Big Data in the Danish Industry: Application and Value Creation

Abstract
The development within storage and processing technologies combined with the growing collection of data has created opportunities for companies to create value through the application of Big Data. This article focuses on how small and medium sized companies in Denmark are using Big Data to create value. The research is based on a literature review and on data collected from 457 Danish companies through an online survey. The article looks at Big Data from the perspective of SMEs in order to answer the following research question: To what extent does the application of Big Data create value for small and medium sized companies? The findings show clear links between the application of Big Data and value creation. The analysis also shows that the value created through Big Data does not arise from data or technology alone but is dependent on the organizational context and managerial action. A holistic perspective on Big Data is advocated, not only focusing on the capture, storage, and analysis of data, but also leadership through goal setting and alignment of business strategies and goals, IT capabilities, and analytical skills. Managers are advised to communicate the business value of Big Data, adapt business processes to data-driven business opportunities, and in general act on the basis of data. The article provides researchers and practitioners with empirically based insights into *how* the application of Big Data creates value for SMEs.

1. Introduction
The concept of Big Data is attracting a lot of attention in both the mass media and the academic literature, and data is seen as a competitive resource and new means of creating value for organizations. However, in a report from 2013 by the Danish Business Authority (Erhvervsstyrelsen, 2013), Big Data was identified as a hard-to grasp and unwieldy concept that many companies lacked experience with. The report categorized the companies actively working with Big Data into two groups. The first group consists of large, often multinational companies with long-standing experience in business intelligence and analytics. The second group consists of relatively small and young companies, i.e. startups, focusing on business opportunities with regard to Big Data. The two groups of companies represent only a small part of the total number of companies in Denmark. The large majority of companies are small and medium sized companies, which have limited experience with Big Data. As a consequence, there is a lack of knowledge and therefore value in studying this large and diverse group of companies. This is also emphasized by extant literature. SMEs often find access to extensive consumer data prohibitively expensive (Donnelly and Simmons, 2013). "Small and medium-size businesses are often intimidated by the cost and complexity of handling large amounts of digital information" (Simon, 2013), which put them "at a severe disadvantage to big competitors that had the financial muscle" (Donnelly and Simmons, 2013) to collect, analyze and act upon data on, e.g., customer behaviors and market trends. Donnelly and Simmons (2013) call for more research focusing on SMEs, which is echoed by Simon (2013) who wants "attractive alternatives for companies that can't afford to—or simply don’t want to—hire their own data scientists" (Simon, 2013). Against this backdrop, it is the aim of this article to investigate the extent to which the application of Big Data creates value for small and medium

sized companies. Specifically, the article addresses the following research question: To what extent does the application of Big Data create value for small and medium sized companies? In focusing on value, we follow (McAffee & Brynjolfsson, 2012) in asking how Big Data will help companies improve business performance. In other words, what is the business value of being data-driven. Our research is based on an in-depth literature review combined with empirical data from an online survey. The literature review describes state-of-the-art knowledge on Big Data. This knowledge forms the basis for the survey, which was used to collect data from a sample of small and medium sized companies. The data was collected through an online survey, which was designed specifically for the purpose of this article. The survey yielded responses from 457 small and medium sized companies, which in turn form the basis for our analysis of whether and how Big Data is creating value for small and medium sized companies. Based on the literature review and our analysis of the empirical data, we discuss our findings and the implications for researchers and practitioners.

The term "Big Data" implies that size is a defining characteristic. However, other characteristics are also mentioned in the literature. Laney (2001) suggests that "Volume", "Variety", and "Velocity" (sometimes referred to as the Three V's of Big Data) are key data management challenges, and according to Gandomi and Haider (2015) "the Three V's have emerged as a common framework to describe big data" (Gandomi and Haider, 2015: 138). Volume and Variety refer, respectively, to the magnitude and heterogeneity of data, whereas Velocity refers to the speed at which data are generated, analyzed, and acted upon. More recently, IBM has added "Veracity" as a fourth "V" (see, e.g., http://www.ibmbigdatahub.com/infographic/four-vs-big-data), which refers to the uncertainty of data. For an extensive account of Big Data definitions, including the additional characteristics of "Variability" and "Complexity" proposed by SAS as well as "Value" introduced by Oracle, please see Gandomi and Haider (2015).

The article is structured as follows. First, we introduce our choice of analytical framework. Second, we present our approach to reviewing the literature, followed by an account of state-of-the-art knowledge on Big Data. Third, we analyze the empirical data by applying statistics and qualitative content analysis. Last, but not least, we discuss our findings, the implications for practitioners, and avenues for future research.

2. Analytical Framework

For the purpose of studying the complex concept of Big Data, we decided that an analytical framework was needed to guide and structure our research efforts. Such a framework provides us with structure and overview, and it guide us in interpreting and understanding the concept of Big Data from all relevant perspectives. For these reasons we have chosen the DELTTA model by Davenport (Davenport, 2014) as our analytical framework. The DELTTA model is established specifically for the purpose of analyzing and understanding the concept of Big Data. Thus, the DELTTA model defines Big Data by dividing the concept into six elements. Each element of the DELTTA model is clearly defined, and each element adds insights into the Big Data concept. The six elements of the DELTTA model are summarized in Table 1.

Table 1. The six elements of the DELTTA model

Element	Description
Data	Capture, storage, and analysis of high quality data characterized by high volume, velocity, and variety. This element includes the processes of preparing data for analysis. Capturing, processing, and structuring data for analysis is an integral part of any Big Data project.
Enterprise	The entire organization understands the opportunities created by Big Data and is willing to make the appropriate changes to take advantage of these opportunities. Big Data is not seen as a technical IT project, but as an integrated part of all relevant business processes of the company.
Leader	The Leader and Enterprise elements are closely related. It is the responsibility of the leader to ensure that Big Data is integrated into every part of the company. This responsibility includes the willingness to act on the basis of data. Senior management is actively looking into opportunities created by Big Data.
Target	Target is closely related to the Leader element in the sense that the leader should decide the direction and goals of Big Data projects. The company should strategize the use of Big Data in accordance with the goals of the company and the level of IT and data maturity of the organization.
Technology	The Technology and Data elements are closely related. Technology in combination with Data forms the foundation for the other elements. Big Data is mainly driven by developments in storage and processing technologies. Without technologies to capture, store, and retrieve large amounts of data, a company cannot realistically hope to create value through Big Data.
Analysts	The Analysts element represents the people aspect of Big Data. In relation to Big Data, the Analysts element focuses on the skillset that a company needs in order to successfully execute Big Data projects. The Analysts element covers all the technical roles, which are needed in Big Data projects. The Analysts element is closely related to the Data and Technology elements in the sense that analysts must be able to understand and handle data using the available Big Data technology.

As an analytical framework, the DELTTA model helps us structure our research, compartmentalizing the analysis into manageable parts. Dividing the analysis into six parts enable us to look at each element of the DELTTA model individually and the relationships between elements.

In this article, the DELTTA model serves a number of purposes. First, it helps us structure the literature review. The literature review describes state-of-the-art knowledge on Big Data and is structured according to the six elements of the DELTTA model. Second, the survey, which is distributed to a sample of companies for the purpose of empirical data collection, is also structured around the DELTTA model. This structuring ensures that all relevant aspects of Big Data are covered in the survey. Third, the DELTTA model supports our research by structuring the statistical analysis of the data. In line with the survey, the analysis is divided into the six elements of the DELTTA model. The analysis looks into each element as well as the relationship between them. Finally, the DELTTA model is used in the discussion of the results.

3. Review Methodology

The literature review is based on the guidelines and recommendations by (Webster & Watson, 2002) and (Okoli & Schabram, 2010). According to (Fink, 2005), a quality literature review must be systematic in following a methodological approach, explicit in explaining the procedure by which it was conducted, comprehensive in its scope by including all relevant material, and reproducible by other researchers following the same procedure in reviewing the topic. Acknowledging that “the quality of literature reviews is particularly determined by the literature search process” (vom Brocke et al., 2009: 2206), in this section we describe in detail how the literature was identified and analyzed.

The purpose of our literature review is to identify papers, which can contribute to an understanding of how Big Data can be applied to create value from an organizational and business perspective. The level of analysis in this literature review is the organization. Papers written at another unit of analysis are excluded unless they contribute to an understanding of the business application of Big Data within organizations. We focus on companies, but papers reporting on other types of organizations are included to the extent that they offer relevant insights. The goal of the literature review is to identify relevant papers as a solid foundation for the survey. Our article seeks to address the research question at a general and not domain or industry specific level. The literature is selected in support of this goal, i.e. we are focusing on general business perspective papers on Big Data. Papers focusing on industry or domain specific application of Big Data are only included to the extent that lessons learned are distilled and generalized across industries and domains.

Based on the taxonomy by vom Brocke et al. (2009) and following Cooper (1988), we characterize our literature review as illustrated in Table 2. (1) We focused on the research outcome described in the analyzed articles with (2) the goal of integrating the findings of existing studies based on (3) the key concepts of the DELTTA model. We strive for (4) a neutral representation with (5) general scholars as target audience. Finally, we limit our review to literature that is considered pivotal or central to the topic of Big Data.

Table 2. Taxonomy of literature reviews (vom Brocke et al., 2009; following Cooper, 1988)

Characteristic		Categories			
(1)	focus	research outcomes	research methods	theories	applications
(2)	goal	integration	criticism	central issues	
(3)	organisation	historical	conceptual	methodological	
(4)	perspective	neutral representation	espousal of position		
(5)	audience	specialised scholars	general scholars	practitioners/politicians	general public
(6)	coverage	exhaustive	exhaustive and selective	representative	central/pivotal

The Scopus and Web of Science (WoS) citation databases were used in identifying relevant literature. WoS and Scopus are often used in combination for bibliometric analyses, because their coverage differs substantially, for example with regard to the Arts and Humanities field (Mongeon and Paul-Hus, 2016). Scopus covers more journals and includes most journals indexed in WoS, but WoS has more exclusive journals in the field of Natural Sciences and Engineering. Although using these citation databases introduces biases (favoring, e.g., English-language journals), there is no “suitable alternative to WoS and Scopus when it comes to performing multidisciplinary and international bibliometric analyses“ (Mongeon and Paul-Hus, 2016: 226). For example, Google Scholar's "suitability for research evaluation and other bibliometric analyses has been highly questioned because of the sporadic coverage of non-English literature, various inconsistencies (e.g., indexation of non-existing journals) in the data, and a lack of transparency of the coverage" (Mongeon and Paul-Hus, 2016: 226). Moreover, both Scopus and WoS provide access to leading IS journal articles and conference papers (vom Brocke et al., 2009). Since research on Big Data is still embryonic in nature, most research is expected to be reported in conference papers. The literature review therefore includes both journal articles and conference papers. Books and other non-scientific material is excluded to ensure that only peer-reviewed articles and papers are included, which is in line with vom Brocke et al. (2009) emphasizing that "it is commonly recommended to focus on articles published in scholarly journals" (vom Brocke et al., 2009: 2213). Furthermore, by thus explicating our choice of literature sources, we also adhere to the recommendations by vom Brocke et al. (2009) that "the process of excluding sources (and including respectively) has to be made as transparent as possible in order for the review to proof credibility" (vom Brocke et al., 2009: 2207).

3.1. Search Criteria

Since the survey focuses on value creation through business application of Big Data, the literature search criteria should reflect this choice of subject. To ensure that all relevant papers are identified and included in the review, synonymous words were included owing to the fact that there is no established terminology within emerging research fields like Big Data. The search is limited to papers written in the English language, assuming that most of the peer-reviewed literature on the topic is written for academic journals or conferences.

The main search criterion is that papers contain the words "Big Data". There is no generally accepted abbreviation of this concept, and it is assumed that these search words are only spelled, sequenced, and combined in this particular way (i.e. "Big Data"). The search is, however, not case sensitive. Since, our research focuses on the application of and value creation through Big Data within companies, the search also includes "value", "application", "company", and synonymous words. The value creation aspect is covered by "value" and "valuable" as well as the synonyms words "benefit", "beneficial", "profit", and "profitable". The words "benefit", "profit", and "value" are used in combination with a wildcard operator (e.g. "benefit*") in order to include compound words and plural nouns. The "application" aspect is more difficult to capture. The word "application" has several meanings (e.g. a request or petition and the act of applying something). In order to capture the use of Big Data for business purposes, we included "business case" in our search for relevant literature. In searching for the literature, the chosen unit of analysis is the organizational level as previously mentioned. The words "organization", "company", and "corporation" were included, and a wildcard was again added to account for plural and compound words. Accounting for our choice of keywords, conforms to the guidelines by vom Brocke et al. (2009) who stress that "particularly the applied keywords have to be documented precisely, so that other scholars can evaluate whether they sufficiently match the topic under investigation" (vom Brocke et al., 2009: 2214).

The concept of Big Data is relatively new and most papers about Big Data are from 2005 and up until today. As a pragmatic means of reducing the number of papers and focusing on up-to-date research, we decided to limit the search to papers from 2010 and onward. This selection criterion ensures a focus on the most recent research with perspectives on the technological possibilities of the 2010s. Forward and backward searches (see subsection 3.3) minimized the risk of excluding older but highly relevant papers. Papers in the two literature databases are extracted by using the querying tools provided for each database. The results of the database queries are presented in Table 3.

Table 3. Search statements

Database	Queries	Results	Explanations
Scopus	PUBYEAR > 2010 AND TITLE-ABS-KEY("Big Data") AND TITLE-ABS-KEY("value*" OR "valuable" OR "benefit*" OR "benefic*" OR "profit*" OR "profitable" OR "business case") AND TITLE-ABS-KEY("organization" OR "company" OR "corporation") AND DOCTYPE(AR) OR DOCTYPE(CP)	The search yielded 290 journal articles and conference papers.	"AR" is an abbreviation of article. "CP" is an abbreviation of conference paper.
Web of Science	(TS=("Big Data") AND TS=("Business case" OR "value*" OR "valuable" OR "Benefit*" OR "Benefic*" OR "Profit*" OR "Company" OR "corporation" OR "organization") AND PY=(2011-2015) AND DT="Article")	The search yielded 339 journal articles.	"TS" is an abbreviation of topic. "PY" is an abbreviation of publication year. "DT" is an abbreviation of document type.

The total number of papers selected from the two databases for further screening was 629. This number includes duplicate papers that are found in both databases. The next step of the literature review was screening the selected papers.

3.2. Screening the Selected Papers

Searching through the two databases resulted in the identification of 629 potentially relevant papers. The next step was to screen the papers and determine their relevance in relation to our research. For that purpose we established three selection criteria. Firstly, the paper should provide insight into at least one of the six elements of the DELTTA model. Secondly, the paper should have an organizational level of analysis and not be limited to any particular domain or industry. Thirdly, the paper should not focus purely on technical aspects (hardware and software) of Big Data. Big Data is enabled by new technologies for the capture, storage, and analysis of data. In the context of the DELTTA model, storage and processing technologies are, however, treated in terms of their possibilities and role in Big Data. We therefore decided to exclude papers that describe, compare, or review specific types or brands of hardware or software. Many papers include the subject of Big Data only as a minor part, and they were discarded. A lot of papers describe the potential of Big Data to specific companies or kinds of businesses. A few papers focus on Big Data implications for schools and educational systems. These papers were also not included. A number of papers were selected at first only to be discarded after a more thorough review of their content. In cases where the relevance of the papers was unclear, the papers were included and later subjected to a second reading. During the review, the contribution of each paper was categorized under one or more elements of the DELTTA model. A number of articles contribute to more than one element. All contributions were placed in a concept matrix as advocated by (Webster & Watson, 2002). In the end, titles and abstracts of all 629 papers were read, resulting in 26 papers being selected for inclusion.

3.3. Backward and Forward Searches

Backward and forward searches were conducted. The backward search involved looking through the reference lists of all selected papers for the purpose of finding additional relevant papers, which had not been discovered in the initial searches in Scopus and Web of Science. This search involved browsing the titles of the referenced papers in order to decide whether any of the papers might be relevant to include. Only titles, which were obviously not relevant, were discarded. All other papers were selected for further study and evaluated according to the same selection criteria as the other papers. The backward search yielded another two papers. The forward search was performed by identifying and evaluating the papers which reference the previously selected papers. The Scopus and Web of Science databases were used to locate these papers. The evaluation followed the same procedure as the backward search. The forward search resulted in another two papers being selected. The literature search process is illustrated in Appendix B.

4. Literature Review

In the following, state-of-the-art knowledge in the literature is summarized for each element of the DELTTA model. All selected papers have been categorized according to the DELTTA model, and each paper is contributing to at least one element of the DELTTA model. The contribution of each paper is presented with regard to the particular element of the DELTTA model.

4.1. First Element: Data

The extant literature looks at data from different perspectives. Data, including sourcing of data and data quality, is key to value creation. Data has no inherent value to businesses and becomes valuable only when it is placed in relevant contexts. This is no more apparent than in the article by (Miller & Mork, 2013), which presents a value chain perspective on data. From this perspective, data travels through a value chain from its source through a process of quality assurance to the end receiver who uses it as a basis for decision-marking.

The paper by (Debortoli, Müller, & vom Brocke, 2014) focuses on the differences between Business Intelligence and Big Data. From a Data perspective, Business intelligence uses structured data residing in company-internal databases, whereas Big Data seeks to extract value from semi-structured or unstructured data originating from sources outside the organization. (Chen, Mao, & Liu, 2014) describe a value chain for Big Data divided into four phases: data generation, data acquisition, data storage, and data analysis. Similarly, (Miller & Mork, 2013) present a similar value chain with an emphasis on how data moves through the value chain to become a basis for making informed decisions. At the input end of the value chain, the paper by (Barton & Court, 2012) encourages creative sourcing of data, internally from other departments and externally from public databases. The paper by (Joseph & Johnson, 2013) introduces the notion of overproduction and underconsumption of data. The paper suggests that overproduction of data is analyzed and either reduced or consumed.

The security aspect of Big Data is the focus of the paper by (Sagiroglu & Sinanc, 2013). The paper points out the weaknesses of storing data centrally and stresses the importance of controlling data access both physically and electronically.

In terms of value creation, (Power, 2014) stresses that value from data is not created as a function of size but through context and presentation. In a similar vein, the paper by (Boyd & Crawford, 2012) argues that data taken out of context loses its meaning and value, and that Big Data has no extra value due to sheer size compared to small data. In order to create value from unstructured data, the paper by (Beath, Becerra-Fernandez, Ross, & Short, 2012) points out the importance of documenting the workflows that create and use unstructured data. Another and more direct way of creating value from data is discussed by (Najjar & Kettinger, 2013) who propose selling data to other organizations.

The quality of data is the primary concern of (Hazen, Boone, Ezell, & Jones-Farmer, 2014). The intrinsic quality of data is described along four dimensions (accuracy, timeliness, consistency, and completeness). The paper introduces methods for monitoring and controlling data quality. In the paper by (O'Leary, 2013), the challenges of securing reliable data are described through a case study of mobile device, sensor-based apps. Data reliability is challenged, on the one hand, by variations in user incentives and behavior and, on the other hand, by variations in data depending on the type of mobile device.

Finally, two papers take a critical stance by questioning the value of Big Data. The paper by (Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011) discusses the notion of too much data. In a survey by Intel (Intel, 2012), 200 IT managers were asked to rank the top three sources of data in terms of value, and traditional data came out on top despite all the hype about unstructured data.

4.2. Second Element: Enterprise

Big Data and value creation is not only about Data and Technology. For a company to truly gain value from Big Data, use of data for decision-making and other purposes must be part of the organizational culture. All employees need to understand and trust data, and they should become accustomed to asking questions like "what does the data say?" and trust the answer when the data is not in line with commonly held beliefs.

(Phillips-Wren & Hoskisson, 2015) quote a paper by Weill & Ross saying that the alignment of technology, people, and organizational resources in becoming a data-driven company is difficult. The paper by (McAffee & Brynjolfsson, 2012) emphasizes that the most important question of any data-driven organization is not "what do we think?" but "what do we know?". According to (Beath et al., 2012), IT departments are, however, unable to cope with the proliferation of information by themselves. The challenge of interpreting and using data to improve organizational flexibility and business performance of an organization necessitates close cooperation between IT and business managers. (Rajpurohit, 2013) expresses this sentiment by saying that "business domain understanding and technology solutions need to work hand in hand to deliver effective analytics solutions". This is furthermore echoed by (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015) who state that reaping the benefits of Big Data requires an alignment of the organizational culture and capabilities across the organization. Referencing (Barton & Court, 2012), they stress that a key challenge is making Big Data trustworthy and comprehensible to all employees. (Barton & Court, 2012) state that "the lead concern expressed to us by senior executives is that their managers do not understand or trust Big Data based models". Organizations are, however, not equally mature in terms of analytical capability. The paper by (Lavalle et al., 2011) categorize organizations based on their analytical capabilities. They identify three levels of analytical capability: aspirational, experienced, and transformed.

4.3. Third Element: Leader

The Leader and Enterprise elements are closely related in the sense that management needs to show their trust in data ahead of any organization-wide business process changes. A manager who trusts data more than intuition sends a powerful message to the rest of the organization, and it paves the way for changing the culture of a company into one that relies on data for its internal processes.

The paper by (McAffee & Brynjolfsson, 2012) points to specific actions that leaders may take in order to lead the Big Data transformation of companies. The first thing is to ask questions like “what does the data say?” when faced with difficult decisions, followed by questions like “where do the data come from?” and “what kind of analyses have been performed?”. The second thing is to allow themselves to be overruled by data; “few things are more powerful for changing a decision-making culture than seeing a senior executive concede when data have disproved a hunch” (McAffee & Brynjolfsson, 2012). Another approach to Big Data adoption is described by (Gopalkrishnan & Steier, 2012) who suggest that leaders ask three questions: 1) “What is the business problem?”, 2) “is the available data suitable for problem solving?”, and 3) “what is the ROI of Big Data?”. The paper by (Rajpurohit, 2013) emphasizes the value in learning from failures and the need to analyze the gap between potential and realized value. (Phillips-Wren & Hoskisson, 2015) discuss the organizational and managerial challenges in transitioning from using data to relying on analytics and integrating Big Data into organizational decision-making. Despite challenges, (Tallon, 2013) points out that data governance and information management are of increasing strategic importance to organizations. Although the use of Big Data may offer companies strategic advantages, the case study by (Najjar & Kettinger, 2013) highlights the importance of balancing the advantages of information transparency across business partners against the loss of power from information sharing with customers, suppliers, and competitors. Similarly, (Barton & Court, 2012) elaborate on these advantages “in a deliberate effort to weave Big Data into the fabric of daily operations” (Barton & Court, 2012). Meanwhile, (Mcneely, 2014) cautions leaders not to focus on technology and be aware that “there is a huge gap between our ability to acquire data and our ability to make effective use of data to advance discovery” (Mcneely, 2014). Instead, (Ebner, Bühnen, & Urbach, 2014) suggest that senior management asks three questions in order to determine how to deal with Big Data: 1) “Do we have a Big Data or an IT infrastructure problem?”, 2) “are we lacking critical information that the use of a Big Data solution will help us acquire?”, and 3) “what are our analytical requirements?”. (Power, 2014) also warns leaders of the dangers of putting too much faith in systems and Big Data models, and points to the 2008 financial crisis as an example of the failure of data-driven models to accurately factor in financial risks. Instead, (Beath et al., 2012) recommend senior managers to commit to three practices: 1) Identify your sacred data, 2) define the workflows relying on unstructured data, and 3) use data to improve business processes. Furthermore, based on a large-scale survey, (Lavalle et al., 2011) conclude that “the leading obstacle to widespread analytics adoption is lack of understanding of how to use analytics to improve the business”, and that “lack of management bandwidth due to competing priorities” is an obstacle to adoption of analytics.

4.4. Fourth Element: Target

Any company needs to start by asking what the goal or purpose of applying Big Data is. Big Data is a solution to which business problem? Start with the question before asking about possible solutions and how data can help.

Gopalkrishnan & Steier (Gopalkrishnan & Steier, 2012) stress the importance of having one or more organizational goals as a basis for establishing and continually monitoring the business case for any Big Data investment. Likewise, (Barton & Court, 2012) emphasize that the desired business impact should drive decisions regarding data sourcing, model building, and organizational transformation. The paper by (Lavalle et al., 2011) advocates starting with the problem (i.e. the question) rather than the solution (i.e. the data). (Mcneely, 2014) warns of the dangers in basing decisions on correlations instead of an in-depth understanding of Big Data. (Phillips-Wren & Hoskisson, 2015) mention description, prediction, and prescription as three ways in which analytics supports target management and provides value to an organization. According to (Joseph & Johnson, 2013), Big Data analytics also facilitates business process redesign. More generally, (Rajpurohit, 2013) points out the importance of seeing analytics as a means of transforming data into valuable insights. To that end, (Tallon, 2013) argues that establishing data management practices, which balance value creation and risk exposure, is a new organizational imperative for achieving competitive advantage and maximizing value from Big Data. The relationship between competitive advantage and the application of Big Data is studied by (Kamioka & Tapanainen, 2014). Their paper concludes that a positive impact on competitive advantage depends on extensive and systematic Big Data usage. The (Hospitals and Health Networks, 2014) paper elaborates by suggesting that data is used in a structured manner in pursuit of relevant questions (i.e. business targets).

4.5. Fifth Element: Technology

New technologies for capturing, storing, and analyzing data must be combined with more traditional technologies. Big Data technologies should be used alongside existing legacy systems. The combination of traditional and Big Data storage technologies help reduce costs while creating value.

(Philip Chen & Zhang, 2014) call for new techniques and technologies to be developed. Multidisciplinary approaches (computer science, economics, mathematics, and statistics) are required for the purpose of discovering valuable information in Big Data. With regard to technologies, (Barton & Court, 2012) discuss how legacy systems may challenge the application of Big Data. They problematize whether existing systems are able to handle the data required for real-time decision support. (Ebner et al., 2014) concludes that a hybrid strategy combining relational database structures and the MapReduce programming model (framework for large-scale data processing) is preferable and most likely to create value. In terms of storage, (Beath et al., 2012) argue that a company's IT department should take the lead in creating a reliable and cost-effective solution. The paper suggests a three-tier data storage solution, each tier having different configurations and applications. (Intel, 2012) predicts that the current mix of batch and real-time delivery of data will change, and that more and more data will be delivered in real-time. The (Hospitals and Health Networks, 2014) paper is even more specific and describes the goal as being a move from retrospective to real-time analytics and eventually predictive analytics.

4.6. Sixth Element: Analysts

There is general agreement that the skills of analysts are needed in order to create value out of Big Data. These analysts need to work together with managers and domain experts to realize this value. A company needs to carefully consider the need for particular skills before hiring analysts.

(Sagiroglu & Sinanc, 2013) reason that companies should not only employ managers and analysts with insights into applications of Big Data; they also need to invest in education and training of key personnel.

The different requirements for job positions within Business Intelligence and Big Data jobs analyzed by Debortoli et al. (Debortoli et al., 2014) who look at the wording of job advertisements. They conclude that Big Data requires skills within software engineering and statistics. Similarly, skills and job descriptions of data scientists are discussed by (Davenport, 2012). The paper describes how to attract and retain data scientists with the skill set required to create value from Big Data. The skills of data scientists are also the topic of the paper by Davenport et al. (Davenport, Barth, & Bean, 2012). A data scientist needs to understand analytics, have skills in statistics and mathematics, understand the business, and possess good communication skills. The new organizational role of Chief Data Officer is described by (Ebbage, 2014). The Chief Data Officer is characterized as someone who knows how to use data across an organization and is able to chart a course for the data scientist to follow. (Power, 2014) argues that managers need to understand what data scientists can do and not do for a company before hiring any. (Gerhardt, Griffin, & Klemann, 2012) describe the role of the so-called data infomediary who is viewed as an employee who does the matchmaking between data originators and data beneficiaries. Finally, (Viaene, 2013) explains the need for domain experts and data scientists to work together, leveraging their different competencies in order to create value.

4.7. Mapping State-of-the-Art Literature

The six elements of the DELTTA model enable us to look at different aspects of Big Data individually. Looking at each aspect individually helps us understand how each element contributes to value creation. Hence, the literature review creates an overview of state-of-the-art knowledge of value creation from the perspective of the DELTTA model. Table 4 shows the concept matrix resulting from our literature review, which provides a map of the literature on Big Data with the DELTTA model as ‘compass’. Although the DELTTA model allows us to focus on each element in turn, it does not help us understand how the six elements influence each other. A large part of the papers in the literature review contribute to an understanding of two or more elements of the DELTTA model. This observation reveals a close relationships between some elements in the DELTTA model. Looking at Table 4, there is however no clear pattern between the six elements of the DELTTA model. Each paper included in the literature review looks at Big Data from the perspective of companies, but they focus on different aspects of Big Data. In order to view Big Data from a more holistic company perspective, it is necessary to include empirical observations from the collected data. The empirical data was collected for the purpose of understanding the relationship between applications of Big Data and value creation from the viewpoint of Danish companies. This data has been analyzed and the findings are presented in the following section.

#	Reference	Data	Enterprise	Leader	Target	Tech-nology	Analysts
1	(Barton & Court, 2012)	X	X	X	X	X	
2	(Beath et al., 2012)	X	X	X		X	
3	(Boyd & Crawford, 2012)	X					
4	(Chen et al., 2014)	X		X	X		
5	(Davenport, 2012)						X
6	(Davenport, 2013)						X
7	(Debortoli et al., 2014)	X					X
8	(Ebner et al., 2014)			X		X	
9	(Ebbage, 2014)						X
10	(Gerhardt et al., 2012)						X
11	(Gopalkrishnan & Steier, 2012)			X	X		
12	(Hazen et al., 2014)	X					
13	(Hospitals and Health Networks, 2014)	X			X	X	
14	(Intel, 2012)	X				X	
15	(Joseph & Johnson, 2013)	X			X		
16	(Kamioka & Tapanainen, 2014)				X		
17	(Lavalle et al., 2011)	X	X	X	X		
18	(McAffee & Brynjolfsson, 2012)		X	X			
19	(Mcneely, 2014)			X	X		
20	(Miller & Mork, 2013)	X					
21	(Najjar & Kettinger, 2013)	X		X			
22	(O'Leary, 2013)	X					
23	(Philip Chen & Zhang, 2014)					X	
24	(Phillips-Wren & Hoskisson, 2015)		X	X	X		
25	(Power, 2014)	X		X			
26	(Rajpurohit, 2013)		X	X	X		
27	(Sagiroglu & Sinanc, 2013)	X					X
28	(Tallon, 2013)			X			
29	(Viaene, 2013)						X
30	(Wamba et al., 2015)		X				

Table 4. Concept matrix

5. Empirical Research

In order to better understand how Big Data is used in practice to create value, an online survey was created and distributed to a sample of Danish companies. The unit of analysis is small and medium sized private sector companies (SMEs). Small and medium sized companies are defined as companies with 249 employees or less. This definition corresponds to that of Statistics Denmark (www.smvportalen.dk/om-smvportalen/definition-af-smv), i.e. the central authority on Danish statistics. The definition of small and medium sized companies is solely based on number of employees. Turnover or any other accounting-based number is not part of the definition. The Danish definition may vary from that of other EU countries. All organizations are for-profit companies. By focusing on for-profit companies, the definition of value is limited to economic profit.

5.1. Constructing the Survey

The survey is structured around the DELTTA model, covering all six elements of Big Data described by the framework. The survey focuses on both the value creation and application aspects of Big Data. Thus, the survey contains two questions for each element of the DELTTA model. The questions are phrased as statements, and respondents are asked to express their level of agreement on a five-point Likert scale. The scale ranges from strongly agree to strongly disagree and includes a neutral response. Strongly agree is attributed the value “1” and strongly disagree the value “5”. All questions are phrased as positive statements, which makes it easy for respondents to understand each question and provide an accurate response to the statement.

Because each question is specific to a particular element of the DELTTA model, the responses to the statements are also narrowly focused, which strengthens the external validity of the survey. In the introduction to the survey, it is emphasized that no prior knowledge of Big Data is assumed or needed. Therefore, companies with no or limited experience with Big Data were also included in the survey. The survey questions have been carefully phrased taking the broad spectrum of potential respondents into consideration. The questions have to be specific enough to ensure valid answers but without assuming an understanding of or prior experience with Big Data. As a consequence, we made it possible to answer the questions in such a way that the responses would reveal the level of experience with Big Data. Respondents were also encouraged to elaborate their answers through qualitative comments.

All respondents received the same questions in the sense that their responses to each statement did not affect the sequence or content of subsequent questions. Asking all respondents to answer the same questions also supports the external validity of the survey. The survey contains questions regarding the company, e.g. number of employees and the company’s general use of data. These questions serve to confirm a random selection of companies, since it is important for generalization purposes that the companies vary in terms of age, number of employees, and types of businesses.

Due to the survey being aimed at different types of businesses and not requiring any prior knowledge of Big Data, the concept of Big Data needed to be explained in such a way that most respondents would be able to understand it. The explanation of Big Data used in the survey is based on the various definitions in the literature identified during the review. Big Data was explained as “Data of very high volume and complexity which compared to ordinary data requires special skills, technologies, and tools to capture and use”. Furthermore, the distinction between data and Big Data was characterized as blurry, and the respondents were asked to rely on their judgment and knowledge of their companies in deciding whether to characterize their data as Big Data or ordinary data.

The survey includes two questions for each element of the DELTTA model yielding 12 questions in total. This was a conscious choice given the complexity of the subject and that we set out to collect responses from a heterogeneous sample of companies in terms of prior experiences with and knowledge of Big Data. The respondents have answered these questions based on perceived application and value of Big Data, which introduces the risk of misunderstanding one or more questions, resulting in misleading answers. The risk is, however, reduced by the sheer number of respondents. More importantly, special attention was paid to the wording of questions and the terminology used.

Prior to distributing the survey, it was reviewed by peers with particular attention to the wording and use of terminology in the survey. Subsequent changes were made, particularly with respect to the explanation of Big Data. Balancing the need to make the survey easily comprehensible to the group of diverse respondents and ensuring the external validity of the survey through the use of appropriate Big Data terminology were our main concerns. Ongoing discussions among the authors and survey adjustments helped us achieve this goal.

5.2. The Respondents

The respondents were selected from the Danish Business Register (http://datacvr.virk.dk/data/). The companies were chosen based on their number of employees, which is registered in the database. In addition, companies were selected based on their geographical location. Companies are categorized according to the region in which they are situated, and we decided to include both the Danish capital and rural regions due to differences in demography as well as industry composition and density across regions. Some companies were deselected because they had not registered valid e-mail addresses in the database. A valid e-mail address is required for survey distribution purposes. All companies are registered in the Danish Business Register by company type, which allows for the identification of privately owned companies.

Two selection criteria were applied. First, the sample was limited to companies with fewer than 250 employees. Second, only for-profit private companies were selected. This inclusive approach to sampling provides a basis for generalizing the survey results across industries and types of private businesses. The selection process resulted in a sample of 4043 companies.

The survey was sent by e-mail to the company address registered in the Danish Business register. This is typically a general purpose contact address. Therefore, the e-mail encouraged the recipient to forward the message to the employee best qualified to participate in the survey. This person was described as a management level employee, preferably with an understanding of both the IT and business side of the company. Due to the broad variety of companies, role descriptions and job titles were not mentioned.

5.3. Distribution of the Survey

The survey was distributed using SurveyXact, which is a web-based tool for developing and sending out surveys. Out of the 4043 e-mails, approximately 400 were returned because of delivery failures. A number of respondents declined to participate in the survey. 471 companies selected for participation in the survey were later discarded, primarily due to invalid e-mail addresses. Reminders were sent out within a week, and the survey remained active over the following week. At the end of the two week period, 457 responses had been received. The responses were subsequently exported to the statistical analysis software SPSS for analytical purposes.

The number of survey invites arriving at the intended e-mail addresses was 3572, and the number of completed responses is 457, which translates into a response rate of 12%. This response rate is considered normal taking into account that the survey was aimed at the management level (Baruch, 1999). A total of 109 responses were only partially completed. The majority of partial responses did not include answers to the 12 questions about Big Data. This is in line with a report by the Danish Business Authority (Erhvervsstyrelsen, 2013), finding that many small and medium sized companies decline to answer surveys about Big Data due to limited understanding of and experience with Big Data.

The answers to the six questions about the application of Big Data and the six questions about value creation form the basis for our data analysis. The responses to the 12 statements are used as 12 separate variables in SPSS. The 12 statements are found in Appendix A. Statistics regarding the responding companies can be found in Appendix C.

5.4. Data Analysis

An exploratory factor analysis was performed in SPSS in order to identify factors (combination of variables) explaining Big Data application and value creation. The 12 variables derived from the DELTTA model were subjected to principal axis factoring with the purpose of identifying latent variables in the data. The SPSS correlation matrix shows that all variables have correlations greater than 0.6 with all other variables. All details of the correlation matrix can be found in Appendix D. The result of the Kaiser-Meyer-Okin measure of sampling adequacy is 0.941, which is well above the threshold of 0.6 for factor analyses (Tabachnick & Fidell, 2014). In addition, the ratio between the number of variables and the number of observations is also above the recommended ratio of 1:5 (12 variables and 457 observations), which means that the Bartlett's test is irrelevant and might be misleading. Cronbach's alpha for the factor analysis is 0,971. This reflects the close relationship between the included variables.

The six elements of the DELTTA model were subjected to linear regression. The purpose of performing the regression analysis is to analyze the close relationship between the elements of the DELTTA model identified by the factor analysis. The linear regression shows the degree to which one element of the DELTTA model can predict the other five elements. Each element includes one variable for Big Data application and one for value creation. Each element was tested against the other five elements. The results show predictability ranges from 0.37 to 0.73. Finally, the 12 variables were subjected to mean value calculations. The results are elaborated in the following.

In order to compare and align the results of the literature review with the survey, we adopt triangulation as it allows for cross-checking and validation from several sources (Miles et al., 2014). Thus, triangulation is applied as a technique to show how our use of multiple data sources (qualitative survey data, quantitative survey data, and extant literature) produces a rich understanding of Big Data.

5.5. Survey Results

In the following, we present our findings from the survey. These findings reflect the *perceived* rather than the *actual* value created through the application of Big Data. This is a consequence of our research design and asking respondents to express their *opinions* rather than *facts* (which would be methodologically infeasible). A word of caution: When interpreting the survey results, associations should be interpreted as correlations rather than causations. A high degree of predictability among variables does not necessarily imply that A causes B (or vice versa) but only that they correlate.

5.5.1. Factor Analysis

The principal factor analysis resulted in high correlations between all 12 variables. With a high loading on all 12 variables, the factor *Big Data application and value creation* was identified. A total of 75,6% of the variance is explained by this factor. The high degree of correlation between all 12 variables suggests one or more strong latent variables behind the *Big Data application and value creation* factor. The latent variable(s) influence(s) the 12 variables, which manifests itself in the dependence among them. The high degree of explanation is a testament to the strong relationship between the six elements of the DELTTA model. This relationship between the elements of the DELTTA model are further examined by applying regression analysis.

5.5.2. Regression Analysis

The regression analysis confirms the close relationship between the six elements of the DELTTA model. The regression shows the degree to which responses in relation to one element of the DELTTA model predict responses to another element of the DELTTA model. The strong mutual influence among the six elements of the DELTTA model suggests that a company must focus on all the elements in order to maximize the value from the application of Big Data. For instance, the Enterprise element (the need for Big Data acceptance by, and application throughout, the whole organization) predicts 64% of the variance of the Data element (capture, storage, and analysis of high volume, high velocity, and high variety data). The strong predictive power suggests that quality data and data handling must be combined with an understanding of Big Data throughout the company in order to create real value. Other examples of strong predictive power among the six elements of the DELTTA model are found in Table 5 and 6. The regression calculations are divided into Big Data application and value creation.

Application

The lowest degree of prediction is between the Target and Leader elements. The response to Target predicts 37% of the response to Leader. In contrast, the highest degree of prediction is between Analysts and Technology. The response to Analysts predicts 68% of the response to Technology. The strong predictive power can be interpreted as a high degree of similarity in the responses. Seen from an application perspective, this means that the use of Big Data is viewed similarly across companies. This in turn indicates relatively low variance in the combinations of responses. The similarity in response patterns fits with the assumption of latent variables identified in the factor analysis.

Table 5. Results of regression analysis of Big Data application

	Data	Enterprise	Leader	Target	Technology	Analysts
Data	1	n/a	n/a	n/a	n/a	n/a
Enterprise	0,64	1	n/a	n/a	n/a	n/a
Leader	0,60	0,52	1	n/a	n/a	n/a
Target	0,39	0,44	0,37	1	n/a	n/a
Technology	0,57	0,45	0,47	0,41	1	n/a
Analysts	0,57	0,48	0,50	0,48	0,68	1

Value Creation

The lowest degree of prediction is between the Target and Data elements. The response to Target predicts 40% of the responses to Data. The highest degree of prediction is between Enterprise and Data. The response to Enterprise predicts 73% of the response to Data. As with application, the combinations of responses to the statements related to value creation are relatively similar. From the perspective of value creation, it indicates a relatively high level of agreement among respondents with regard to value creation. This is also in agreement with the assumption of latent variables identified in the factor analysis.

Table 6. Results of regression analysis of Big Data value creation

	Data	Enterprise	Leader	Target	Technology	Analysts
Data	1	n/a	n/a	n/a	n/a	n/a
Enterprise	0,73	1	n/a	n/a	n/a	n/a
Leader	0,61	0,64	1	n/a	n/a	n/a
Target	0,40	0,45	0,49	1	n/a	n/a
Technology	0,61	0,64	0,58	0,49	1	n/a
Analysts	0,51	0,51	0,47	0,47	0,64	1

5.6. Mean Calculations

The mean calculations show the distribution in the responses to the 12 statements. All questions are phrased using positive statement, e.g. “Big Data is being actively applied”. Using a negative statement, the same question would be “Big Data is not being actively applied”. If a company is actively applying Big Data, the response to the positive statement is *agree* with an associated value of two (see below). With regard to the negative statement, the response would be *disagree* with an associated value of four. This would, however, result in the mean values not being comparable across statements. Because all questions are phrased as positive statements, the responses are comparable across all 12 statements.

The results are based on 457 responses. The response value should be interpreted as follows: A value of one translates into *strongly agree*, two equals *agree*, three is *neutral*, four means *disagree*, and five corresponds to *strongly disagree*. Given these values, low values suggest agreement and high values imply disagreement. For example, the value of 3,43 for Big Data application with regard to the Target element of the DELTTA model (see Table 7) is between three (meaning *neutral*) and four (being *disagree*). The mean score of 3,43 can therefore be interpreted as respondents tending to slightly disagree with Big Data being applied for business strategizing and goal setting.

Table 7. Mean calculations of Big Data applications and value creation

DELTTA Model Element	Application	Value Creation
Data	2,58	2,50
Enterprise	2,94	2,69
Leader	2,64	2,62
Target	3,43	3,25
Technology	2,78	2,79
Analysts	2,96	2,93

6. Survey Analysis

6.1. The *Big Data Application and Value Creation* factor

The one factor resulting from the principal factor analysis suggests that to the extent that Big Data is applied, value is created in roughly 75% of all cases. An important characteristic of a good factor analysis is that it makes sense. As previously mentioned, the high degree of explanation by this factor suggests the existence of one or more latent variables. A latent variable is found in the framework. The strong relationship and mutual influence between variables is revealed by the regression analysis, displaying a high degree of predictability among the six elements of the DELTTA model. A latent variable is also found in the sample of survey respondents. The companies taking part in the survey are similar in some respects. All respondents are from small and medium sized companies. In general, these companies have limited resources (competencies, money etc.). They are limited in terms of their Big Data investment capabilities and will carefully weigh the costs and benefits by establishing business cases and calculating ROI. The companies responding to the survey may be considered adept at turning the application of Big Data into value.

6.2. The DELTTA Model

Having investigated the overall ability of small and medium sized companies to turn application of Big Data into actual value, the next step is looking at each element of the DELTTA model. The statements of the survey can be found in Appendix A. For each element of the DELTTA model, respondents were given two questions asking them to respond to statements about Big Data application vis-à-vis value creation. By zooming in on the differences (mean response value) between application and value creation, new insights are generated.

6.2.1. The Data Element of the DELTTA Model

The Data element of the DELTTA model is predicted by the Enterprise and Leader elements. The responses to the Enterprise element predict 64% and 73% of the responses to the Data element (Big Data application and value creation), and responses to the Leader element predict 60% and 61% of the responses. This suggests that data does not create value by itself. In other words, having large amounts of high quality data is not enough. Big Data initiatives require management involvement and Big Data must be accepted and used throughout the company in connection with various business processes. The answers to the questions concerning Data have a mean response value of 2,58 and 2,50 (see Table 7), which is close to *neutral*. The difference between the application and value creation scores might indicate that data is being used in the companies but that the respondents are unsure about the extent to which it creates value.

6.2.2. The Enterprise Element of the DELTTA Model

Enterprise is predicted by Leader and Technology (both 64%). Leadership involvement is a prerequisite for Big Data application across the different parts of a company. Big Data technology facilitates access to data across business processes in a company. In terms of the Enterprise element of the DELTTA model, the mean responses are 2,94 and 2,69 (see Table 7) with the application value being lower than the value creation aspect. This implies that the respondents do not see Big Data being applied across their companies, and that they are unsure as to whether Big Data creates value to their companies as a whole.

6.2.3. The Leader Element of the DELTTA model

The Leader element of the DELTTA model is mainly predicted by Technology (58%). This is interpreted as the company leaders allowing Big Data initiatives to be influenced if not controlled by technological possibilities. Big Data is of course also about technology, and the basic premise is that data management, i.e. data storage and analysis, is enabled and facilitated by IT. The mean values of the responses are 2,64 and 2,62, which are almost identical. The fact that respondents answer in the negative with regard to management involvement suggests that leaders of small and medium sized companies should be more involved in Big Data initiatives.

6.2.4. The Target Element of the DELTTA Model

The Target element of the DELTTA model is predicted by all the other elements. This suggests that goal achievement in terms of Big Data application and value creation requires an interplay between technology, data, and the involvement of both management and the organization as a whole. The mean values of the responses are 3,43 and 3,25. In other words, the respondents answer in the negative, which suggests that small and medium sized companies are not adept at setting targets for Big Data initiatives aligned with their business strategies and goals.

6.2.5. The Technology Element of the DELTTA Model

The Analysts element of the DELTTA model predicts 64% of the Technology element, which indicates a close relationship between the use of technology and analytical skills in Big Data. By implication, the Target and Leader elements do not seem to influence the application and value creation through Technology in any noteworthy degree. The mean values of the responses are 2,78 and 2,79. This indicates lack of technology use and consequently a low degree of value creation from its application.

6.2.6. The Analysts Element of the DELTTA Model

The responses to the Analysts element are mainly predicted by Technology, showing a close relationship between analytical skills and technological use in the application of and value creation from Big Data. This also indicates that the Leader and Target elements do not influence this people factor of Big Data to the same extent. The mean values of the responses are 2,96 and 2,93. The answers are almost *neutral*, implying uncertainty regarding the application of and value creation from Big Data competencies.

7. Discussion and Conclusion

This research, seeking to investigate the degree to which the application of Big Data creates value, has yielded a number of findings. First of all, our research shows a correlation between the application of Big Data and value creation. The close relationship between application and value creation is highlighted by the principal factor analysis, which points to one factor that describes 75,6% of the variance in the 12 variables.

Second, our research shows that the six elements of the DELTTA model affect each other. The fact that each of the six elements predicts the variance in other elements points to a high degree of interdependency among the elements of the DELTTA model. From the perspective of private companies, this means that creation of real value through the application of Big Data depends on all six elements of the DELTTA model being addressed.

Third, our research reveals important insights into the close relationship between application and value creation by analyzing respondents' survey responses to 12 statements regarding Big Data.

The responses to the Data element shows that companies currently apply data and that it is perceived as creating value. The similarity in responses indicates that application and value creation (mean response values of 2,58 and 2,50 respectively) go hand in hand. This is in line with (Power, 2014) who emphasizes that data has no value in itself but becomes valuable through its use in particular organizational and business contexts. Likewise, Boyd & Crawford (Boyd & Crawford, 2012) stress that data without context is of no value. The results confirm this in the sense that respondents see data as creating value in the specific contexts of their companies. Our qualitative content analysis of survey responses shows that companies use both structured and unstructured data from internal as well as external sources. Internal data include financial, sales, CRM, ERP, and usage statistics data as well as mails and use cases. External data include those from social media, industry reports, and public databases (Eurostat, ECB etc.) as well as GIS and EDI data. There is tendency to use structured data more. As one respondent says: "We use unstructured data to a lesser extent because the validity, completeness etc. is not good enough."

The *neutral* responses to the statements related to the Enterprise element reveal that respondents are not sure how Big Data is used across their companies and how it creates value to different business processes and parts of the organization. According to (Lavalle et al., 2011), the average company would be placed at the aspirational level of analytical capability. Our research shows that the companies are not yet at the level where they continually ask themselves "what do we know" as suggested by McAffee & Brynjolfsson (McAffee & Brynjolfsson, 2012). Meanwhile, our analysis of the qualitative survey comments reveal that companies use data for many different purposes across the enterprise. Generally, data is used for, e.g., production planning, daily operations, KPI management, as well as purchasing and logistics decisions. More specifically, data is used to better understand and cater to customer needs. Data is thus used to analyze customer needs and behaviors, offer product recommendations, improve customer and after-sales service, measure degrees of customer satisfaction, understand user experiences, perform web analytics, personalize marketing campaigns, tailor products to customer preferences, and distill learning from customer complaints and product returns. The focus is on customer loyalty, retention, and resale. One respondent comments: "With accurate information about our customers, we are able to spot potential problems and act proactively based on the information."

In terms of the Leader element, management in an average company is aware of the possibilities for Big Data application and value creation. However, considering the importance of management involvement, the mean response value is low. This may be interpreted as managers not communicating the importance of Big Data to the rest of the organization, which goes against the recommendations by (Gopalkrishnan & Steier, 2012) and (McAffee & Brynjolfsson, 2012). Nevertheless, the qualitative survey comments indicate that managers use data for decision support, including marketing efforts, competitor analyses, business strategy adaptation, investment decisions, quotations, human resource management, as well as budgeting and forecasting. One respondent says: "Data help identify focus areas, which enable management to make better decisions and establish action plans for a specific area."

The responses to the statements about the Target element reveal that goals have not been defined in many of the 457 companies participating in the survey. With reference to the papers by (Gopalkrishnan & Steier, 2012) and (Barton & Court, 2012), which emphasize the importance of clear goals in guiding the use of Big Data, the companies still face the challenge of connecting Big Data to business strategies and business processes. However, our qualitative content analysis shows that the use of customer data enables companies to detect and react to new or changing patterns in general markets trends as well as specific customer behaviors. One respondent asserts: "When we see a negative tendency, we often react to it even before the customer is aware of it."

In connection with the Data element, Technology is identified as the backbone of Big Data supporting the other four elements. Technology supports or drives the pursuit of Big Data targets, but technology is not an end in itself. Data storage and processing are important aspects of technological use, and the extant literature describes different data storage strategies. Whereas Ebner et al. (Ebner et al., 2014) recommend a hybrid strategy combined with the use of both traditional databases and new types of data storage, (Beath et al., 2012) suggest a three-tier data storage strategy to reduce costs. The qualitative survey comments clearly confirms the link between the Data and Technology elements. Data from, e.g., ERP, CRM, and case handling systems, are used internally for monitoring and improvement of business processes. According to one respondent: "The business logic and processes are trimmed continuously with greater service orientation and more efficient operations in mind." Lean and process innovation are made possible by the use of data. One respondent stresses that "by dividing a work process into smaller activities and analyzing each activity, we are able to optimize the individual activities and the entire process."

Last, but not least, responses to the statements concerning Analysts, indicate uncertainty with regard to how Big Data competencies are utilized and whether they create value. This is problematic considering the extant literature. Previous research suggests different kinds of job roles in relation to Big Data. Firstly, the paper by Davenport et al. (Davenport, Barth, & Bean, 2012) advocates employing data scientists as a means of creating value. Secondly, the paper by (Sagiroglu & Sinanc, 2013) underscores the importance of focusing on educating and training key personnel. Thirdly, (Viaene, 2013) emphasizes the need for data scientists to work together with domain experts in order to create value out of Big Data for any company. Yet, the qualitative survey comments reveal that companies use data to provide employees with an “Analyst’s” overview of projects, sales, and more. This provides structure and enhanced understanding of employees' contributions to business goals, which in turn improves employee satisfaction. In the words of one respondent: "More structure leads to greater job satisfaction." It also helps management improve the work environment, allocate employees to work activities depending on business needs, and improve business processes.

This study has several implications for researchers and practitioners. For one, our research provides insights into how and to which extent the application of Big Data creates value to small and medium sized companies. The empirical data allow us to address the question from the perspective of companies that are working with Big Data on many different levels. In response to our research question “To what extent does the application of Big Data create value for small and medium sized companies?”), we are able to conclude that Big Data is perceived as creating value to the extent that the six elements of the DELTTA model are addressed. This in turn leads us to recommend that managers pay attention no only to capture, storage, and analysis of data (the Data element), but that they demonstrate leadership through explicit and clear goal setting (the Target element), aligning business strategies and goals with IT capabilities (the Technology element) and analytical skills (the Analysts element). This managerial responsibility also extends to communicating the importance and value of Big Data in supporting and driving the business, adapting business processes to take advantage of identified opportunities (the Enterprise element), and acting on the basis of data (the Leadership element). Out study reveals the importance of not only communicating but also showing employees how Big Data is or should be used, for what purpose, and with which benefits in mind. This is a prerequisite for their being able to support Big Data initiatives and help realize planned benefits. With regard to other practical implications, managers are advised to take an active role in strategizing, implementing, and using Big Data. Big Data is a powerful tool for both management and business innovation. Widespread Big Data adoption requires, however, that managers acquire greater understanding of potential applications and benefits of business analytics (Lavalle et al., 2011). Meanwhile, we lack knowledge of the particular competencies and skillsets needed by managers and employees in coping with the challenges of Big Data application. This paves the way for future studies. Speaking of research implications, additional empirical studies of Big Data are needed to extend the insights of this article. In this article, we have relied on the DELTTA model for analytical purposes. The DELTTA model has proven to be a useful analytical framework when investigating the complex concept of Big Data. Future studies may provide additional knowledge by extending the empirical data collection to include large companies, and by relying on other conceptualizations of Big Data. Moreover, our research has included all types of businesses and companies from all industries. Future research may investigate the relationship between Big Data application and value creation at a more detailed level by looking at specific organizations or company types. The bird’s eye perspective in this article carries with it the advantage of yielding knowledge that can be generalized across companies, but this comes at the expense of a more detailed understanding of the hows and whys of Big Data. Our study also reveals limitations in a survey-based, quantitative study of Big Data. Thus, the qualitative survey comments reveal that respondents struggle with the distinction between data and Big Data. One respondent remarks: "The blurry line between big and small data makes it difficult to answer the questions precisely." Future research may address this limitation and close the knowledge gap by focusing on qualitative case studies of concrete Big Data initiatives.

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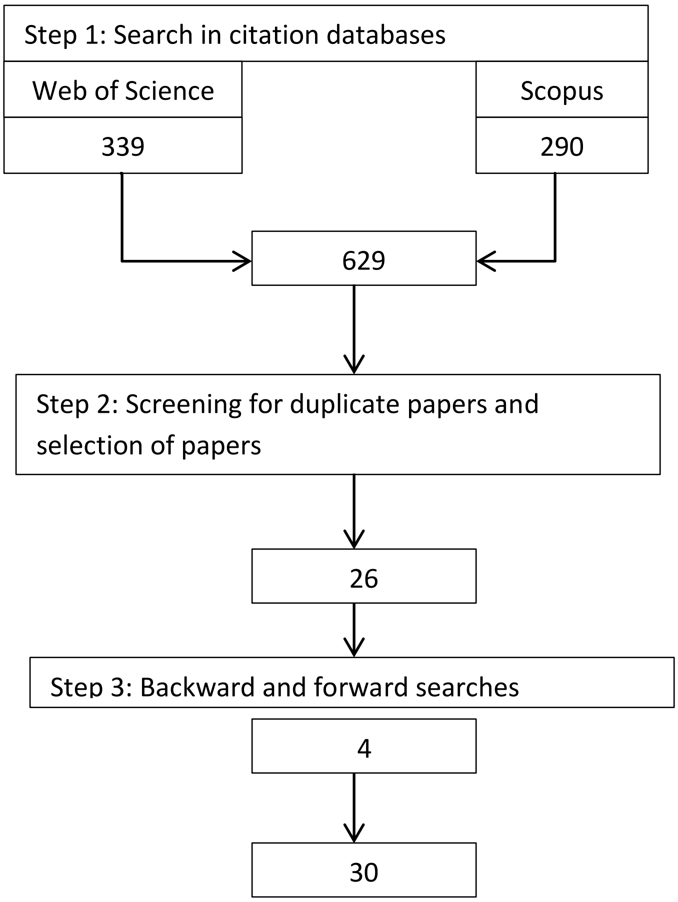
Appendix A: Survey Questions

The survey, which has been developed for the purpose of collecting empirical data for this article, is based on the DELTTA model. The survey includes two questions in the form of statements for each element of the DELTTA model. The first statement concerns the application of Big Data (see the "Application" column in Table A.1). The second type of statement focuses on value creation through the application of Big Data (see the "Value Creation" column in Table A.1). All statements were answered with one of the following responses: *strongly agree*, *agree*, *neutral*, *disagree*, and *strongly disagree*.

Table A.1. Statements of selected survey questions

DELTTA Model Element	Application	Value Creation
Data	Big Data (our own) is being actively applied	Big Data (our own) is creating value to our organization
Enterprise	We apply Big Data across the entire company	Big Data creates value to the whole organization
Leader	The management understands how Big Data is being applied in our organization	The management knows how the application of Big Data creates value to our organization
Target	Our organization has specific targets for the application of Big Data	Our organization monitors the value creation and ensures that the goals for Big Data application are being realized
Technology	We have technologies that enable the application of Big Data	Big Data technologies support value creation in our organization
Analysts	Our organization applies relevant Big Data skills	Big Data competencies are prerequisites for the success of our business

Appendix B: The Paper Search Process



Appendix C: Respondent Statistics

Description	Options	Number of respondents	Percentage
Age of company	Less than 5 years	23	5%
	Between 5 and 15 years	121	26%
	Older than 15 years	313	69%
Number of employees	Fewer than 10	96	21%
	Between 10 and 49	237	52%
	Between 50 and 250	124	27%
Type of industry	Farming, forestry, and fishing	7	2%
	Production and utilities	118	26%
	Building and construction	67	14%
	Trade and transportation	95	20%
	Information and communication	46	10%
	Finance and insurance	7	2%
	Property trading and rental	7	2%
	Business services	13	3%
	Others	97	21%

Appendix D: Correlation Matrix

Correlation Matrix[a]

		s_appl_BD	s_BD_val	s_appl_BD_org	s_BD_val_org	s_man_appl_BD	s_man_BD_val	s_targ_BD	BD_targ_real	s_tech_BD	s_BD_tech_val	s_appl_BD_comp	s_BD_comp_succ
Correlation	s_appl_BD	1,000	,890	,801	,835	,777	,797	,629	,659	,753	,782	,753	,713
	s_BD_val	,890	1,000	,787	,857	,764	,783	,575	,633	,711	,781	,725	,715
	s_appl_BD_org	,801	,787	1,000	,843	,721	,769	,665	,673	,671	,717	,694	,670
	s_BD_val_org	,835	,857	,843	1,000	,775	,802	,610	,675	,733	,799	,730	,716
	s_man_appl_BD	,777	,764	,721	,775	1,000	,909	,607	,671	,688	,745	,705	,650
	s_man_BD_val	,797	,783	,769	,802	,909	1,000	,635	,703	,726	,765	,739	,682
	s_targ_BD	,629	,575	,665	,610	,607	,635	1,000	,875	,638	,660	,696	,648
	BD_targ_real	,659	,633	,673	,675	,671	,703	,875	1,000	,669	,703	,736	,689
	s_tech_BD	,753	,711	,671	,733	,688	,726	,638	,669	1,000	,848	,823	,745
	s_BD_tech_val	,782	,781	,717	,799	,745	,765	,660	,703	,848	1,000	,833	,803
	s_appl_BD_comp	,753	,725	,694	,730	,705	,739	,696	,736	,823	,833	1,000	,794
	s_BD_comp_succ	,713	,715	,670	,716	,650	,682	,648	,689	,745	,803	,794	1,000
Sig. (1-tailed)	s_appl_BD		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	s_BD_val	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	s_appl_BD_org	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000
	s_BD_val_org	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000
	s_man_appl_BD	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000
	s_man_BD_val	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000
	s_targ_BD	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000
	BD_targ_real	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000
	s_tech_BD	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000
	s_BD_tech_val	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000
	s_appl_BD_comp	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000
	s_BD_comp_succ	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	