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Searching for big data
How incumbents explore a possible adoption of big data technologies

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ABSTRACT

Big data is often described as a new frontier of IT-enabled competitive advantage. A limited number of exemplary firms have been used recurrently in the big data debate to serve as successful illustrations of what big data technologies can offer. These firms are well-known, data-driven organizations that often, but not always, are born digital companies. Comparatively little attention has been paid to the challenges that many incumbent organizations face when they try to explore a possible adoption of such technologies. This study investigates how incumbents handle such an exploration and what challenges they face. Drawing on a four-year qualitative field study of four large Scandinavian firms, we are able to develop a typology of how incumbents handle the exploration of and resistance to adopting big data technologies. Directly affecting the incumbents' exploration are two aspects that separate the adoption of big data technologies from that of other technologies. First, being an elusive concept, big data technologies can mean different things to different organizations. This makes the technologies difficult to explain before an investing body, while it simultaneously opens up possibilities for creative definitions. Second, big data technologies have a transformative effect on the organization of work in firms. This transformative capability will make managers wary as it might threaten their position in the firm, and it will create ripple effects, transforming other systems besides those directly connected to the technology.

1. Introduction

In the debate about the significance of big data for business, the phenomenon is often presented as a technology-based avenue to competitive advantage: a new frontier of IT-enabled experimentation, innovation, and customer centricity (Chen, Chiang, & Storey, 2012; Davenport, 2013; McAfee & Brynjolfsson, 2012; Parmar, Mackenzie, Cohn, & Gann, 2014). Much of this debate was initially driven by simplistic and optimistic notions often stemming from various evangelists, consulting firms, and other practitioners (e.g., Anderson, 2008;Chui, Manyika, & Bughin, 2011; Mayer-Schönberger & Cukier, 2013). Harnessing big data can allegedly produce outcomes recurrently described as ranging from better overall financial performance and optimized business prioritization to increased customer insight that can favorably affect innovation (Davenport, 2014; McAfee & Brynjolfsson, 2012; Pigni, Piccoli, & Watson, 2016; The Economist, 2012; Westerman, Bonnet, & McAfee, 2014). While the possibility for such outcomes to manifest themselves cannot be questioned, they have hitherto mostly been of a hypothetical nature, and to the extent that they reflect reality, it has mostly concerned a few actors that are repeatedly referred to in the debate as successful examples (cf. Goes, 2014). Among other things, these actors tend to have highly digitized operations, to be data-driven companies, and to have been frequently, but not exclusively, born digital, i.e. having embraced digital technologies since their inception. Examples of such firms are Amazon, Dell, eBay, Facebook, Google, LinkedIn, Netflix, Procter & Gamble, Target, Tesco, UPS, Walmart, and Zara (Davenport & Harris, 2007; Manyika et al., 2011; Smith & Telang, 2016; The Economist, 2010; Westerman et al., 2014).

However, the vast majority of organizations, particularly incumbent organizations, which make up the largest part of the economy, are not yet conversant with big data (Goes, 2014; Sanders, 2016). While many of these organizations understand that they operate in data-rich environments, they do not understand how to exploit that data (Ross, Beath, & Quaadgras, 2013). Vendors who promote various sets of technologies (e.g., Frizzo-Barker, Chow-White, Mozafari, & Ha, 2016; Wang, Xu, Fujita, & Liu, 2016) that, they argue, can enable clients to manage big data through, for instance, big data analytics (BDA) operations, often do so by adding to the choir of simplistic and optimistic chants (e.g., IBM, 2011; IBM, 2012; Manyika et al., 2011). Frequently the various sets of technologies are offered as generic solutions to problems that are not easily identified as such by the incumbents. The level of confusion only increases in organizations that are considering

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buying a set of technologies as these sets form a rather fragmented landscape of technologies (Goes, 2014). Judging from the aforementioned exemplary companies, positive big data outcomes are related to systematic and coordinated efforts “as part of an overarching strategy championed by top leadership and pushed down to decision makers at every level” (Sanders, 2016:27).

Despite the attention and significance attributed to big data by scholars lately (e.g., Abbasi, Sarker, & Chiang, 2016; Agarwal & Dhar, 2014; Chen et al., 2012; George, Haas, & Pentland, 2014; Goes, 2014; Kallinikos, 2013), very little is known about how incumbents explore and, if possible, implement big data technologies and what challenges are associated with such endeavors. Yet, it is incumbents that stand to gain the most when such technologies, in various forms, are applied in their organizations (e.g., Gandomi & Haider, 2015; Varian, 2013).

This paper presents a study that contributes to closing this gap. The question driving our investigation is, how do decision makers at incumbents evaluate the significance of big data for their organizations? By “evaluate” we mean, how do they go about exploring a possible adoption of big data technologies? For instance, how do they explore the merits of these technologies as well as investigate and satisfy necessary organizational preconditions and requirements showing that the technologies will ultimately result in beneficial outcomes, should they be implemented? The overall purpose of this paper is to investigate aspects – challenges and opportunities – that drive incumbents toward a positive or a negative conclusion on the adoption of big data technologies.

Our empirical basis consists of a four-year field study of four Scandinavian incumbents. The firms are large, nationally and internationally operating organizations that all explored the possible adoption of big data technologies. We followed their key project leaders in charge of these projects through recurrent roundtable discussions, personal interviews, visits, and presentations. Our interaction with them granted us insight into these projects and into the challenges and opportunities faced.

The rest of the paper is structured as follows. In the next section, we provide background to the phenomenon of big data’s use in business and its rise in importance. Here we deal with big data’s ascribed characteristics and the essence of the phenomenon, which we argue is a new form of knowledge production. The section that follows explains our research strategy. In section four we begin with a brief background of the incumbents before we depict each of the incumbent’s efforts to explore the significance of big data at its organization. This within-case analysis is followed by a cross-case analysis in section five where our main findings are presented. Section six offers a discussion on the findings, before the final and concluding section.

2. The rise of big data

The information era (Beniger, 1986; Castells, 1999; Katz, 1988; Lyon, 1988) has been marked by increasingly pervasive digital technologies that have reconstituted organizational life and action. It has propelled the proliferation of data and has led to the formation of increasingly complex information environments in contemporary organizations (Kallinikos, 2006). While rich in data and information, organizations are many times poor in knowledge as they have difficulties turning that data and information into actionable knowledge (Caesarius, 2008). Efforts to harness data and capture their value have continuously been reported in the last decades (e.g., Caesarius, 2012; Chaudhuri, Dayal, & Narasayya, 2011; Davenport & Harris, 2007; Garcia Martinez & Walton, 2014; LaValle, Hopkins, Lesser, Shockley, & Kruschwitz, 2010). However, most of these efforts have yielded limited results and have been difficult or even impossible to sustain over time.

Big data is a product of the information era. It feeds off the everyday generation, storage, and distribution of voluminous sets of data, in widely varied formats, at extreme velocity, and with increasing granularity. This proliferation of data is prompted historically by several interrelated factors, all of which can be traced back to the introduction of compatible and interoperable digital mediating technologies (Kallinikos, 2011): first, the process of digitization that has been ongoing for decades following the infusion of information technology (IT) and increasingly more advanced database technologies in organizations (Kallinikos, 2006; Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007; Zuboff, 1988); second, the emergence and development of the Internet, when digitization entered in a first wave the personal sphere and instigated social and cultural changes (Kjaerulff, 2010) as well as introduced new communication capabilities, altered work conditions (Cramton, 2001; Hinds & Mortensen, 2005), and radically changed the possibilities for information management (Jacobs & Yudken, 2003; Zittrain, 2008); third, the advent of social media, when digitization entered in a second wave the personal sphere and permeated the everyday lives of people, introducing a participatory mode of culture (Bruns, 2008; Jenkins, 2006) that affected collaboration (Wagner & Majchrzak, 2007) and innovation (von Hippel & von Krogh et al., 2003); fourth and finally, the arrival of network-connected artifacts that operate without the need for human involvement, popularly known as the Internet of Things (IoT). These artifacts are network-connected, uniquely identifiable technical artifacts, primarily sensors like cameras and RFIDs, which can provide a combination of actions such as detecting, recording, and responding by default (Borgia, 2014).

Contrary to the phenomenon’s name, big data’s novelty rests neither on size nor on any other characteristic specifically but on what these characteristics collectively imply in terms of the complexity found in the data structures it represents, the manners by which the data can be captured, and the ways they can be managed (cf. Agarwal & Dhar, 2014; Manovich, 2011). Big data, therefore, is a new phenomenon in that it breaks away from previous and more traditional ways of dealing with data in organizations (Kallinikos, 2013). Traditional IT tools, instruments, and techniques used in organizations have not been designed to take advantage of big data (Constantiou & Kallinikos, 2015).

New technologies and solutions that permit BDA promise a different way by which to transform data into valuable, actionable, and even automated decision support (e.g., Markus, 2015). These technologies are often concerned with various forms of data operations such as data discovery, data integration, and data exploitation (e.g., Miller & Mork, 2013; Wang et al., 2016). However, while this is technically correct, it is fundamentally wrong to equate big data with data operations. The significance of big data has less to do with data and more to do with knowledge. Big data proposes an altogether new form of knowledge production that rests on the computational manipulation of complex data sets with algorithmic accuracy to generate insights that were previously deemed impossible (Boyd & Crawford, 2012).

This sounds like an intriguing proposal, but as with any knowledge production form, it has its limitations. For example, it relies on data that is often de-contextualized, much of it produced outside of the organization by a multitude of actors (and devices), and later aggregated for analytical exercises (Constantiou & Kallinikos, 2015; Kallinikos, 2013). In this case, equating “big” with “better,” “whole,” or “complete” is troublesome. Furthermore, claims on capturing reality truthfully by being inherently objective are questionable as not all of reality is quantifiable and not all that is quantifiable is a relevant representation of reality (cf. Porter, 1995). Besides, quantification does not surrender truths easily without interpretation. This knowledge production’s relationship to reality, which fundamentally drives incumbents’ interest in big data technologies, is governed by its modes of measuring. These modes are by default authorized to also alter or reshape reality, since measuring per definition involves applying a particular perspective through which reality can be detected, identified, and visualized. This new knowledge production form proposed by big data has, therefore, its intrinsic flaws. This, however, does not mean that it lacks merit; the benefits have been hailed by many and can appear rather obvious. The question is rather to what degree and under what circumstances these benefits surrender themselves to incumbent

Table 1
Basic data of the studied incumbents.
Source: Incumbents' annual reports, 2014.

Incumbent	Industry	Employees in thousands	Turnover in billion SEK	No. of countries with operations	Market position
A	Appliances	60–65	110–115	> 60	Market leader
B	Retail	5–10	25–30	1	Runner-up
C	Entertainment	< 5	5–10	1	Monopoly (segment)
D	Insurance	< 5	35–40	1	Market leader (segment)

organizations. These are questions hitherto unanswered.

While insightful, existing empirical research is limited both in number and in scope compared to conceptual research (Frizzo-Barker et al., 2016). Much of the empirical research, for instance, deals with big data in a highly abstract manner (e.g., Bughin, 2016; Chen, Preston, & Swink, 2015; Marshall, Mueck, & Shockley, 2015), builds on anecdotal evidence (e.g., Davenport, 2014), or is limited in its attention to incumbent organizations (e.g., Westerman et al., 2014). This, however, is not surprising as genuine big data outcomes in incumbents are in the making and have yet to largely materialize (Sanders, 2016). In general, such efforts are time consuming and resource demanding, and they deal with technologies that have the mandate to radically change incumbents by reconfiguring existing organizational arrangements. Being tools and instruments, big data technologies do not simply aid or automate the analysis of data but also have the capacity to transform the part of reality that they focus on (e.g., Kallinikos, 2009; Yoo, 2015a). The possible transformation that incumbents undergo when introducing these technologies can, therefore, be labeled open-ended as outcomes are largely unknown a priori. For instance, what initially may be an effort to create a digital representation of an analog reality, such as a process, can end up reconfiguring or even making the analog reality obsolete. The limitations of the physical world are not always reflected in the digital world. The reason is that digital artifacts are governed by a fundamentally different set of properties than their physical equivalents (Ekbia, 2009; Kallinikos, Aaltonen, & Marton, 2013; Kallinikos, Aaltonen, & Marton, 2010; Yoo, 2015b; Yoo, Lyytinen, Boland, & Berente, 2010; Zittrain, 2008). It is these properties that big data technologies draw upon to grant organizations the capability of conducting BDA operations: for example, efficient manipulation, modeling, testing, and experimenting with data in real-time, cost-effectively and in a highly distributed manner within and beyond the boundaries of the organization. Hence, introducing big data technologies is related to both financial and other risks that incumbents may be less inclined to take, particularly if the value in return is unknown.

3. Research strategy

To study the problem at hand we used a qualitative field study to generate a framework for understanding incumbents' exploration of the possible adoption of big data technologies (Yin, 1994). Our focus in this process was on identifying and defining the rationale behind decisions made leading up to the firms' choices about pursuing these technologies. To capture relevant information, we developed a mixed-methods approach combining roundtables with interviews, visits, and observations, and also secondary data.

In order to understand the development of the decision-making process, we needed a longitudinal study. As noted by Fichman (1992:197), "the organizational adoption … is not typically a binary event but rather one stage in a process that unfolds over time and the organizational decision process … frequently involves complex interactions between vested stakeholders." Longitudinal studies are characterized by permitting the "observation, description and/or classification of organizational phenomena in such a way that processes can be identified and empirically documented" (Kimberly, 1976:329). The processes in our study can be described as a series of interconnected processes that were led by individual actors (the project leaders) to ultimately reach a final verdict of introducing big data technologies or not, for the time being. Consequently, the project leaders' beliefs, assumptions, actions, and knowledge were assumed to be subject to change along the way, and as these factors changed, so too, it was assumed, would the outcome of the incumbent's involvement with big data. We therefore followed four firms for four years through the process of reaching a decision of whether or not to introduce big data technologies. We also continued beyond the decision when firms elected to go ahead with the adoption of big data technologies.

The participating organizations were self-selected: we presented an offer to participate in roundtables about big data to over 600 firms from a database of the largest Scandinavian firms and the largest local offices of international firms. In the end, 19 firms choose to participate in the roundtables, and we started the discussions during the autumn of 2012. Out of these 19, only four participated to an amount that made it possible to understand and analyze the rationales driving them forward. Project leaders of the other firms contributed with comments on the processes in the four focal companies.

The four firms (see Table 1) are representative of the Scandinavian industry structure and vary in size from about 5000 employees to close to 65,000. All companies are thus rather large from a Scandinavian perspective. The respondents had all been charged with handling the big data issue in their respective firm, and none of the firms had worked with big data technologies when the roundtables started. All respondents had been working with their firms for at least three years, and they all had positions that involved working with data manipulation, spanning from head of analysis to head of customer/consumer insight to head of development.

The problems of adopting big data are new to many organizations. All of the studied firms witnessed similar issues. Experience from other firms as well as academic knowledge was therefore assumed to have bearing on the situation at hand. We used a roundtable format to work on these issues, and formalized the format into six steps in the following manner (Davison, Martinsons, & Kock, 2004; Susman & Evered, 1978):

1 *Assessment of the situation (pre-roundtable)*; this was made following an iterative process where the firm representative (project leader [our respondent(s)]) and one of the authors defined and discussed the issue before the roundtable discussion. This stage included from one to three semi-structured interviews and discussions (lasting between 30 and 45 min) as well as e-mail conversations to define the challenges and main problems faced and to come up with the information needed by the other participants in order to make it possible to discuss the problem at the upcoming roundtable.
2 *Problem presentation (roundtable)*; the firm representative conducted a presentation of the challenges and main problems, followed by an academic perspective on the problem by one of the authors. This took approximately 2 h.
3 *Diagnosis (roundtable)*; the firm representative led a group discussion leading to a diagnosis of the situation. Participants were encouraged to use their own firm experience to help analyze the problem. This took approximately 2 h.
4 *Action planning (roundtable)*; the firm representative led group-wide action planning leading to a joint action planning document. This

took approximately 2 h.

5 *Action taking (post-roundtable)*; the firm representative (project leader [our respondent(s)]) took action. This was done after the roundtable.
6 *Feedback (post-roundtable)*; the next roundtable started off with a description of what had been done and the problems that had surfaced. Feedback was also provided by all other participants on their individual projects.

All in all, we carried out ten roundtables between November 2012 and June 2014. For each roundtable, one of the involved firms presented their big data challenges and main problems. Most of the firms wanted to discuss relevance for their organization, but without clear ideas on how to commence the initiation of BDA. Detailed notes were taken by two persons at the roundtables, as recording them would have made open discussions harder. The authors participated actively in the roundtables. Our main role in the groups was to provide generalized pictures of how BDA is used in various industries and to actively drive the companies toward a better understanding of the issues. We thus were active in co-creating an understanding about big data's use in business, but we attempted not to suggest to the participants any direct solutions on issues; rather, we attempted to function as something of a devil's advocate in scrutinizing their thoughts.

We followed up the roundtables with more in-depth interviews carried out between September 2013 and October 2014, and then with short but recurrent follow-ups on the progress until November 2016. These interviews were also semi-structured but different in scope from the pre-roundtable interviews. While the former were centered on specific issues that were currently on the firm representative's agenda before a roundtable, these additional interviews were more comprehensive in scope and encompassed queries on the whole process so far. The questions posed focused on understanding what the firms, as represented by their project leaders, thought about the adoption of big data technologies, what the challenges faced were, and (if applicable) how they were overcome. The interviews also covered issues that were unclear during the roundtables and issues that might have been sensitive to mention in the roundtables. Moreover, attempts were made to get a post hoc description of the exploration process as perceived by the respondents. Follow-up interviews were made to uncover new developments in the projects. The interviews were mainly conducted by phone and lasted between 30 and 90 min.

In these four firms, a total of 24 interviews were conducted during the data collection phase, of which eight were pre-roundtable interviews, six were shorter follow-up interviews, and the rest were more comprehensive in-depth interviews. All interviews were recorded when possible and transcribed; otherwise, detailed notes were taken. Notes were also taken from the observations. Extensive secondary data was collected from the companies in the form of annual reports, articles in the press, vendor case descriptions, presentations, and other available material about the firms. This made it possible to cross-check claims made by the respondents and hence increase the reliability of the empirical material.

The data analysis was carried out using the matrix suggested by Miles and Huberman (1984). In a constant comparison (Yin, 1994) we connected items that belonged together by examining transcripts and notes after each roundtable and interview. We thus tried to find patterns and code them into categories and themes used to create tables comparing the processes in the four firms. The categories and themes were developed for each roundtable until we reached a saturation point where no new themes surfaced. Emerging concepts were checked through the sample by using interviews, thus creating a more rigorous approach to developing the framework. These concepts thus functioned as sensitizing categories (Glaser & Strauss, 1967) that made it possible to see and structure the data. We also engaged in triangulation to increase the validity of the concepts in two ways: we used secondary data to check the emerging framework, and we used comments and questions from other participants who saw the phenomena in a different light. In the next section, we present the data and analysis in two steps: First, we briefly present the four incumbents and conduct a within-case analysis of the processes. Second, we present a cross-case comparison of the four cases.

4. The incumbents – background and within-case analysis

The four incumbents studied all have a long history of existence. All four were founded in part or through mergers during the early decades of the last century. They have all grown to become major domestic actors within their fields with the exception of one incumbent that has managed to become a major actor internationally. The domestically operating incumbents employ between 5000 and 10,000 people, while the internationally operating incumbent employs about 65,000 people. All four incumbents operate predominantly in consumer markets, albeit in different industries: home appliances, retail, entertainment, and insurance. Furthermore, incumbents A and B are goods-centered firms, while incumbents C and D are service-oriented firms. Being service-oriented firms, incumbents C and D have been identified as the two incumbents with the comparatively highest digitization level of their value chain. This means that the primary activities of their value chains are to a great extent carried out digitally or with extensive digital support (see Table 2).

4.1. Incumbent A

Incumbent A is a home appliance manufacturer and global market leader in its industry. The industry is rather fragmented with many local and global actors, but incumbent A is the largest. It has production and sales all over the world with the bulk of production in Asia and the bulk of sales in Europe and North America. Goods in most markets reach the customers' point of purchase through local distributors and retailers, which leaves the incumbent with no direct end-customer interface. Due to incumbent A's decentralized structure, company-wide projects such as big data have to get local approval from the divisions.

Incumbent A has been reluctant to adopt various underlying big data technologies in their products. Instead, it believes that the consumer-driven product development process should be applied to investigate whether or not add-on services of various kinds can indeed provide value to customers, before the incumbent starts to focus on the technology that can bring this about. Connected products could, for instance, help bridge the lack of end-customer interface and help establish a relationship with customers. This could create both better

Table 2
Products and value chains of the incumbents studied.
Source: Incumbents' annual reports, 2010–2014.

Incumbent	Product diversity	Customer interface	Primary activities of value chain (*excellence in italics*)
A	Diverse	Distributors	*R&D*, inbound logistics, *manufacturing*, outbound logistics, marketing and sales, service and aftermarket operations
B	Limited	Stores	Inbound logistics, operations, *outbound logistics*, marketing and sales, customer service
C	Limited	Stores, online	R&D, production, *distribution*, marketing, *customer service*
D	Diverse	Offices, online	*Ratemaking*, underwriting, *marketing and sales*, claims and reinsurance

customer and better product insight that could be used to deliver more value to the customer by, for instance, distributing individualized information on preventive maintenance, energy smart operation of products, and more. In comparison, some competitors have already taken a leap forward and are experimenting with various types of underlying big data technologies. Many have, for instance, embraced IoT; they have equipped and upgraded their products to enable the provision of new services such as security, surveillance, remote operation, and energy monitoring.

The respondent from incumbent A holds the position of head of customer insight. Being responsible for various market research operations, he was charged by his manager to look into BDA as a potential source for new revenues. The incumbent has a long history of working with traditional market research techniques like focus groups and surveys to better understand its customers, but it has also experimented with observation, especially when entering new markets. These labor-intensive techniques have served well in developing knowledge on how the products are used and what the customers want to get out of using them. Both the head of customer insight and the head of marketing had been pestered by vendors trying to sell various analytics tools and especially big data applications.

To better understand what working with BDA could entail, the respondent spent time exploring what incumbent A's competitors and similar manufacturing firms in the area were doing. The respondent concluded that no one was doing much in this area yet. Meanwhile, the incumbent's chief technology officer (CTO) had been looking at IoT technologies, which he believed could be critical for their products. With these technologies, the firm's appliances would be able to communicate with a wide range of products, creating a fertile basis for possible services to be developed in the near future. However, for such communication to be viable, there needs to be a common communication protocol. The incumbent therefore joined an alliance of technology companies to pursue this issue, but the results were disappointing, despite efforts to persuade manufacturers and technology vendors to settle for a common protocol. A common communication protocol is nevertheless inevitable. Working on IoT will lead to large volumes of new data being gathered, and as launching IoT will be accompanied by developing a new central IT infrastructure, the incumbent might soon see a new situation in which BDA can be an add-on technology.

A troublesome experience in the recent past with trying to implement a new, company-wide IT system added to the incumbent's reluctance to pursue new, large IT projects. Given the intricacies of such efforts spanning several decentralized business units, there would have to be a clear understanding of how these units would benefit before committing resources. As no such case could be made, the respondent terminated further BDA inquiries.

4.2. Incumbent B

Incumbent B is a retailer that carries a range of fast-moving consumer goods through its extensive network of physical stores throughout the country of operations. The firm is a runner-up in an industry where the lion's share of the market is concentrated in a few large actors. Incumbent B has, despite its position, struggled for years with continuously declining market share, low profitability, and low brand attractiveness. A series of major cost-reducing decisions have made it hard to find resources for IT-related investments. The incumbent is in dire need of becoming more appealing both to current and to more profitable prospective customer segments, but it lacks both knowledge and the sets of products to become more customer-centric. The main reason behind this situation is the archaic strategy employed, which sustains a less effective organizational arrangement and marketing tactics that originated with the firm's inception.

Unsurprisingly, the marketing and sales department was first to identify significant opportunities with big data. BDA would help the incumbent understand current customers better and become a first step toward creating more value to them, which in turn could attract further customer segments. However, getting there would require major investments to modernize the firm's neglected IT infrastructure. Turbulence in the top management positions has made it difficult to make these kinds of strategic decisions, and one of many projects that have been put on hold has been the necessary overhaul of the incumbent's IT systems.

Big offline and online retailers like Walmart and Amazon are well known for their use of digital information to create value. In smaller markets, like the Scandinavian market, other mechanisms like economies of scale and access to prime locations have been more important. Fast-growing online retailing has forced incumbents to start looking at possibilities for using information to their advantage.

The respondent is the head of consumer insight. She has worked with different kinds of analytics for a long time in several organizations. Joining incumbent B, she realized that using analytics was not prioritized; instead, keeping an influential group of longstanding customers happy was. This group was, however, getting older, with a majority being retired. As a consequence, customers were slowly declining in number and also buying less. According to the respondent, BDA could help turn around the negative sales trend, but a clear pilot case must be found with fast return on investment. Demonstrating that digital information could be used to increase revenues and lower costs could sway top management into making the necessary investments. The first step in starting to use analytics had already been made in that all point of sales (POS) data from all the stores are stored in a new database from which it is easier to extract data. It is a well-known fact in the firm that the digital infrastructure is not up to industry standard and that there is need of an overhaul. Changes, however, have to be adapted to a storyline of possible cost savings, and thus necessary investments in a modern database and modern analytics have to be framed as a way to cut costs.

By using data from the POS database, the firm could identify products that would probably appeal to customers and that are often paired with other products. The method of analysis for finding these products is not BDA, but to sell the idea of investing in an IT infrastructure in which BDA could be carried out, the project leaders framed it as being a big data project. As the average purchase amount of the customers who got these offerings increased, the project leaders could show that analytics can affect the bottom line.

The next project is to transfer inventory and shelf data to the new database and to invest in further layers of analytic capability to be able to handle shelf space and distribution more efficiently. This project has been touted as a way to decrease costs by needing less shelf space in stores without losing sales. The project managers have managed to get approval for this project as well, and if it is successful they have a larger third project in mind that will truly make it possible to start using BDA in the firm.

The incumbent is thus using not BDA but BDA-adjacent technology to create value for the organization. This stepwise process is necessary in order to get resources in a firm that is fighting to stay afloat. By selling the projects as big data projects, the managers hope to build up a contemporary IT infrastructure that can be used to run BDA and thus exploit information to create value for the firm.

4.3. Incumbent C

Incumbent C operates within the gambling and betting industry in one Scandinavian country. It is a state-owned firm enjoying a monopoly position in certain segments. The market has been strictly regulated, but the competition has changed decisively since entertainment services went online, particularly when they became accessible through mobile phones. Major foreign actors entered the market, often operating from countries with laxer rules and regulations, drawing customers away by offering more attractive terms and conditions.

The new actors are born digital companies: they use state of the art technologies to conduct BDA operations in order to analyze customer behavior and to improve their offerings. Compared to its competitors, incumbent C is in a dilemma. Regulations require the incumbent to generate profits while simultaneously combatting gambling addiction. Incumbent C therefore competes under terms that impede pursuing the same strategies as the new entrants, which seek to maximize profits. Every new product is subject to governmental approval, and the government's restrictive nature makes business expansion difficult to achieve.

The limited mandate to change has turned the firm conservative and unwilling to instigate major transformation processes. However, fear of losing relevance in a new global market is driving parts of the incumbent to work toward transforming the firm. To them, BDA is an important tool to gain a better understanding of customer behavior, which in turn would create a basis for better customer service. Should the firm not invest in such technologies and not change its way of carrying out business, they argue, it will in the long run risk losing market share to foreign actors. Yet, other parts of the incumbent do not recognize the need to adopt such technologies, as they understand the owner of the incumbent to be happy with their performance as it is.

Considerable resources have been spent in the last few years digitizing the value chain to cut costs and to create a more flexible business model. During the process, weaknesses were revealed in the IT architecture, and a new CIO with experience in digitization was hired and given the mandate to continue the work. The CIO decided on an open-source IT platform that would grant the incumbent flexibility and make it possible to use BDA to compete. The IT platform was used to develop systems for fraud detection and for the identification of customers with destructive gaming behavior. BDA is today also used to monitor various systems and to provide early warnings when systems are strained, thus making it possible to avoid system failures and create a stable IT environment for all involved actors.

There are thus successful projects in-house that could be used to deal with the main problem: the customer interface and the creation of new products that appeal to a younger customer segment. The firm has picked the low hanging fruit by using BDA on relatively small internal datasets where speed is of essence and where the new technology can create information used by small departments with high competence in the area of analytics. In doing so they have created dispersed units with competence and technology, but without much interaction. There is, however, a high degree of uncertainty on how to take the next step. How does the firm go about using BDA to enhance the gaming experience of its customers and develop new products?

The manager in charge of this project, our respondent, is a business developer with considerable experience from working with digitization and analytics, but with limited experience of big data applications. He was charged to find ways to use BDA to enhance the customer experience and to connect to the younger clientele the firm had lost to its competitors.

The three big data projects (on fraud detection, identifying risk behavior, and avoiding system downtime) were all straightforward and could have been done using other analytics platforms. Winning over the younger customer segment was a more difficult project for the respondent. He researched the subject and contacted vendors working with competitors for information. He concluded that incumbent C had to offer mobile betting, where most of the young customers' betting is done. This was in stark contrast to the incumbent's dominance in the segments of older and less tech-savvy customers who prefer to use computers or betting shops.

Launching a mobile platform in the form of apps for Android and iOS phones was a successful move. The incumbent also succeeded in making the apps easy to use for existing customers. Their website interface, developed originally for customers with an Internet connection, had become popular, and the incumbent wanted to keep the mobile interface as similar as possible. The first mobile version launched was a web app and the second a hybrid app that is still in use today.

Competitors use native apps. Compared with hybrid apps, native apps can be used offline, have more functionality, and make it possible to collect more data on customers and their betting and gaming habits. Our respondent, therefore, proposed a new native mobile app to be launched together with a set of new games to attract new customers. The app could help collect data on how, when, and where people used it, thus creating a better understanding of various customer groups. This knowledge could be used to develop new offerings and enhance the gaming experience of the customers. But neither the owners nor the top management were interested in this solution. They decided instead to further develop the hybrid app. The respondent's plan was aborted, and he decided to leave the firm as he felt he lacked the support to make necessary investments and the freedom to develop new games.

Incumbent C thus has the IT platform in place to work with big data applications, but internal issues with governance, organizational silos, and unclear directives from the board and owners have hindered it from taking the next step.

4.4. Incumbent D

Incumbent D is an insurance firm operating in a Scandinavian country. The firm is a market leader in its segment, and like many competitors, it has entered other parts of the financial services industry. Today it offers a wide range of financial services to both private and business customers. During recent decades, the industry has witnessed significant growth, increased deregulation, and the entrance of major global competitors. Despite its modest size compared to other European markets, the industry is home to a number of small actors, but the majority of business is in the hands of a few large companies, among them incumbent D.

Any technology that can help harness the value of the massive amounts of structured and unstructured data that the incumbent collects is of significant interest. Not only is the data vital to the incumbent's business operations that rely heavily on decision support, the incumbent's data management is subject to both national and international laws. Consequently, how it collects, stores, and analyzes data affects the outcome of its whole value chain. For instance, risk management, value assessment, and fraud detection – all central to the firm's operations – rely on data.

"Local" discussions about big data among different groups in the incumbent initially failed to gain management's attention, as much of their strategic focus was on ensuring compliance with newly introduced legislation. Eventually, however, C-level executives picked up these discussions and quickly realized that BDA could provide the incumbent with fundamental advantages. They assigned a project group the task of not only exploring these technologies but also developing and implementing them. Rightly designed, they argued, BDA could change the currently centralized, manpower-heavy and time-consuming process of providing decision support to the firm's many decision makers. Decision support could become decentralized, continuous, and to a large extent automated and hence both faster and more accessible throughout the organization. This could serve the incumbent in many ways; better, faster, and more accurate decisions could be made throughout the firm that would benefit both the incumbent and its clients. Compared to the other three incumbents, incumbent D managed to push the furthest with a systematic and coordinated effort to develop and implement big data solutions in its IT infrastructure.

The respondent from incumbent D is the head of the analytics department, a unit that provides decision support to the many decision makers. Decision support prior to the big data effort meant producing physical and Excel-based reports. The actual process was centralized and the responsibility solely that of the analytics department. Typically, the department would receive a request for a report on a topic. The respondent would examine the request, investigate the information sources needed, and assign the task to one or more analysts, who would then manually search for the information in the IT systems and put together the report. Today, three years later, the work conducted at the analytics department is different. The department focuses more on information provision to decision makers than on conducting analyses themselves. Big data technologies have contributed to creating a new analytics environment where the analytic capability is more distributed and to a large extent automated.

For the analytics department, the nature of today's decision support has meant going from working independently and in a rather isolated fashion to working in close collaboration with the IT department and with numerous external sourcing partners in order to bring real-time information to decision makers. Much of the respondent's work today concerns development and maintenance of the analytics environment's IT systems. Consequently, new competencies have had to be acquired and developed not least for the employees at the analytics department, such as advanced IT competence, particularly about how to develop, implement, run, and maintain BDA systems.

Initially, the phenomenon of big data gained the respondent's attention because officers in the firm are responsible for keeping themselves updated on issues within their domain. Hence, he was not assigned the task at first, but the obligations of the role he held made him actively try to make sense of the phenomenon. Discussions with colleagues (particularly in the IT department), vendors, and other external partners followed. After all, the respondent said, the media buzz about the subject made it difficult to ignore. But the media buzz only resulted in his attention. What pushed him to further understand the significance of big data was the internal information processing procedure at incumbent D. This procedure became an important driver that eventually led to the firm's exploration process. The incumbent was using an old and cumbersome procedure based on a vision that every single piece of data collected, structured and unstructured, had to be restructured and categorized. On paper the directions were simple, but in reality, the process was cumbersome given the limitations of the incumbent's traditional IT tools and instruments. Realizing that this procedure was doomed to fail was the single most important driver to begin analyzing the significance of big data. Furthermore, the then-existing analytic capacity was highly limited. For instance, the databases used a language that did not allow for advanced searches. In the worst case, the respondent said, doing a search would turn up no results, and the analytics department would not know how to proceed.

The growing data flows pressured the incumbent to find a better solution. For instance, legislation requires the incumbent to log all data produced on its websites. In case of an error, the incumbent must be able to "rewind" customers' actions. The incumbent analyzes customer behavior online to increase the efficiency of the customer interface and of offers made, which produces large amounts of data that have to be stored every day. The significance of big data slowly but steadily became obvious to our respondent.

The call to explore the adoption of big data technologies also came from other groups within incumbent D, such as from controllers, insurance officers, and claims adjusters. Thus, what started as "local" discussions eventually got the attention of the management, and a formal project group was created, co-driven by our respondent, and assigned a relevant budget. The group consisted of a mixture of people ranging from IT administrators and IT developers to officers with different functions.

It became clear to our respondent that using big data was all about developing and completely upgrading the firm's decision-support environment in order to provide the right decision maker with the right information, at the right quality and at the right time. Big data solutions could help alleviate the pressure, and the analytic capability could become distributed and to a large extent automated. Instead of providing the other departments at the incumbent with reports, the analytics department would focus on delivering relevant and real-time information to them. Information provision then would replace analysis and the production of various forms of reports.

Not only was the project group to evaluate technologies and investigate organizational preconditions, it was also given the mandate to go ahead with the development and implementation. The reason was simple: those making decisions needed information about the deals and cases they were working on, such as the information to prepare for a customer meeting, to monitor customer profitability, to support additional sales, or to analyze how well a campaign had worked. The benefits, therefore, were clear to a large majority of the employees before the adoption commenced.

The focus during the exploration as well as the development and implementation processes was mostly technical in nature; it was about dealing with legacy systems, conflicting systems, and databases as well as dealing with the complexity of having multiple data structures. Not much effort was spent on non-technical tasks such as developing user competence, adding new roles, changing the value chain, or making organizational arrangements. According to our respondent, these aspects were not necessary at the time, because much of the firm's operations were already digitized, with the roles set and the value chain prepared for data-driven operations. Users worked on deals and cases using a number of IT applications and systems, but the decision support was outdated, manual, and slow. Now, the new analytics environment combines information from multiple sources and provides users real-time information through a simple interface. This, our respondent said, makes decision makers feel more in control of the deal or case they are working on at the moment.

5. The incumbents – cross-case analysis

The studied firms represent four distinct approaches to exploring the possible adoption of big data in incumbent organizations (see Table 3). We have one incumbent that lacks both the willingness and the technological capability to explore (incumbent A), one incumbent with the willingness to explore but lacking the technological capability (incumbent B), one incumbent lacking the willingness to explore, but with the technological capability (incumbent C), and one with both the willingness and the technological capability to explore (incumbent D).

Affecting the four approaches are variations in the key conditions identified: first, the digitization of the value chain, which affects the recognition of and later the utilization of the advantages that big data technologies bring with them; second, the in-house technical competence that can help bridge the current and future states of the incumbents' technological capability by connecting solutions to problems;

Table 3
Studied incumbents' distinct approaches and key conditions to introducing big data.

	Approach		Key conditions		
Incumbent	Willingness to explore	Technological capability	Value chain digitization	In-house technical competence[a]	User competence[a]
A	No	No	In part	Poor	Poor
B	Yes	No	In part	Poor	Poor
C	No	Yes	All parts	Fair	Fair
D	Yes	Yes	All parts	Good	Fair

[a] Scale used: very poor, poor, fair, good, very good.

and finally, the incumbents' user competence that can turn hypothetical advantages into realized benefits.

5.1. Willingness to explore

The willingness to proceed with an exploration is an important first step in incumbents' sensemaking process of big data. Without it, incumbents may face difficulties understanding the significance to their organization. This, in turn, hinders incumbents from translating the generic solutions (systems, applications, etc.) offered by vendors and other external developers into solutions for specific problems, prohibiting the introduction of big data into incumbents.

In our cases, the willingness to proceed with an exploration rests primarily on two interrelated yet distinct aspects: a sense of urgency and/or a sense of opportunity. We find that the former aspect can be driven by both internal as well as external factors, while the latter is driven only by external factors, since opportunity is connected to what new technology can bring about when introduced into an existing setting.

One significant internal factor driving the sense of urgency mentioned by our respondents is the need for increased efficiency to stay competitive. This need concerns finding alternative ways of conducting operations in order to achieve better performance: doing things right; that is, faster, better, and hence more cost-efficiently. Competitive pressure, on the other hand, is identified as a significant external factor that drives the sense of urgency. This parallels the notion found in previous research. For instance, research on technology adoption in general and IT adoption in particular suggests that competitive pressure is a powerful driver of IT adoption (Banerjee & Golhar, 1993; Gibbs & Kraemer, 2004; Jeyaraj, Rottman, & Lacity, 2006; Ramamurthy, Premkumar, & Crum, 1999; Son & Benbasat, 2007; Teo & Ranganathan, 2009; Zhu, Kraemer, Xu, & Dedrick, 2004). Finally, a significant external factor driving the sense of opportunity and mentioned by our respondents is the benefits associated with big data technologies. Previous research on technology adoption has emphasized a positive relationship between perceived benefits and technology adoption (e.g., Iacovou, Benbasat, & Dexter, 1995; Lin & Lin, 2008). However, some studies have found perceived benefits to be insignificant (e.g., Chau & Tam, 1997; Lian, Yen, & Want, 2014). Many of the explanations focus on issues that do not rely on the technology per se; for instance, poor recognition of the benefits due to limited knowledge, myopia, or resistance to change (e.g., Anderson & Tushman, 1990; Barden, 2012; Gibbs & Kraemer, 2004).

The four incumbents vary in terms of willingness; two have the willingness and two lack the willingness to proceed with exploring the introduction of big data. This variation is related to how weak or strong their sense of urgency and sense of opportunity are.

In the case of incumbent A, the (lack of) willingness to proceed is based both on a weak sense of urgency and on a weak sense of opportunity. The first step of our respondent to evaluate whether or not to proceed with an exploration at all was to examine what competitors do and what similar manufacturing companies in other industries do. When he concluded that neither competitors nor similar firms were doing much, he stopped further efforts. Meanwhile, his colleague, the incumbent's CTO, saw equipping the firm's products with IoT technology as an opportunity for the firm to add value through additional services to customers. He pursued the standardization of IoT, since a future exploration process was contingent on a common protocol for manufacturers and technology vendors. When this protocol failed to transpire, the CTO stopped further efforts. Thus, for incumbent A, the aspects of urgency and opportunity were both weak. Furthermore, the main driving factors of both aspects were external: for the sense of urgency, the adaptation and use of big data technologies among competitors, and for the sense of opportunity, the common protocol among manufacturers and vendors.

For both incumbent B and incumbent C, there is a sense of urgency and willingness to pursue based on a sense of opportunity in parts of the organization. The individuals in these parts are driving the process to the best of their abilities, but top management in both organizations lacks a sense of urgency and a sense of opportunity because of its poor understanding of the technologies. Organizational factors are thus slowing down the process: the proponents are trying to demonstrate how BDA can be an important part of the solution to the long-term survival of the organizations, while top management has other priorities. In incumbent B the drivers are trying to create a sense of opportunity by introducing small-scale analytics project with clear positive outcomes with a belief that by demonstrating the value added to the organization they will get the necessary resources to update the IT infrastructure in the firm. This renewal of tools would make it possible to introduce BDA into the organization and thus add value in other parts of the value chain as well. In incumbent C the process of introducing BDA has taken a different path. The firm had digitized most of its business processes, but with layers of legacy systems, it was hard to run the IT infrastructure in an efficient manner. The IT department was constantly busy solving other problems, but renewing the IT infrastructure was a priority. The newly hired CIO, who had a good reputation in the business, managed to push through a major investment in new systems and software, which could be used for BDA. The other top managers see the opportunities to some extent, but they want to focus on other aspects of the business model.

In contrast, the willingness to proceed in the case of incumbent D is based on both a strong sense of urgency and a strong sense of opportunity. Both aspects are driven primarily by internal factors and are directly related to the incumbent's vital decision-support environment. The sense of urgency was driven first by an information-processing procedure at the analytics department, which the respondent identified as outdated and soon to fail given the increasing data flows and amounts of information that needed processing. Second, the analytic capacity of the current IT infrastructure was limited and did not allow advanced operations. Third, there was a call by several groups within the firm such as insurance officers and claims adjusters for better decision support. These and other minor factors created a strong sense of urgency in incumbent D, positively affecting its willingness to explore the introduction of big data. Our respondent also highlighted the opportunities in the sense of benefits that big data technologies could bring to incumbent D. Using big data technologies, a completely different decision-support environment could be developed that would decentralize analytic operations and move them from the analytic department to the firm's decision makers. The decision-support system would be equipped with automated analytic features that rely on real-time information but also permit users to pursue analytic investigations manually through a range of built-in tools and access to information stemming from various parts of the value chain as well as from outside sources. The sense then of opportunity, in this case, revolved around the technology being able to possibly provide the right decision maker with the right information, at the right quality and at the right time. Thus, for incumbent D, the aspects of urgency and opportunity were both strong, which resulted in the willingness to explore and introduce big data.

5.2. Technological capability

The incumbents' technological capabilities, here understood as the existing set of digital technologies (current IT infrastructure in the broad sense), and their affordances play an important role in the exploration of big data, since these factors may limit the scope and pace of the exploration and of possible future introduction (Collins, Hage, & Hull, 1988). Existing sets of technologies create path dependencies that resist change due to, for instance, increasing returns of investment over time and network externalities (e.g., Dosi, 1997; Shapiro & Varian, 1998). The technological capability is closely linked to the incumbents' level of digitization through the affordances of the technologies in use, which limit what activities can be operated digitally and the fashion by which they can be operated digitally.

In our cases, all four incumbents had digitized parts or most of their value chain. Digitization of primary activities constitutes a basic requirement for the introduction of big data. Without it, the introduction becomes a more cumbersome effort, since it must be preceded by a process of digitization. Having only parts of the value chain digitized with no further effort to digitize the rest of the value chain creates a risk of poor recognition of the potential benefits of BDA during exploration as well as fragmented implementation and use of BDA later. The latter may in turn result, as Sanders (2016) notes, in unclear advantages and a lack of real insight and competitiveness. Furthermore, digitization is not a homogenous act, and the manner by which primary activities are digitized may affect the outcome of BDA operations. Primary activities that make up the value chain are themselves composed of various processes. For instance, marketing and sales involve numerous processes; the former includes market research and market communications, while the latter includes prospecting, needs assessment, objection handling, and more. How these processes become digitized or the form of digital support they receive affects the affordances of BDA operations.

5.3. Technical and user competence

All of our respondents acknowledged that introducing big data technologies in their organizations would not only require an overhaul of their existing IT infrastructure (hardware, software) but also in various degrees new competencies, both temporary and permanent. The former relates to the period of transformation and includes primarily external partners such as vendors and consultants, while the latter relates to the post-transformation period and includes new competencies in the form of new employees or the support of existing employees to develop new skills. While incumbent D followed a path of relatively ordered development of technical competence paired with hiring new staff and training existing staff to handle the new tools, the other three firms displayed a more disordered process. Employees need to adopt and use the new technology in order for the firm to realize the benefits (Jasperson, Carter, & Zmud, 2005). However, the adoption of big data technologies entails a technological shift that may affect competence. According to Tushman and Anderson (1986), such shifts can be competence-enhancing for some organizations, but competence-destroying for other. Furthermore, one single organization can experience both effects simultaneously. For existing firms, the shift is usually destroying some competencies that thus demand unlearning (Hedberg, 1981; Nystrom & Starbuck, 1984), while simultaneously enhancing other competencies. Moreover, access to technical competence is an enabling factor when introducing new technologies (Attewell, 1992). Tambe (2014) showed that investments in big data technologies rendered higher returns in geographical areas with access to plenty of technical expertise like San Francisco (Silicon Valley) and New York (Silicon Alley).

Incumbent C has gone through a digitization of most of the value chain and thus transformed organizational arrangements to include extensive IT support at all levels. However, the mindset of managers in the firm is still set to earlier arrangements, and as results in the form of profit levels are still satisfactory, the future problem of competitors taking market share from the firm has not necessitated change, in the view of those managers. The technical competence developed at lower levels in the firm frequently clashes with the lack of technical competence at higher levels, and hiring a new CIO was seen as a step in the right direction, but besides handling the IT infrastructure, the new CIO has not managed to change the view of how the company should use said infrastructure to develop a new business model. Incumbents A and B, on the other hand, have low technical and user competence as both companies need to digitize large parts of the value chain to be able to reap the potential benefits of big data tools.

Research has consistently indicated that executive behavior, influence, and support are crucial for the adoption of technological innovations (Armstrong & Sambamurthy, 1999; Bassellier, Benbasat, & Reich, 2003; Jarvenpaa & Ives, 1991; Jeyaraj et al., 2006; Leonard-Barton & Deschamps, 1988; Lian et al., 2014). Often-mentioned rationales behind this argument are that executives as decision makers can ensure resource allocation sufficient to meet the needs of an adoption process, and that executive-level management can endorse important organizational changes (Tushman & Nadler, 1986) and can champion the adoption and use of particular innovations that can help reduce organizational resistance (Bassellier et al., 2003; Thong, Yap, & Raman, 1996). Hence, executive-level support is essential for the adoption of big data technologies, particularly in firms that risk becoming subject to substantial change processes. However, this support is conditioned by the level of knowledge and experience the executive members possess about the innovation and its advantages (cf. Armstrong & Sambamurthy, 1999). In our four cases, only the respondent at incumbent D managed to get strong executive-level support. While he emphasized that management's knowledge about big data was limited initially compared to that of the big data project group's, it did grow during the effort, particularly as the business case became more clear. This translated into resources being allocated not only for the exploration of a possible adoption but for the adoption itself.

The case at the other three incumbents was different. The respondent in incumbent A was convinced that he would not be able to get this necessary executive-level support in the foreseeable future, and therefore the drive to introduce BDA halted before it could get any traction. In incumbent B the respondent, as well as other drivers in the company, used subterfuge to get IT infrastructure in place that could be used for BDA: the proponents called analytics projects big data projects even though they did not use BDA. In incumbent C the head of IT used an overhaul of a partly obsolete IT infrastructure to include tools that could be used for BDA, and also has the organization use these tools for analytics projects that could have been carried out without BDA.

6. Discussion

At incumbent firms, respondents' typical initial response to the phenomenon of big data is to try to make sense of it. As the initial confusion about what the somewhat elusive technology entails gives way to an understanding of the general area, the respondents start to struggle with the meaning for their organization. However, understanding the significance for their organization is difficult. The generic solutions offered by vendors are not translated into solutions to specific problems without considerable effort. These efforts include investigating the merits of the technologies, their preconditions, and how the preconditions can be satisfied in relation to the operations of the incumbent, before deciding on a possible adoption. Such efforts are, needless to say, vital for the adoption of big data technologies in incumbents. They hold the power to assign practical relevance to an otherwise abstract phenomenon that is surrounded by many illusive claims about the qualities it holds. Without such efforts, respondents and other actors stand little chance of understanding the value that big data technologies can bring to their organizations. Without this clear understanding of the local consequences, it is almost impossible to go beyond the considerable hype surrounding the concept of big data. But once an understanding develops, it is possible to verbalize the possible benefits to the organization in a way others can understand.

In addition to local consequences, actors at incumbents must understand the costs to the organization as well as to significant actors whose work and position will be affected by adopting big data technologies. Each of the four companies in this study has a long and at least partly successful history, and the person proposing changes to the way business is done must prove there will be benefits. Part of the process of making sense of what investing in the new technology can do for the firm is, therefore, to find ways to demonstrate these benefits to others.

Because such investments can be sizeable, few incumbents will risk investing without an assessment of what they can get in return.

Our four cases represent four distinct ways of handling the problem of demonstrating that the benefits of adopting big data will outweigh the costs, and thus gaining support for the adoption. The respondent from incumbent A claimed that it would be impossible to show the benefits in a conclusive manner, and therefore the adoption process was never started. At incumbent B, the respondent and others could not get the necessary investments to demonstrate the benefits, so they did something else and called it big data. At incumbent C, the respondent adopted big data technologies and used them for processes where other technologies would have sufficed, to demonstrate big data's viability. At incumbent D, the respondent together with colleagues managed to get support for making the necessary investments to start working with big data technologies and could proceed.

These four ways of handling the exploration of and resistance to adopting big data technologies can be developed into a typology: the first is *capitulation*, the second is *subterfuge*, the third is *expansion of an investment decision,* and the fourth is a *normal investment decision*. The elusiveness of the concept of big data makes it both harder to demonstrate what it is and how it can benefit the organization, and easier to frame adjacent phenomena as big data. The hype around big data gets firms to look into the technology, while the opaque nature of the technology makes it hard to understand the costs and benefits in situ.

The first situation, capitulation, arises when the driver sees considerable opposition to change, simultaneously with a lack of external motivating factors and a lack of internal, top-management support. If competitors are successfully using big data technologies, that gives the respondent leverage in discussions with significant actors. And, even if top management tasks someone with looking into the possibilities of using big data, there might be no support for making changes. The second situation, subterfuge, arises when there is a lack of top management support but the drivers are heavily invested in adopting the technology. The drivers will use the means at their disposal to demonstrate the viability of the technology, even when they lack the necessary resources to do so. The third situation, expansion of an investment decision, arises when an investment decision can be amended with technology that the driver believes in. Once the driver has access to the technology, he needs to demonstrate its viability to be allowed to take the next step. The fourth situation is a typical investment situation. The drivers gain support for an investment decision and work to realize it.

In the cases, we see two parallel sensemaking processes in the respondents: making sense of the meaning of the technology and of possible applications within the organization, and making sense of the costs and benefits as seen by significant actors in the organization. For the respondent from incumbent A, the understanding that it would be difficult to get acceptance for an adoption without a clear proof of concept combined with the difficulties of finding applications that could be realized without substantial investments in hardware, software, and competence led him to halt the process. At incumbent B, much of the sensemaking was connected to understanding the technical and competence demands, realizing what their competitors were doing, and seeing how far the organization could be pushed in making investments in new technology as well as in hiring and developing competence. At incumbent C, the sensemaking process revealed that the rest of the organization had a poor grasp of what the new technology could be used for, and that this lack of understanding could be used to develop an IT architecture within which it would be possible to work with big data applications. Incumbent D had a continuous sensemaking process as the technology was implemented.

The elusiveness of the concept of big data can be both confounding and liberating for the respondents. In the beginning of the process, they all attempted to understand what it was; the respondent at incumbent A continued to ask the question, "what is big data?" through the process. For the respondents from incumbents B, C, and D, this same elusiveness was liberating after the initial confusion, as they could define big data in a way that suited their goals. At incumbent B, big data was about gathering and analyzing customer data; at incumbent C, it was about handling platforms for consumer interaction and use; and at incumbent D, it was about carrying out work processes in a more efficient way.

We also see that the significance assigned to big data by an incumbent depends on the incumbent's exploration effort. Such efforts require, at least initially, both a willingness to explore a possible adoption of big data technologies and a technological capability that can help further define and concretize what an adoption might entail for the incumbent, and that can support a future adoption. In our cases, we have identified the willingness to explore to be driven by a sense of urgency and/or a sense of opportunity. The sense of urgency can, for instance, stem from internal pressure to increase efficiency in the incumbent's primary activities, or from external pressure such as that from competitors who pursue the adoption of the same or similar technologies in their value chains. The sense of opportunity relates to the identification of advantages that these technologies can bring about directly or indirectly to the incumbent if introduced. A strong sense of urgency and/or a strong sense of opportunity creates viable incentives, and hence a willingness to proceed with an exploration.

The willingness to proceed is only part of what affects incumbents' efforts to understand the significance of big data to their organization. The other part is the incumbents' technological capabilities: the existing digital technologies used in their primary activities and what these technologies can afford. Since big data technologies are digital in nature, they rely on and draw upon what an existing digital infrastructure can provide. Hence, incumbents with a low level of digitization have difficulty translating generic solutions into solutions to specific problems with any precision. Such a translation will be more hypothetical in nature, risking a less clear understanding of the technology's significance to the firm.

Incumbent D showed that an incumbent that assigns big data a high significance also seems to view big data technologies as transformative. This incumbent has a clear understanding of the technologies' merits, and of the preconditions and requirements of the organization and how these can be satisfied. If it pursues the adoption of such technologies, it understands the implementation and use of them as a way to increase both efficiency and effectiveness in the organization's primary activities. In contrast, incumbents who ascribe big data limited significance view such technologies as add-ons or patches that can be applied to their existing set of technologies and can lead only to efficiency-enhancing effects in their operations. Such a fragmented implementation and use can lead to the technologies delivering limited value in return.

7. Conclusion

We set out to show how incumbents evaluate the significance of big data for their organizations and to investigate aspects – challenges and opportunities – that drive incumbents toward a positive or a negative conclusion on the adoption of big data technologies. Considerations about adopting new technologies have many similar traits across incumbents, like uncertainty about the meaning of the new technology and uncertainty about how to adapt organizational processes to the new technology. Big data is to some extent different in two aspects: the concept is elusive and can mean different things to different firms, and it can have a transformative effect on the organization of work in the firm. This elusiveness makes it difficult to explain what the technology means but also opens up possibilities of defining the technology in creative ways, thus making it possible to gain support and funds to introduce it. The transformative capability of big data makes managers wary as it might threaten their position in the firm, and creates ripple effects, transforming other systems besides those directly connected to the technology.

To gain a better understanding of the transformative effects of big data, we need to study more incumbent organizations that have gone through the transition. Incumbent D, however, is one of few such companies we have been able to identify. The transition seems difficult for incumbent firms to complete, as so few manage to go through it. Gaining support in an organization for introducing the new technology seems to demand a logic connected to exploitation, effectiveness, and efficiency, while calls for exploration and development often falls on deaf ears. This is somewhat of a paradox as the technology is sold by vendors mainly as a tool for exploring data and information (cf. March, 1991).

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