts have not yielded a significant return.

> *"We have such a large diverse base of assets. That puts different requirements on IT. It's hard to make a sound business case. The benefits are not clear enough. We have 60 million passengers a year. The process begin with the parking gate and end with the boarding on the plane. Everything can happen in between. And when you're programme estimate is 2.5 billion…you need a lot of time to get it sorted. Our industry is based on minimal margins with a set budget forecast of 3 years. That makes it very challenging to say the least.* [Business Change Agent]

Knowing that digital natives capture big returns, the question raises if this also applies the hard-wired universe of service and distribution.

> *"Top management seems committed and is very approachable. It's a risk/reward consideration in the investment decision process. We have accountability toward our main airline and it's hard to get a clear view how these technologies are going to develop and return on investment is going to be."* [Business Change Agent]

The second biggest challenge at the moment is getting shared commitment not within the organisation but also with all external stakeholders in the value chain

> *"With all our internal- and external stakeholders in the value chain there is not always a shared interest and thus no shared commitment. Not everyone has a similar mindset. And you definitely need shared commitment for the large scale projects".* [Business Change Agent]

4.4 Within-Case Study 4

The company group under study for the fourth case has a rich history that stretches back more than 170 years. It is an insurance and asset management company with a leading position in the Netherlands and a strong presence in Europe and Japan. It the moment of study it employed 11.500 people, operated in 18 different countries, managed over 15 million customer policies and had a market capitalization of 10.9 billion euro. The group aims to deliver high-quality retirement services, insurance, investments and banking products to retail, SME, large corporate and institutional customers and has a focus on profitable growth through product and distribution diversification, improving underwriting performance and customer satisfaction and through digital transformation of the businesses.

Although the group has a strong foundation, the changes in their operating environment continue to be unpredictable and fast-paced. The group considers digitalization a game changer for their industry and recognizes the increased competition in the market, but regards new technologies which enable further individualization and drive further innovation in the sector as an opportunity. It however, also faces non-traditional competition. Technology has not only changed the rules of the industry, it has also changed the rules of competition and the barriers to entry. Innovation from existing players and non-traditional players is making competition fiercer. In particular, small specialized FinTech[5] companies, who are entering the market at a rapid pace, can disrupt the market (especially for traditional players).

To capture the many opportunities of changing consumer behavior, and the use of new technology, the group needs to develop and sustain a flexible and practical approach towards these developments. They need to remain responsive, be more agile and accelerate change. The group considers it critical to successfully implement a digital strategy to meet and beat their customer expectations. They aim to differentiation through excellent customer experience by continuously digitalizing the customer touchpoints and leveraging customer

[5] Financial technology, also known as FinTech, is an economic industry composed of companies that use technology to make financial services more efficient. Financial technology companies are generally startups trying to disintermediate incumbent financial systems and challenge traditional corporations that are less reliant on software. (McAuley, 2014)

intelligence and analytics. New technologies and digitalization enable them to create more personalized offerings, based on individual customer profiles and become more relevant in the lives of their customers[6].

> "*Top management recently decided to centralize our data, work on data quality and improve our data governance. We split our data management in a team 'today' and 'tomorrow'. Within the tomorrow team we are trying the put data in a more meaningful view for the future."* [Manager Team Data Management]

Big data and analytics have climbed to the top of the corporate agenda. Management commitment to the use of big data is high. Digitization including big data is clearly a priority. It's the way forward for the group to improve their understanding of the customer. These new approaches can help the group make decisions in near real-time to determine what will increase sales and user engagement and has the potential to drive a radical transformation in marketing for instance.

> *"It's mostly used for improving internal processes and improving existing products and services. Especially with damage insurance products. There it is all about the principles of risk. Now we do this basically on large populations with statistics. With big data we can do this more on an individual level. For us big data is mostly about variety and velocity or near-real-time analytics. By better organizing our internal data and adding external data we aim to create more holistic view of our customer and improve our predictive modeling."* [Manager Team Data Management]

Like the other companies under study the group also found that laying the groundwork is not an easy task and it takes a lot of work just to be able to access all the available internal data. The first step was to start by centralizing data from multiple sources so it could be analyzed more easily. It turned out to be quit hard to align the silos of data across the whole enterprise needed to capture and analyze the valuable information.

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[6] Information obtained from interviews, official company documents like presentations, internal- and external communications and/or annual reports.

> *"The technical or IT challenge is not the 'hard' analytics. 80% of the work is getting your data in order."* [Manager Team Data Management]

> *"We have a lot of IT legacy. It's a programme that can take years. It will be a challenge for some time."* [Manager Team Data Management]

The group is now learning to create the will and skill to use data throughout the organisation and is how to overcome internal resistance. They found the organization was not prepared for the required changes.

> *"For most business department it is a relatively unknown phenomenon. The traditional quants we have understand it quickly, but the business in general like commerce, customer relation or marketing, don't fully understand its potential."* [Manager Team Data Management]

The group is also discovering that transforming your organisation to take advantage of big data is hard. For instance how do you get your frontline managers to engage?

> *"Until now big data has been mainly an IT party. Although not very sophisticated, the technology was there. However from the business side there was no sense of urgency or understanding of its potential."* [Lead Business Analyst]

> *"Some departments are invested to maintain the status quo and at the most innovate incrementally. We would like to work more revolutionary".* [Lead Business Analyst]

To close the gap between IT and the business they placed to also deploy product owners to act as liaisons and contemplating on establishing a central think-tank.

> *"The Product owners[7] act as liaison between the business and IT. Their primary task it to bring all stakeholders closer together."* [Manager Team Data Management]

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[7] The product owner is commonly a lead user of the system or someone from marketing, product management or anyone with a solid understanding of users, the market place, the competition and of future trends for the domain or type of system being developed.

> *"I would like to establish a central think-tank within the business where we can collect all issues encountered, appoint an owner and discuss possible solutions*." [Lead Business Analyst]

The group also finds that working with big data requires changes to all echelons. For instance, in the way many executives now make decisions. As for investment decisions they must now learn to trust their instincts more over hard metrics and dare to experiment over judging on experience.

> *"There is a structural site to it. The way we evaluate IT investments does not match to what we want to achieve with big data."* [Lead Business Analyst]

> *"It is harder to create a sound business case as the benefits with big data application are as clear as we like. It's harder to define SMART benefits. You can make an estimate of the investment, and as we are mostly digital already it usually isn't considered a very large investment, the benefits still remain unclear. This does need a specific mindset on management level. They must trust their gut feeling and dare to experiment more. In some spots in our organisation that is considered quite exciting."* [Manager Team Data Management]

> *"I think it's mostly in the mindset of middle management. We should put more effort in business information planning. There is a team, but it lacks a clear vision, clear scope and budget"* [Lead Business Analyst]

As to the people aspect the organization is becoming aware that it need creative, curious and preferably business savvy people which are also comfortable in working with data and capable of drawing insights from it. Managers and business users frequently lack confidence in analytics and seem not convinced it will improve their decision making, or managers simply don't understand the analytics or the recommendations it suggests. However, they do acknowledge that you need teams of people with complementary skills for this. Increasing the adoption of big data analytics turns out to be a real change management challenge.

> *"There is little trust in data. That is a problem. At the moment we are not capable to capitalize on big data opportunities. We are just not ready. You can already notice this when defining requirements. The business does not know which questions to ask"* [Lead Business Analyst]

> *"In mainstream media it seems like a data scientist is godlike. They suppose have all the knowledge. What we see here is that they do have trouble communicating to the business and tend to be a bit 'autistic'. We think more in teams of people with complementary skills. For instance also people from the social sciences like psychology and sociology. People who are well trained in statistics, are curious and like to discover new things. We noticed they do well too."* [Manager Team Data Management]

As data now must flow across internal boundaries, this often goes against the DNA of the current organization and creates friction.

> *"We aim to centralize data and want to make it available across the enterprise. However, what happens in practice is that is that we as a team don't have the mandate to pull it off. We think too much in silos of information."* [Lead Business Analyst]

What stands out is that the organization relies on a generally decentralized approach. They now think however a more centralized approach with higher levels of senior level support might help break down the barriers in adopting big data analytics on a larger scale.

> *"Until recent IT has been clearly in the lead. Starting this year the board is spelling out their ambition more clearly and that we should all engage. It now more centrally directed and now that it is coming from the top we hope the business and IT will learn how to work closer together"* [Manager Team Data Management]

> *""We should establish proper governance first. It's a useless exercise to setup large scale projects before we do. And the organization must feel the sense of urgency. There is no mutual trust. And without it we can move forward. That is a significant cultural issue. "I believe very much in a process-oriented discussion. We need to get into agreement on the process and were everyone's responsibility lies in the value chain".*
> [Lead Business Analyst]

4.5 Cross-Case Analysis

To gain a deeper understanding and explanation a cross-case search for patterns have been done. This iterative process started with the development and presentation of an initial set of theoretical propositions based on evidence from the first case (Paré, 2004). These initial propositions were then used as a vehicle for generalizing to other cases. The emergent findings from the first case were then be systematically compared with findings / evidence from the second case and so on. The central idea was to iterate towards a theory that fits the data, where cases which supported the emergent theory enhanced confidence in its validity, and cases which do not support the theory provide an opportunity to refine and extend the theoretical model (Eisenhardt, 1989).

The first case is an example of an organization for which the most relevant area of application is to build new product or service offerings with the ultimate goal of transforming business models to create a sustainable competitive advantage. The company believes it can benefit from big data and sees great strategic potential. The IT component has become a core business and is seen as an important component in accelerating innovation. Although the business case for big data has been negative by default IT has been able to gain enough support with top management. The innovation budget of 100 million investment budget for which 20 million is budgeted for big data initiatives is substantial.

Although it first encountered issues on the structural dimension in terms of centralization of data and infrastructure, the current data architecture and IT infrastructure is flexible, scalable and agile enough to facilitate the business. The company found that you do not only need people with hard analytical skills, but also lots of supporting staff increasing the need for communication and shared understanding on all levels (strategic, tactical, operational). Not only technically skilled people, but people who can identify and formulate new business models. The business however struggles finding the right way of leveraging their data assets and even to define desirable outcomes based on big data. It should for instance be using IT to support constant business experimentation and to test new products, innovations in customer experience and new potential business models. This shows that the business does not understand IT and suggests IT is being underutilized at the moment as the business fails to utilize existing IT resources to the fullest extent possible.

The data scientists seem to poses better business acumen and IT skills, and are therefore fulfilling a liaison role between business and IT. However, the perception is that this has not led to enough new ideas on themselves. The innovation team is therefor also mining the whole organisation for new ideas which also changes the way the organization communicates on all levels (strategic, tactical, operational). These new forms and ways of communication can enable both IT and business to have a clear understanding of the organization's strategies, business and IT environments and will need to lead to higher levels of shared understanding and commitment. However, the consensus is that business should take the lead, while it is not able to at the moment. While IT is generally very ambitious and eager, they feel immobilized and can't move forward the way they would like. Arguably IT could to be involved more in developing corporate strategy.

This cases all have been rated with a low, medium or high score on the different business-IT alignment practices. These scores are based on the findings in the within case analyses and was rated according to the measurement as explained in the chapter §3.7.

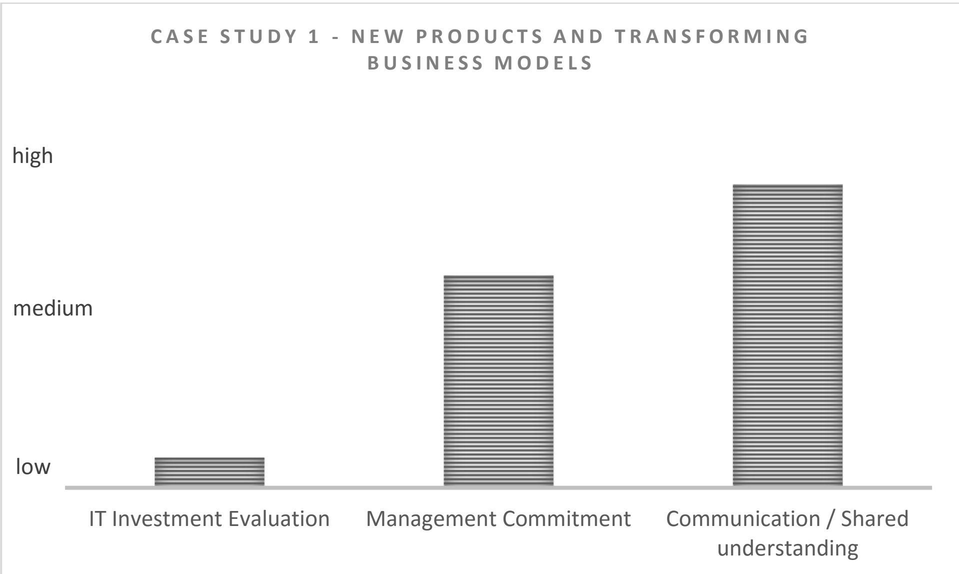

Figure 6 Case-study 1 scoring on business-IT alignment practices.

Although it's a direct competitor of the first company, the second case is has slightly different characteristics. It mostly to focusses its big data initiatives on improving existing products and services, improving internal processes from a more marketing focused innovation perspective. They think big data will help them get incremental improvements in marketing, supply-chain and management decisions, a more holistic view of their customers and businesses, enabling better and more accurate decisions. The management has made a commitment to make significant investments in big data. That helped them build a basic but a substantial supporting infrastructure, while internal support and commitment had to be secured without figuring out how it's going to be used and even who was going to use it.

However, they found that to get the data together into an integrated form that can be used across the company needed involvement from a lot of stakeholders and a very large basis of supporting skills. This placed new requirements on the way the projects were organized and the way they communicated. Again every level had to be involved to get the job done.

Although admittedly underestimated by the business, the technical IT part turned out not to be the biggest challenge. The current business workforce had been operating in the same way for many years and were not used to doing things differently. That brought up a real change management challenge. They need a lot more people that can create the connection and link with the business and is there biggest challenge to date.

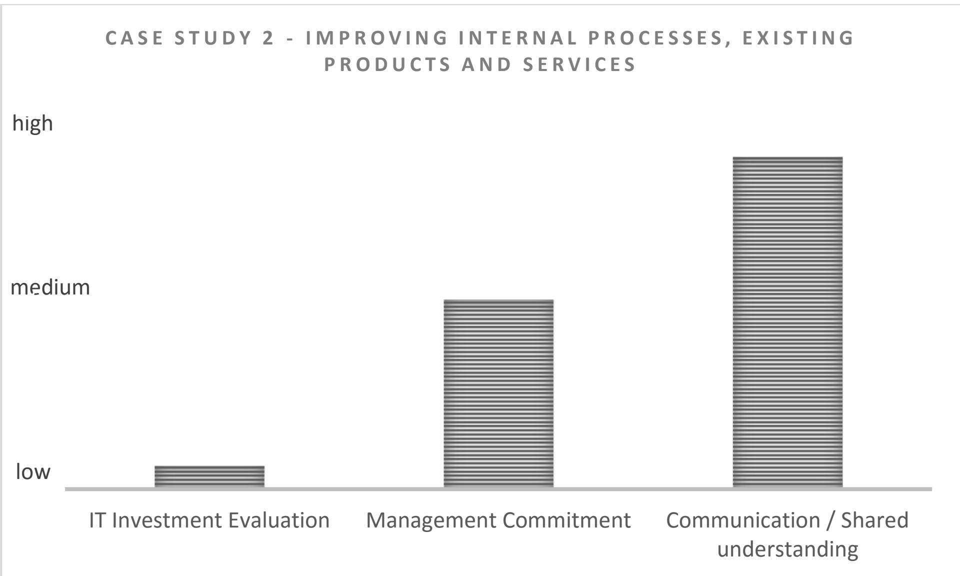

Figure 7 Case-study 2 scoring on business-IT alignment practices.

The third company is in a completely different industry. The group regards supply chain innovation, the ongoing digitization and big data as important opportunities. The group sees a lot of potential using big data analytics to improve internal processes. As the first two cases this company also faced the challenge of data integration, data management, data quality and data governance before it could start using big data in a proper way. To create a point of accountability and ownership for the company's data a 'data board' was established which is now responsible for establishing the organization's data architecture, the required governance structures, policies and guidelines to ensure data quality and management. Although IT sometimes needs to update the business on the importance of proper data governance practices, the business is clearly in the lead. To main issue at the moment however does not seem to be the analytic mindset, but the fact that big data-analytics investments raised questions about the magnitude and timing of the returns on such investments as the company's asset based is very large and diverse and thus it's very hard to create a sound business case to invest in data analytics on a large scale. Second big challenge would be getting shared commitment not within the organisation but also with all external stakeholders in the value chain.

This case the scoring on alignment practices for this case is as follows.

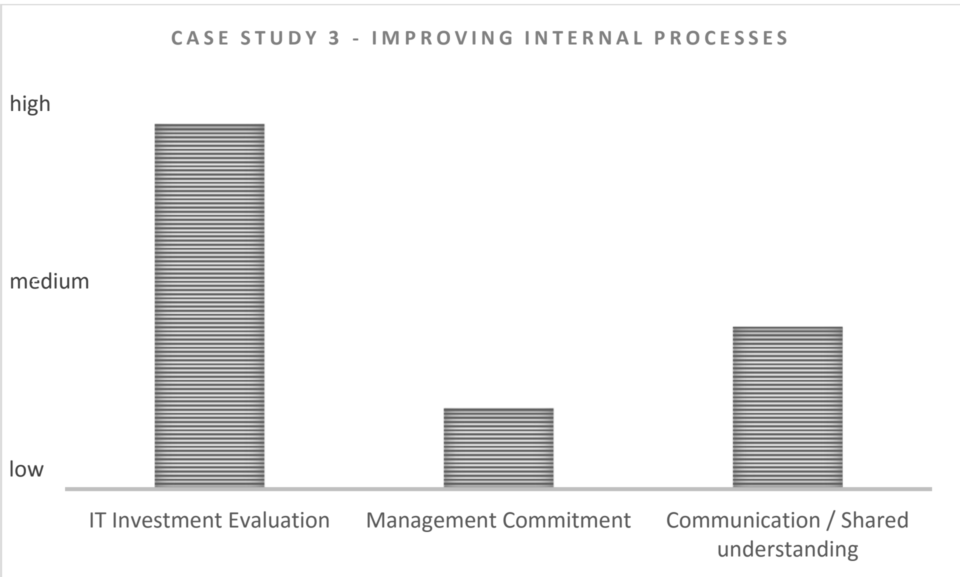

Figure 8 Case-study 3 scoring on business-IT alignment practices.

The fourth company under study also it starts with impact on the structural dimension. Like the other companies under study the group also found that laying the groundwork is not an easy task and it takes a lot of work just to be able to access all the available internal data. It turned out to be quit hard to align the silos of data across the whole enterprise needed to capture and analyze the valuable information. Following this technical challenge it also faced the inevitable challenges that seem to come with realizing large-scale benefits from big data analytics. Its lacks shared commitment amongst the different departments and business units, and managers clearly lack understanding and confidence in regard to the IT department, big data analytics and hesitate to employ it. This is holding the company back in realizing potential large-scale benefits. The organisation did make progress by establishing liaisons between the business and IT and hope to be able to overcome some of the barriers by a more centralized approach with higher levels of senior level support. From all cases this case seem to be most affected on the alignment practices overall and suffered the most from their decentralized approach as it was very hard to align all stakeholders since the lacked the necessary management commitment.

This case the scoring on alignment practices for this case is as follows.

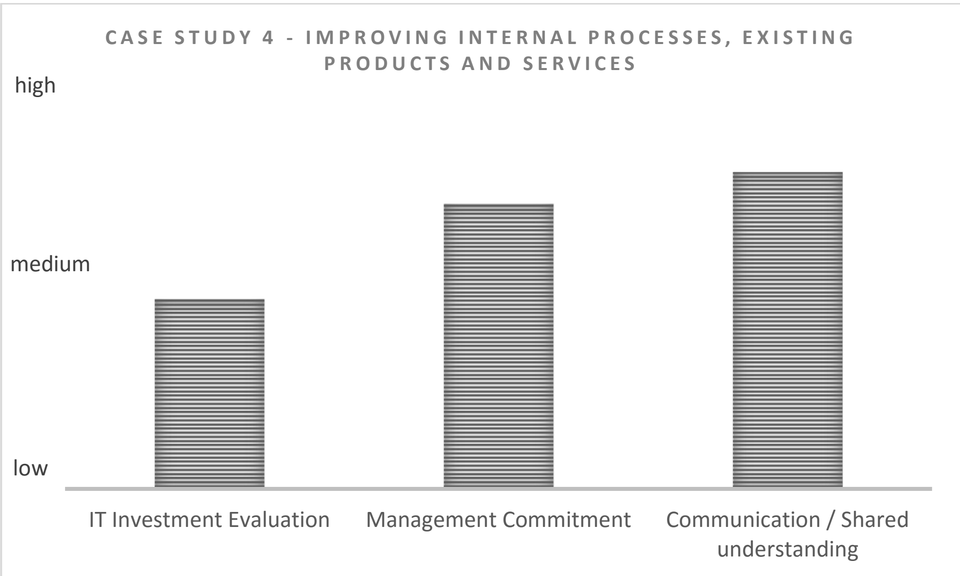

Figure 9 Case-study 4 scoring on business-IT alignment practices.

The following chart compares the total perceived impact on business-IT alignment per case compared to the other cases under study.

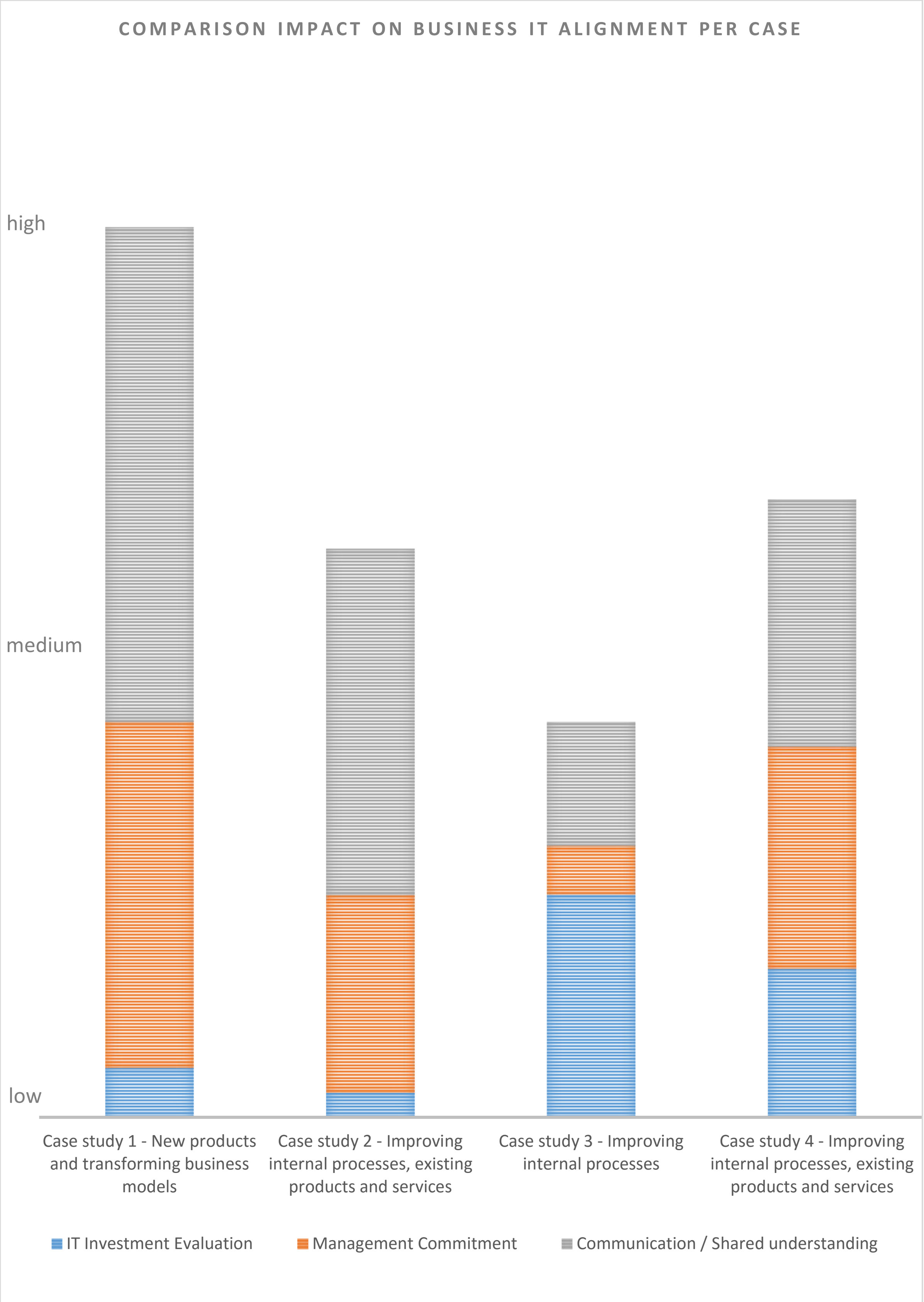

Figure 10 Case-study impact comparison on business-IT alignment practices.

5 Discussion

This research study focused on the business-IT strategic alignment in a big data context and aimed to improve and broaden the knowledge and understanding of the concept of business-IT strategic alignment in theory and practice, as well as to determine how organizations manage to achieve and sustain strategic alignment in relation to the four areas where big data analytics can be relevant: improving existing products and services, improving internal processes, building new product or service offerings, and transforming business models. Chapter two identified the basic concepts and theory of big data and business-IT strategic alignment and based on literature, the concepts, dimensions and practices of business-IT alignment and have been identified. Chapter three introduced the research model which presents the theoretical basis used to answer the research questions of how big data impacts business-IT alignment and how strategic alignment can be achieved. The previous chapter presented empirical studies as illustrative cases. This chapter, based on the presented empirical data in chapter four, discusses the Business-IT strategic alignment in a big data context in practice.

5.1 General findings

There are several general other findings that are worth mentioning. As was expected, big data analytics is creating an inexplicable link between technology and business and places additional requirements on business-IT alignment practices, requiring them to evolve to more mature levels. Big data clearly is not just about accumulating massive amounts of data and big data alone does not guarantee commercial success. Changes in the way of working is required in all the companies we interviewed. Another general finding worth mentioning is that all companies under study encountered privacy and regulatory issue when integrating data from silos across the enterprise for the purpose of big data analytics. However, although this research consistently found a willingness in business to respect and protect personal privacy, the management issues encountered seem more to be the result of a lack of clear standards of privacy practices across jurisdictional boundaries than a business-IT alignment issue. This study also found a consistent shared sense that the existing regulatory environment to lag behind both the growth in data use and developments in technical anonymization and encryption techniques and seems to lack a fair and transparent manner that also respects the needs of the business community. Since from a technology perspective the process to either anonymize and/or encrypt data is fairly easy, this study regards privacy issue as an external alignment (environmental uncertainty, see §2.2.6) issue and was therefore kept out in scope of this research. Furthermore it was found that all four companies utilized some sort of Agile (software development) methodology. Agile project methods demand continuous dialogue between the business and IT. It encourages constant communication and alignment across all stakeholders, leading to parallel development of not only the IT solution but also of training documentation, test cases, external and internal interface validation and development, and user communication (Wailgum, 2007). Furthermore it also advocates collocating business and IT team members and thus creates a situation that is usually absent in traditional business-IT relationships. Agile methods can therefore have a moderating effect on the relation between big data analytics and the business-IT alignment practices selected for this research.

5.2 Structural and intellectual dimension

The evidence showed organizational alignment is a very critical factor in ensuring success in big data projects (Kiron & Bean, 2013), is prompting organizations to rethink their basic assumptions about the relationship between business and IT and their respective roles and are again increasing the need integration of information technology in businesses (Davenport, et al., 2012). However, some researchers will go so far to state that the organization needs to be transformed so that the data and models actually yield better decisions (Barton & Cour, 2012) or big data analytics flip the traditional role and approach of IT on its head (Davenport, et al., 2012). Although this might be true in some cases this research has found no supporting evidence for this to always be the case. Firstly, big data initiatives in larger companies seems to be evolving and integrating with existing structures, rather than being established as new. No organization studied in this research has established an entirely separate structure for big data. Big data has been added to existing business intelligence (BI) team, operations research group, or innovation group and it has not transformed the company in such a way to state that is flips the 'traditional roles on its head'. Business problems are not owned by the data scientists, but still owned by the business. At the end of the day decisions on analytics needed to be led and made by managers. I must mention however that the companies under study still haven't transcended their initial big data initiatives to articulate the full business potential (according to their own perception) of big data to be considered an analytical competitor or to be considered a data-driven company as the benefits achieved are still on a fairly small scale, this research could not find any evidence big data analytics inevitably flip the traditional role and approach of IT on its head to be effective or create value, nor did it find any indication that I might in the future.

5.3 Structural dimension

All cases in this study show above average (perceived) impact on structural dimension on business-IT alignment as the lack of data definition standardization and the technical challenges of, aggregating, linking, integrating, and cleaning datasets across the enterprise are significant and imposes a tedious burden on the companies to make the data usable and requires significant changes in IT architecture and (de)centralization of infrastructure. This often requires closer collaboration between the business and IT where IT often has to challenge the business to think about data quality, ownership and establishing data governance and thus leads to more communication as higher levels of shared understanding is required.

The research suggest that the impact of big data analytics on business-IT alignment is different when the relevant area of application is improving internal processes. This might require (as does in this case) a large capital expenditure to provide every asset with a sensor to be able to include it in the grid. This might even be complicated by having to deal with dependencies on third parties or suppliers in the value chain. Big data application with the goal of improving internal processes in this context will most likely require the biggest change in the way business cases are reviewed at the highest management level. The required investment, measured both in money and management commitment, can be large. Companies in this position will have to fight a "black box" problem. Business managers in this context will have the additional discomfort dealing with the uncertainty, insisting that they must know upfront the payoff from the large capital expenses and from the potential implications of possible disruptive organizational changes. This makes it hard to explain the results in a way that stakeholders can understand as big-data initiatives might deliver unexpected results. And it is nearly impossible to establish solid business cases according to the current IT investment evaluation criteria. However, another way of looking at this is that it will require high levels of (top) management commitment to establish investment priorities to get behind longer-term and larger-scale investments in data and analytics. In other words, senior management needs to bet on big data for the long-term.

Finally, when comparing case study one, two and four, the research suggest that a more decentralized approach in trying to align business and IT seems less effective than a more centralized approach. It seems like a Centre of Excellence (CoE) type model offers more advantages in securing senior level support and thus enterprise wide / cross functional management commitment, and suffers from fewer limitations as it can function cross-business-unit which makes accessing and data sharing easier. I can serve as the focal point for for support at a corporate level. It can also help set the road map, and establishes and maintain different kinds of overarching enterprise level policies which can all help realizing large scale benefits.

5.4 Social and cultural dimension

Cost reduction or improving internal processes can also be a secondary objective or no objective at all. On the other end of the spectrum we have long-established companies whose relevant area of focus for the use of big data is building new product or service offerings, and transforming business models with no significant history of data use. One of the most ambitious things an organization can do with big data is to employ it in developing new product and service offerings based on data (Davenport & Dyché, 2013). Not only is the total accumulated impact on business-IT alignment higher when the focus is on the development of new product or service offerings and/or transforming business models, it also places additional requirements on the skills and behaviors of the employees. This is especially the case for companies which are not native online businesses and/or possess an analytic mindset. The research suggests that it despite having top quality big data infrastructure and tools available it still requires an innovative culture which shared values allow for failures and promote and reward rapid experimentation and double loop learning. You need to not have managers who feel comfortable with this approach, but business managers also need to take the lead. No big data application can substitute for the rigorous and demanding process of figuring out what questions to ask which eventually could lead to not only incremental but also radical product- or business model innovation. This requires a deep shared understanding of the potential and possibilities of big data, a thorough knowledge of the business and last but certainly not least lots of creativity. Figuring out which questions to ask is not easy when you are not used to it. Especially when data will most likely be permanently central to new business model. Big data then should be the key focus of the business. You really need to develop a 'data-driven' culture in that case. Putting data at the center is likely to be especially challenging and the impact is likely to represent a significant impact on communication and the development of shared understanding on the cultural and social dimension of the business-IT partnership. Unless an organisation has high degree of business alignment maturity based on these alignment practices, a shortfall of communication and shared understanding will result in 'underutilization van IT' (Tallon & Kraemer, 2003) as the business fails to utilize existing IT resources to the fullest extent possible. To get ahead of this organizations should prepare for both high levels of communication and shared commitment and fundamental mind-set changes.

6 Conclusion and implications

This study looked at business-IT alignment in a big data context. To my knowledge this has not been done before. Creating insights for practitioners into business-IT alignment is an important objective, since alignment has been ranked as a top priority for managers and executives for years (Luftman & Ben-Zvi, 2010). This research aimed to improve and broaden the knowledge and understanding of the concept of business-IT alignment not only in theory and but also in practice by gaining insight into the relationship between business-IT alignment and big data analytics. We need to understand what facilitates the creation of value from big data projects in relation to the relevant application area.

The empirical results indicate that to create value from big data and big data analytics organizational alignment is a very critical factor in ensuring success in big data projects, is prompting organizations to rethink their basic assumptions about the relationship between business and IT and their respective roles and are again increasing the need integration of information technology in businesses. Overall, big data analytics is creating an inexplicable link between technology and business and places additional requirements on business-IT alignment practices, requiring them to evolve to more mature levels.

However, the interviews produced some interesting results. An important finding from this research is that the exact impact, cannot be generalized across companies of all sorts, and heavily depends on the relevant area of application. The most striking result being that big data analytics seems like more of a logical extension of current operations research practices were the impact remains limited to the strategic dimension as IT investment evaluation require higher levels of (top) management commitment and risk taking propensity, while long-established companies without a significant history of data use might need a full organizational transformation and have a more substantial impact on the social and cultural dimension.

The research also shows that the role of the data scientist is less significant or critical than most literature suggest. Companies do not necessarily need a critical mass of data scientist to create value from big data, but a departments of scale with a broad range of ‘data’ talent which can address the current challenges of their functional areas. It seems that the term or “data scientist” role has become ambiguous and a catchall term to describe a statisticians and mathematician possessing computer science and programming skills, business acumen, and domain expertise in describing the diverse technical, scientific, analytic, and business skills needs required for businesses to use big data. This study consistently found that in order to create value from big data analytics, organizations establish teams of people which poses complementary analytical, business and IT skills and who can effectively contribute their expertise in collaboration with other people and team members, instead of seeking this diverse skill set in a single person or role. As this usually means involving different stakeholders from various functions at various levels from within business and IT departments, the need for a common language increases, and thus requires different forms of communication in order to establish higher levels of shared understanding between them. Not only on a strategic, but also on a tactical and operational level.

6.1 Theoretical implications

The aim of this study was to gain deeper insights into the relationship between business-IT alignment and big data analytics. The goal was to understand how strategic alignment is developed between de different levels and roles in a big data context and how it facilitates the creation of value from big data projects, which in turn supports the effective and consistent use of this information technology over time. The ultimate intent of this study is to gradually build a new theory of how business and IT should be aligned in a big data analytics context.

The degree of impact depends on the relevant area of application. This contradicts the general statements that the leading obstacle to widespread analytics adoption is a lack of understanding of how to use analytics to improve the business (LaValle, et al., 2011) and that successfully exploiting the value in big data requires experimentation and exploration (Dumbill, 2012). Although 'shared understanding' or more specific 'business understands IT' is an important alignment practices the research shows that this is mostly the case in companies whose relevant area of focus for the use of big data is building new product or service offerings, and transforming business models, with no significant history of data use. It is much less the case for companies with an operations research focus as they are more analytic-minded and have a more mature analytics environment. The difference is even stronger when the company internal processes which need to be improved upon depend on a large diverse asset base or business model innovator is long-established established company. Although a big data strategy seems to naturally lead to discussions about the kinds of information and capabilities required, the interviewees in case study three perceived that the cultural aspect within this case is much less impacted then in the three other case studies.

Although both Davenport *et al*. (2012) and Galbraith (2014) argue that in order to capitalize on big data, big data analytics needs to move away from the IT function into the core business and relies heavily on data scientists rather than data analysts as "their upgraded data management skill set — including programming, mathematical and statistical skills, as well as business acumen and the ability to communicate effectively with decision-makers" (Davenport, et al., 2012). The research however shows no that the role of data scientist are less significant than the literature suggests. There seem to be several reasons for this. First, although in two cases (1 and 4) IT had a leading role in developing a big data capability, big data initiatives are mostly business lead or the conclusion was soon reached it should have been led by business. When the relevant area was to build new product or service offerings, and possible transform business models, data scientist were part of the innovation group, whereas companies with an operations research focus saw big data analytics as a logical extension of the operations research group. Data scientist were therefore either included or consulted in the decision making process, but were not made responsible or accountable. No major changes in decision-making rights or shift in power were necessary. The second reason might be that this research found you do not (unlike Davenport, et al., 2012) necessarily need a critical mass of data scientist to create value from big data, but a departments of scale with a broad range of 'data' talent which for instance, as the second and third case suggest, can address the current challenges of their functional areas. Part of the answer however might lie in the fact that it seems like the term or "data scientist" role is ambiguous and has become a catchall term to describe a statisticians and mathematician possessing computer science and programming skills, business acumen, and domain expertise in describing the diverse technical, scientific, analytic, and business skills needs required for businesses to use big data. This study consistently found that in order to create value from big data analytics, organizations establish teams of people which poses complementary analytical, business and IT skills and who can effectively contribute their expertise in collaboration with other people and team members, instead of seeking this diverse skill set in a single person or role. As this usually means involving different stakeholders from various functions at various levels from within business and IT departments, the need for a common language increases, and thus requires different forms of communication in order to establish higher levels of shared understanding between them. Not only on a strategic, but also on a tactical and operational level.

6.2 Managerial implications

This research was initiated with the aim to explore what leaders of organizations and policy makers need to do to capture its value and accelerate general understanding of key organizational challenges and barriers that emerge with deploying big data analytics. A recurring theme creating value from advanced IT like big data analytics applications has been a lack of business-IT alignment.

This research found that the key success factor in overcoming the big data challenge is building strong capabilities that move the business, but what that exactly entails depends on the organizational goals and relevant area of application. This research found that improving internal processes in the context of operations, especially when combined with and large and diverse asset base means drastic change in the way IT investments are evaluated, a and high level of top management commitment. One must be really willing to take a huge bet on big data. This really impacts the strategic dimension of business-IT alignment as the most IT investment evaluation criteria won't allow for such bets to be made. It's very important that top management is involved and committed from the start. On the other hand. When the goal is to build new product or service offerings, and transforming business models, especially in the context of non-native online businesses, or long-established companies without a significant history of data use. Leaders then should further the integration of information technology in the businesses and prepare the organization for fundamental mind-set changes, were new bringing up new ideas are encouraged for all functions and were rapid experimentation and double loop learning is possible. "The new advantages are then based on discovery and agility — the ability to mine existing and new data sources continuously for patterns, events and opportunities" (Davenport, et al., 2012). High levels of communication can enhance shared understanding through working cross-functional between business and IT people. Companies need to create opportunities for collaboration between business and IT people at all levels.

Either way (top) management must undertake some sort of transformational-change and must engage the organization. This research shows the best way to get this started it to look for low-hanging fruit. Choose one or more functions or departments which would benefit most from analytics where a focused investment in big data and analytics that can prove the business case quickly and can prove the value of big data to as many stakeholders as possible as a first step to broader big data delivery. A good way to start would be an easy-to-use decision support tools based on an analytic model that frontline managers can readily understand and adopt and let managers apply their own experience and judgment to the outputs of models and then close the loop by continuously testing the outcomes to improve. In our example such an initial proof-of concept approach can help demonstrate the understanding of additional or new aspects of the customer relationship and advanced business capabilities of big data solutions by applying them to current processes.

When the goal is to build new product or service offerings, and transforming business models in the context of non-native online businesses, or long-established companies without a significant history of data use. Leaders should further the integration of information technology in the businesses and prepare the organization for fundamental mind-set changes, were exploration and bringing up new ideas are encouraged for all functions and were rapid experimentation and double loop learning is promoted. Here high levels of communication must enhance shared understanding through working cross-functional between business and IT people so existing and new data sources continuously mined for patterns, events and opportunities” (Davenport, et al., 2012).

Big data is a tool and a means to an end. As Birkinshaw & Gibson (2004) argued: “Successful companies are not just nimble, innovative and proactive; they are also good at exploiting the value of their proprietary assets, rolling out existing business models quickly and taking the costs out of existing operations [...] and have a clear sense of how value is being created in the short term and how activities should be coordinated and streamlined to deliver that value

(Birkinshaw & Gibson, 2004). It's clear that also with big data analytics the rules of strategic management still apply. Reinventing business models with the help of big data is like any ambitious strategic transformation and must be led by culture. Organizations therefore need to create environments that encourage the knowledge flow, diversity, autonomy, risk taking, sharing, and flexibility on which adaptation thrives (Reeves & Deimler, 2011).

6.3 Generalizability and limitations

This study holds several limitations. First, although this study is performed in three different sectors, the companies under study were selected based on a convenience sample where cases were partially selected because of their accessibility, proximity and judgement to the researcher. Besides that, due to several practical limitations I could not continue to 'snowball' interviewees per case until the point of redundancy was achieved, which has a negative impact on the credibility of developed theory. However, this study did sample 'intensity' based cases involving the same logic as extreme case sampling but with less emphasis on the extremes which can be considered information-rich cases and helped gathering useful data and information. The findings however are unlikely to be representative for different industries or companies operating in different markets. This study can however be generalized within similar industries that have a similar organizational goals and go through similar industry-wide changes.

Second, as small and medium enterprises tend to have small IT units and/or to outsource IT this study was done within relatively large companies as the cases were deemed to be more information rich. Smaller companies in the case study might have brought new findings. However, in spite of this difference, a general statement that can be made from the analysis of this data is that regardless of the size, organizations tend to interpret the factors that can help them to achieve better levels of business and IT alignment in a very similar way (Gutierrez, et al., 2009).

Third, because of their dynamic character only several Business-IT alignment practices (communication, shared understanding, management commitment and IT investment evaluation) have been investigated, however no other Business-IT alignment practices (e.g environmental uncertainty, succesful IT history) have been taken into account which might have brought new insights.

Fourth, data collection error relates to poor survey questions or poor interview techniques (Bryman & Bell, 2007). An important goal of this research was to create insight in how existing business-IT alignment practices were utilized. However, since the alignment practices might be subjected to overlap and ambiguous meaning and definition, it might have been difficult for the interviewees to rate each alignment practice or management issue encountered on relevancy. The interviews were intended to elaborate on how the big data analytics impacted these factors in practice. This sometimes was tough since interviewees, although an interview protocol with explanation had been sent, did not think in similar terms and also did not always separate business-IT alignment practices from other organizational aspects like agile methods or strategic management. Although the interview analysis was based on pre-defined principles it might still suffer from researcher bias and might produce different results if done by other researchers.

Finally, alignment practices complement each other, for example, the impact on one practice increases or decreases the impact on another practice (Vermerris, et al., 2014). On example is the relation between communication and shared understanding. One cannot exist without the other. That same logic holds for the other alignment practices. For example, the value of IT investment evaluation will be limited unless there is sufficient shared understanding to benefit from that, or high degrees of management commitment might lead to a decrease in impact on IT investment evaluation alignment practices as one this might lead to different approaches in evaluating them not on hard metrics, but willing to make a bet on new technologies.

6.4 Directions for future research

While this study makes several contributions to theory on how big data analytics impact business-IT alignment, other studies can build further on the findings of this research.

As we found the all four companies under study were also working according agile methods. Not only might it be interesting the transfer research on agile methodologies to alignment practices that might allow looking at building alignment iteratively (Vermerris, et al., 2014) it will also be interesting to see how the agile principles contribute to establishing alignment itself.

A replication of this study in other another industry would give more insights into differences between industries, for practitioners as well as academics. It would be interesting to see whether the findings also hold true in other industries. A replication of this study based on an ‘extreme’ or ‘deviant’ case sampling strategy could also bring new insights as to the varies impact big data analytics have on business-IT alignment and help identifying and explaining how certain contextual conditions enhanced the effectiveness of coping tactics and how other conditions prevented the adoption of tactics.

Furthermore, as shown in the previous paragraph. While several studies found that shared understanding has an effect on Business-IT alignment (Reich & Benbasat, 1996; Reich & Benbasat, 2000; Chan, 2002; Chan, et al., 2006) most of this research was concentrated around the level of the shared understanding of business and IT executives (Reich & Benbasat, 2000; Chan, 2002). This research found however, that communication and shared understanding in a big data context might be more important on all levels within the organization and even emphasizes the need for communication and shared understanding at a tactical to operational level. It is therefore important that future research takes a wider more granular approach to studying shared understanding on different kind of levels in an organization.

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8 Appendixes

8.1 Appendix 1 – Interview topic list

Strategic / Intellectual dimension

Describe the impact of the use of big data had impacted the practice or need for inter-related IT and business plans and/or a more reciprocal two-way relationship between IT and the business.

Structural dimension

Describe if and how the creation of value from big data impacted the decision-making structure, reporting relationships, (de)centralization of IS services and infrastructure, and deployment of IS personnel, roles and responsibilities, IT investments are evaluated.

Social dimension

Communication

Describe if and how the creation of value from big data impacted the way how communication was established concerning the Business-IT relationship. Consideration are; IT/business executives' communication (face-to face/electronically/or written); project communication between business and IT; liaison roles between IT and business; permanent teams/committees; and integrated roles.

Shared understanding

Describe if and how the creation of value from big data impacted how shared understanding was realized between IT and business (responsible) persons within the project or application. Consideration are: shared understanding about the role of IT in the organization, IT as a competitive advantage, IT to increase productivity, and prioritization of IT investments.

Cultural dimension

Management commitment

Describe how management commitment was established from the beginning and during the project; advantages (/disadvantages) that this management commitment brought to the organization in allocating resources, setting up a steering committee, and sponsoring the project. Common language.

Miscellaneous

Other practices

Discus other business-IT alignment practices that have resulted in a higher (perceived) business value.

Documentation/supporting material

Discuss other documentation or supporting material regarding the discussed topics in this interview.

Follow up/revision of site report

As a follow-up a site report will be made concerning both (high and low valued) projects within the organization. This site report will be send to the interviewee in order for him/her to revise, point out changes or accept it as a final document, which will be incorporated in the eventual end report.

8.2 Appendix 2 – Interview protocol

Objectives of interview

Discuss current situation regarding Business-IT Alignment in a big data context, find (past) issues, worries and structural problems - areas to improve, recommendations - Discuss desired situation regarding Business-IT Alignment (BITA).

General questions

Interviewee information: Current position in the organization, past positions, educational background, other work experience, future outlook.

Project information: Background, purpose or specifics from the big data product (volume, variety, velocity), role of interviewee, other information.

Business-IT Alignment specific questions:

Structural or intellectual alignment

In order to create value from the big data application;

- Did it require changes to the decision-making structure/rights or reporting relationships, If so, why?
(*Consideration are, but not limited to: investment decisions, setting customer priorities, and deciding on new product features, formulation of corporate strategy)*

- Did it require (de)centralization of IS services and infrastructure, and deployment of IS personnel and/or roles and responsibilities? If so, why?
(*Consideration are, but not limited to: data ownership, knowledge transfer, shared commitment)*

IT investment evaluation

- Are the big data product expenditures formally assessed and/or reviewed during its life cycle? Is it done the same way then other IT products? Is it being measured on the same metrics? If not, what is different?

Communication

- Do you think that, in order to create value from the big data product(s) there was a change necessary in the way communication actually takes place? If so, why and how was it solved?

- Where there any structural change made to facilitate a liaison role between the IT and business function for this application? If so, why?

- Was there a need for additional temporary task forces? (e.g., IT project team, new product development team)

- Was there a need for more permanent teams/committees (e.g., IT steering committee), integrating roles (e.g., IT person leads the business quality team) or managerial linking roles (e.g., product management role).

Shared understanding

- Does the use of the big data product require that the business and IT to work closer together (a more reciprocal two-way relationship) in order to create a shared understanding of the possible role of big data in your organization? If so, how was this realized? (*Consideration are, but not limited to: increase productivity of the organization's operations, gain a competitive advance, how to make full use of its capabilities)*

Management commitment

- Do you think the big data product created a need for a mind-set change? (*Consideration are, but not limited to: the need for a common 'language', the acknowledgement that data and information are an important company resource, flexibility in the form of vigilance and smart management approaches in avoiding the 'alignment paradox')*

  If so, does someone lead the shift in corporate mind-set?

- Data and analytics will generate insights that lead to different decisions than does the current process. Were there any disputes and/or is there someone to resolve disputes caused by the new capability?

- Was it necessary to create norms and values concerning data and/or information sharing, transparency, and trust? So each unit has reciprocal access to company data?

General BITA questions:

- Are you getting maximum value from the big data products? Are there any recent of current issues, worries and structural problems - areas to improve, recommendations? What would you suggest to improve the alignment? Any suggestion to improve the business-IT partnership?

- Discus other business-IT alignment practices that have resulted in a higher (perceived) business value.

Documentation/supporting material

Discuss other documentation or supporting material regarding the discussed topics in this interview.