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Debating big data: A literature review on realizing value from big data

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ABSTRACT

Big data has been considered to be a breakthrough technological development over recent years. Notwithstanding, we have as yet limited understanding of how organizations translate its potential into actual social and economic value. We conduct an in-depth systematic review of IS literature on the topic and identify six debates central to how organizations realize value from big data, at different levels of analysis. Based on this review, we identify two socio-technical features of big data that influence value realization: portability and interconnectivity. We argue that, in practice, organizations need to continuously realign work practices, organizational models, and stakeholder interests in order to reap the benefits from big data. We synthesize the findings by means of an integrated model.

1. Introduction

Big data has gained significant impetus as a breakthrough technological development (Fichman et al., 2014) in academic and business communities (Chen et al., 2012). Big data can be defined based on large *volumes* of extensively *varied* data that are generated, captured, and processed at high *velocity* (Laney, 2001). As such, these data are difficult to process using existing technologies (Constantiou and Kallinikos, 2015). By adopting advanced analytics technologies, organizations can use big data for developing innovative insights, products, and services (Davenport et al., 2012).

The opportunities arising from big data analytics[1] for organizations are considered pivotal: big data has been described as, "the mother lode of disruptive change in a networked business environment" (Baesens et al., 2014, p. 629). By adopting big data technologies, organizations expect to gain benefits across many domains, such as e-commerce, e-government, science, health, and security (Chen et al., 2012). What benefits organizations perceive as "value" depends on their strategic goals for adopting and using big data (Ghoshal et al., 2014).

In this paper, we refer to both social and economic value. Social value includes improved social wellbeing in fields such as education (Cech et al., 2015), healthcare (Raghupathi and Raghupathi, 2014), and public safety and security (Newell and Marabelli, 2015). Governments, for instance, can use big data to, "enhance transparency, increase citizen engagement in public affairs, prevent fraud and crime, improve national security, and support the wellbeing of people through better education and healthcare" (Kim et al., 2014, p. 81). Thus, social value comprises benefits for single users as well as larger societal benefits such as employment growth, productivity, and consumer surplus (Loebbecke and Picot, 2015).

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[1] We consider "analytics" to be a part of processing the data and one of the potential first steps in trying to realize value from big data.

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Economic value can be measured by an organization's increase in profit, business growth, and competitive advantage resulting from big data adoption (Davenport, 2006; Davis, 2014; Tyagi, 2003). Economic value often comprises monetary benefits that are appropriated by organizations. For example, organizations that rely on big data to guide organizational strategies and day-to-day operations are expected to perform better financially than organizations that do not (LaValle et al., 2011; McAfee and Brynjolfsson, 2012).

In general, big data is perceived as a source of innovative products, services, and business opportunities (Davenport et al., 2012; Davenport and Kudyba, 2016; McAfee and Brynjolfsson, 2012). Moreover, big data is believed to result in more efficient and effective operations by, for example, optimizing supply chain flows; setting the most profitable price for products and services; selecting the right people for certain tasks and jobs; minimizing errors and quality problems, and improving customer relationships (Chen et al., 2012; Davenport, 2006; McAfee and Brynjolfsson, 2012). Additionally, further economic and social value can be gained from big data through enhanced decision making (Sharma et al., 2014) and more informed strategizing (Constantiou and Kallinikos, 2015).

Thus, both the academic and practitioner-oriented literatures are characterized by a strong focus on the opportunities that big data provides for organizations (Clarke, 2016). However, high hopes and extensive publicity regarding big data do not guarantee the gaining of actual value, and may lead organizations to believe they can gain more value from big data than they are actually able to realize in practice (Ransbotham et al., 2016; Ross et al., 2013). Because initial discussions about the phenomenon are characterized by ungrounded optimism[2] (Arnott and Pervan, 2014), we need to analyze how organizations translate, as well as fail to translate, its potentials into actual social and economic value (Markus and Topi, 2015). Specifically, we are in need of research that analyzes what strategies organizations create to realize value from big data.

In our study, we performed a review of IS literature that discusses organizational changes, drivers, and actions related to big data value realization at different levels of analysis. We respond to the call for focusing on the tensions organizations face in realizing value from big data (Galliers et al., 2015). Our contribution is threefold. First, we identify a total of six debates central to how organizations realize value from big data, at the work-practice, organizational, and supra-organizational levels. We call for empirical studies to show when, if, and how the opposing positions of each debate are relevant. Second, we identify portability and interconnectivity as two socio-technical features that influence how organizations realize value from big data in practice. Third, we argue that to advance theories on big data value realization, the IS field is in need of empirical studies that show how cross-level interactions play a role when organizations realize value from big data. As such, our study extends recent calls for research on the implications of big data use by organizations (e.g., George et al., 2014; Markus and Topi, 2015).

In the remainder of the paper, we begin by describing the methods used to conduct an in-depth systematic literature review. This will be followed by our findings, which we structured around six active debates in the big data literature, at the work-practice, organizational, and supra-organizational levels. Subsequently, we ask what features of big data shape value realization in the context of big data. Finally, we examine cross-level interactions and propose an integrated model that synthesizes our findings.

2. Methods

We performed an in-depth systematic literature review (Webster and Watson, 2002; Jones and Gatrell, 2014) focused on identifying active debates and generating detailed insights into the meaning of these debates. The review consists of search, selection, analysis, and synthesis processes. Our aim was to provide an in-depth analysis of the field rather than providing a descriptive overview (Jones and Gatrell, 2014).

2.1. Search and selection

We aimed to arrive at a set of papers that (1) focus on the adoption, implementation, or use of data (analytics) technologies *by organizations*, and (2) have specifically mentioned the term "big data" in the title, abstract, keywords, or body of the paper.

We began our review by searching within the AIS "basket of eight" IS journals.[3] To account for recent studies that had not as yet been published at the time of searching, we also examined the proceedings of three leading IS conferences: ICIS, ECIS, and AMCIS.[4] To expand our scope and check our coverage, we searched a number of additional IS journals and key journals from the fields of management and organization (see Appendix A, Table A.1). However, the majority of papers that met our criteria appeared in IS journals and the proceedings of the above conferences, indicating that the discussion thus far resides within the IS community for the most part. We considered papers available since 2000, given that this is when large volumes of unstructured data gained momentum (Chen et al., 2012), and up

[2] Receiving tremendous positive attention is typical for "IT hypes and fashions" in their initial stages (Wang, 2010; Swanson, 2012). This emphasizes the need for a critical reflection on how organizations realize value from big data in practice.

[3] http://aisnet.org/?SeniorScholarBasket, accessed 14-11-2014.

[4] ICIS: http://aisel.aisnet.org/icis/; ECIS: http://aisel.aisnet.org/ecis/; AMCIS: http://aisel.aisnet.org/amcis/.

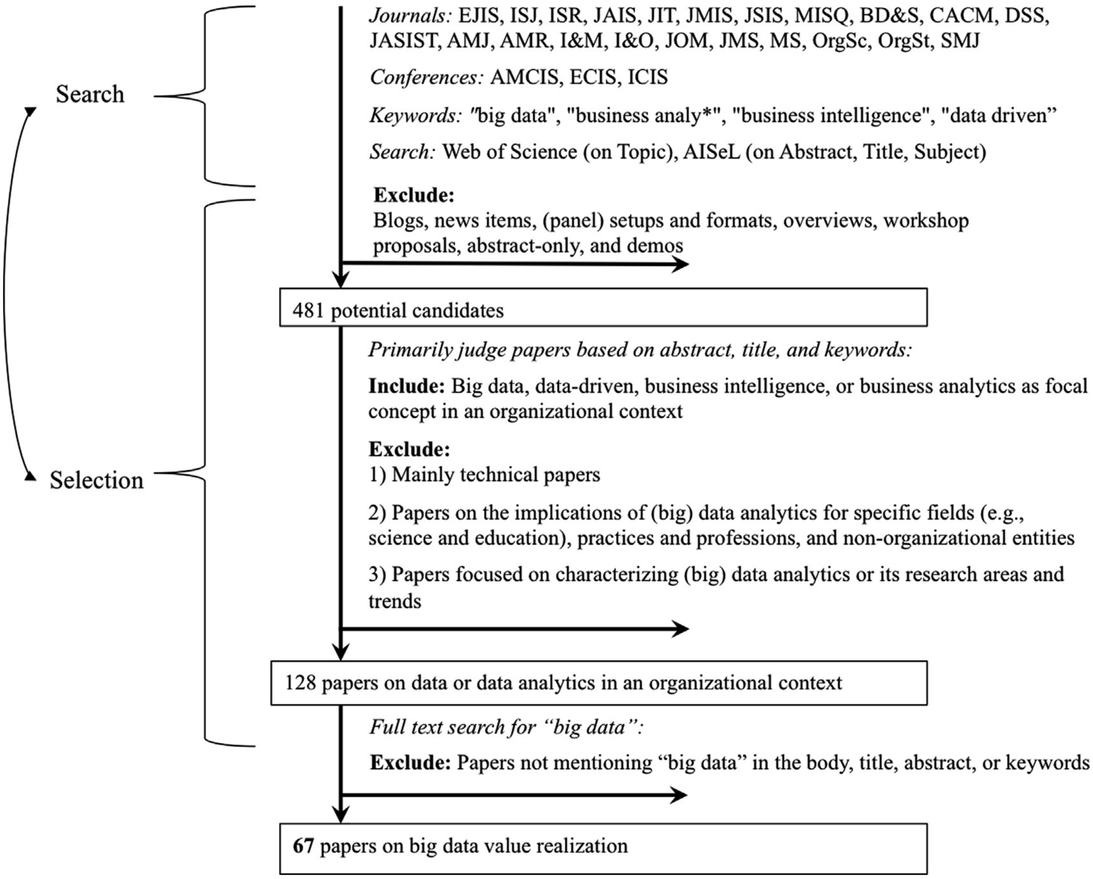

Fig. 1. Search and selection processes.

until the fall of 2016. For the conferences, we considered papers presented in the preceding four years (2012–2015), assuming earlier, quality papers would have reached a journal outlet.

We used Web of Science to search on "Topic" for the journals[5] and the AIS electronic library to search on "Title", "Abstract", and "Subject" for the conferences. We suspected that some papers would not have specified "big data" in the topic, title, abstract, or subject, but are about data or data analytics in an organizational context and could mention the term within the article itself. Therefore, we used three additional keywords to increase the number of potentially relevant search results (Boell and Cecez-Kecmanovic, 2015): "business intelligence", "data driven", and different forms of "business analytics". A detailed overview of the searches performed is shown in Appendix A, Table A.1.

The main selection process involved two rounds. In the first round, we primarily judged papers based on the title, abstract, and keywords. We included papers that treat one or more of the search keywords as focal concepts in an organizational context. In the second round—because our search and selection up until then had had this limited focus—we inspected the full texts of papers in order to check whether the term "big data" had been mentioned in the body of the text. In the case we were unsure about the added value to our focus, two co-authors debated the extent to which the paper addresses the role of organizations, the actual relation with big data, and the originality of insights into big data value realization. As a result of our selection process, we excluded many papers, of which a summary is presented in Appendix A, Table A.2.

Out of 481 potential candidates in the initial pool, we selected 128 papers that focus on data or data analytics in an organizational context. From this sample, 67 papers qualified for inclusion as they discuss how organizations realize value from big data (See Fig. 1). Of these, 19 papers were from the "basket of eight" journals; 33 from the three conferences; 14 from other IS journals, and one from management and organization journals (see Appendix B for an overview of the reviewed literature). The first paper meeting our selection criteria dates back to 2013.

[5] For *Big Data and Society*, we browsed the journal's archives. For the "basket of eight", we also updated our searches after the first revision of the paper, by browsing the journal websites and using their search options to search for relevant papers. See Appendix A, Table A.1 for the specifics.

2.2. Analysis and synthesis of the literature

Our analysis focused on summarizing and analyzing existing theories on big data value realization, highlighting prevailing debates related to this topic, and identifying supporting evidence and gaps in the literature (Jones and Gatrell, 2014). Our aim was to provide new insights that can contribute to future research and thus, to go beyond merely mapping or describing the current discourse. To this end, we engaged in an iterative process of open and selective coding, and synthesizing insights from the selected literature. In our analysis of the papers, we were guided by a review framework (see Appendix A, Table A.3) consisting of (1) the main research question; (2) how big data is conceptualized; (3) what methods are adopted; (4) what IT artifacts are studied in relation to big data; (5) what actions various stakeholders take to realize value from big data, including which drivers and contextual factors shape these actions at different levels of analysis; (6) what theories are used and developed; (7) limitations and suggestions for future research, and (8) the practical implications provided in the studies.

We analytically abstracted codes around *debates* related to how organizations realize value from big data at different levels of analysis (Baum and Rowley, 2005; Davern and Kauffman, 2000), that is, at the work-practice, organizational, and supra-organizational levels. First, by the *work-practice* level, we refer to what individual actors inside organizations *do* with big data in their day-to-day interactions. For example, actors collect and analyze data, discuss insights, make decisions, and act and interact based on data-driven insights. Second, by the *organizational* level, we refer to the structures, norms, resources, and procedures around which organizations coordinate their activities to achieve certain goals. For example, organizations leverage and change their structures, adapt their processes, and design new business models to realize value from big data. Third, by the *supra-organizational* level, we refer to relations with institutional and technological ecosystems (Zott and Amit, 2013), consisting of rival organizations, data providers, regulatory bodies, research institutes, users, and customers, with whom organizations interact. For example, organizations interact with other organizations hoping that they can mutually benefit from exchanging data, while dealing with societal concerns associated with big data.

For each debate, we articulated two opposing positions and examined the relevant actions that different actors take towards each side; the contextual conditions that shape the debates, and the potential implications for supporting or limiting big data value realization. In this way, we were able to articulate and formalize different and sometimes opposing theoretical perspectives, as well as practical tensions that organizations face in realizing value from big data. Summaries of the debates and their grounding in the literature are depicted in Fig. 2, and in more detail through exemplary quotes in Appendix C, Table C.1. We explain each debate in the following section.

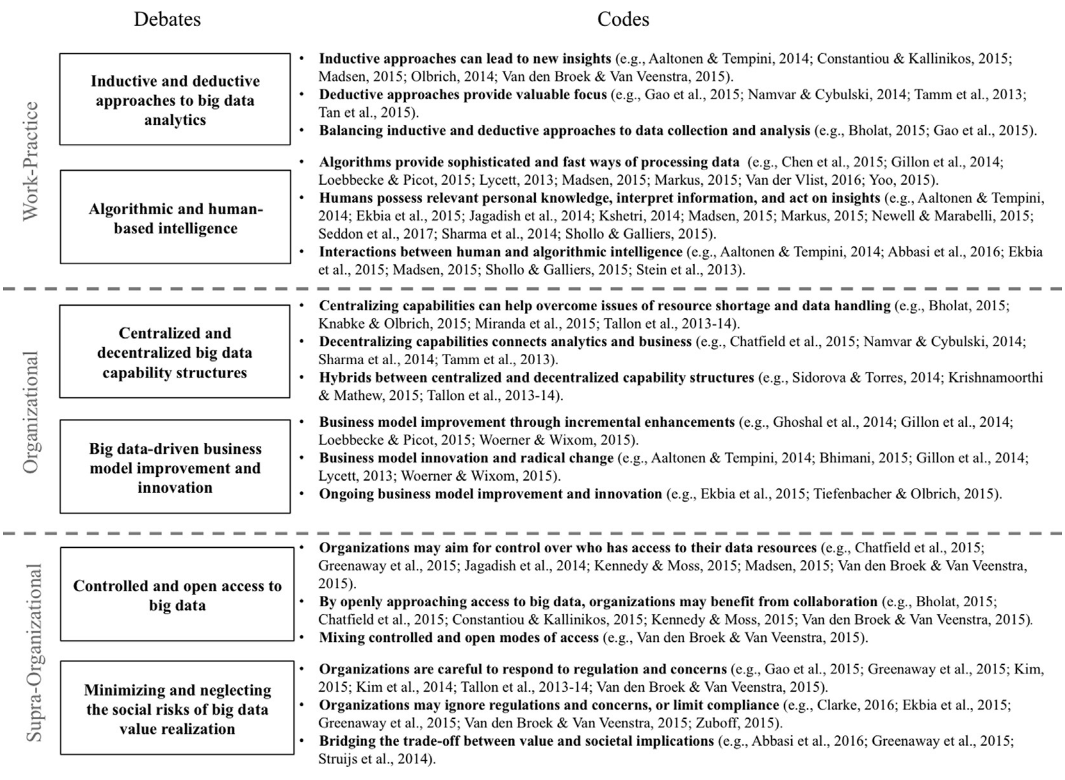

Fig. 2. Summary of debates related to big data value realization.

3. Six debates in the big data literature

We were able to structure insights from the reviewed literature into a total of six debates that form central challenges for organizations when they try to realize value from big data, at the work-practice, organizational, and supra-organizational levels.

3.1. Work-practice level: Working with big data in practice

At the work-practice level, we found two debates regarding how actors work with big data in day-to-day organizational practices.

3.1.1. Inductive and deductive approaches to big data analytics

It is widely acknowledged that "big data" comes from many different sources. These include sources from inside the organization, such as data from ERP systems and transactional data, and data from external sources, such as data offered by third parties, user-generated data, open data, and sensor data (e.g., Zuboff, 2015). As a consequence, data often have not been produced and collected for the same purposes they are eventually used for (Constantiou and Kallinikos, 2015; Newell and Marabelli, 2015).

Depending on the variety (Kim, 2015) and granularity (i.e., the level of detail) of the data (Yoo, 2015), it may be difficult to foresee which insights can be accrued from various data sources ex-ante (Aaltonen and Tempini, 2014; Constantiou and Kallinikos, 2015). The big data trend has created an attitude of collecting data without a pre-defined purpose, promoting a bottom-up, inductive approach to big data collection, exploration, and analysis (Constantiou and Kallinikos, 2015; Olbrich, 2014; Van den Broek and Van Veenstra, 2015). Such an approach "starts from data and then seeks to generate theoretical explanation" (Bholat, 2015, p. 4). For example, Madsen (2015) performed a study on how technological features of digital social analytics (a subset of big data analytics) influenced project work. This study illustrates through the case of one project leader that analysts can make sense of big data by clustering them into predetermined categories, or by choosing to accept categorizations based on computer-detected similarities that were not considered in advance. Such an inductive approach then allows for previously unknown patterns or distinctions (Shollo and Galliers, 2015) to emerge from big data (Aaltonen and Tempini, 2014). As such, data collected for one purpose may also be used for many other purposes, because these data can be combined and analyzed in new ways (Aaltonen and Tempini, 2014).

Tamm et al. (2013) interviewed business analytics experts for a preliminary assessment of their "pathways to value" from big data. Regarding the value of analytics-based advisory services, the experts in this study expressed concerns that insights gained by inductively approaching big data have to compensate for the efforts required to troll through the data without a clear focus or business case. Retention (Tallon et al., 2013–14) of and trolling through large amounts of unstructured data are considered expensive exercises, warranting a particular business focus (Gao et al., 2015). Such a focus may even be "essential for maximizing the likelihood of value realization" (Tamm et al., 2013, p. 12). Thus, scholars also acknowledge a more deductive approach to big data analytics that starts "from a general theory and then uses particular data to test it" (Bholat, 2015, p. 4). Such a hypothesis-driven approach is common, for example, in healthcare settings, where data are collected, processed, and visualized for specific purposes (Tan et al., 2015). A risk of such an approach is confirmation bias, which occurs when decision makers specifically look for data to confirm their hypotheses (Bholat, 2015). For example, a study on the use of data-driven insights—basing its results on interview data with consultants, developers, analysts, and decision makers using business intelligence in their practices—asserts that decision makers sometimes use analytics reports mainly to justify already considered options (Namvar and Cybulski, 2014).

Bholat (2015) argues that induction and deduction are, in practice, two ideal approaches that intertwine and complement each other, which implies the need to balance them. For example, analysts can be given some degrees of freedom to inductively arrive at innovative and creative ideas, but specific boundaries can simultaneously be set around projects they are working on to ensure that business value is delivered (Gao et al., 2015). It can be argued that the extent to which induction and deduction are balanced in practice partly depends on the influence of pre-existing frames of reference, or mindsets, of those who interpret the data (Lycett, 2013; Sharma et al., 2014). This raises the issue of algorithmic and human-based intelligence, which is another debate at the work-practice level.

3.1.2. Algorithmic and human-based intelligence

When processing and interpreting data, human actors can be influenced (Stein et al., 2013), for example, by time constraints and skepticism with regard to relying on data (Namvar and Cybulski, 2014); team compositions (Sharma et al., 2014); visualizations of input and output (Ekbia et al., 2015; Lycett, 2013); relational versus analytic and evidence-based mind sets (Holsapple et al., 2014), and historical insights (Seddon et al., 2017[6]). To mitigate such influences, scholars and practitioners have begun to explore the potentials of *algorithms* that are able to process big data at ever-increasing speeds. Algorithmic intelligence has gained popularity along with the rise of big data and current advancements in technology, and organizations are increasingly able to rely on such intelligence to analyze big data (Madsen, 2015; Newell and Marabelli, 2015).

[6] Although we refer to the print version of the paper by Seddon et al. (2017), an online version of the paper was available at the time of searching.

Arguments in favor of algorithmic intelligence are that algorithms "guide analysts to innovative analytic concepts and categorizations" (Madsen, 2015, p. 11) while avoiding preconceptions and pre-established distinctions (Van der Vlist, 2016). Algorithmic processing generally follows fixed, pre-programmed procedures (Aaltonen and Tempini, 2014; Kallinikos and Constantiou, 2015), but can lead to patterns and insights that had not been considered ex-ante (Madsen, 2015). In the case of artificial intelligence or sophisticated machine learning algorithms, procedures even improve over time (Van der Vlist, 2016). Scholars have referred to many examples of algorithmic intelligence, such as algorithms developing traffic models (Jagadish et al., 2014, p. 91); IBM's Watson (Markus, 2015); self-driving cars (Newell and Marabelli, 2015); fraud detection algorithms (Sharma et al., 2014); loan processing algorithms (Chae, 2014), and recommender systems (Lycett, 2013). Algorithms seem increasingly capable of predicting human behavior in real-time, no longer using data for descriptive ends only, but also for prediction and prescription (Gillon et al., 2014). Alongside big data, algorithms allow for increased automation of operational and strategic decision making (Loebbecke and Picot, 2015; Markus, 2015), which have traditionally been considered complex and therefore requiring human judgment (Chen et al., 2015; Gillon et al., 2014). In situations where algorithms are deployed to operate without human intervention, they actively "shape the world", which gives algorithms an increasingly performative character (Lycett, 2013; Yoo, 2015, p. 64). This is, for example, the case when algorithms learn from and make real-time decisions based on clicking behavior, thereby simultaneously influencing user behavior (Newell and Marabelli, 2015).

Scholars also emphasize the importance of the human intelligence (Ekbia et al., 2015) that is required to examine data and patterns (Seddon et al., 2017), and to derive, deploy, and refine insights (Sharma et al., 2014). Madsen (2015, p.12) found that in some cases of digital social analytics, analysts are "guiding the automated algorithm to reflect categories that are recognizable in the context in which they are going to have an impact". Likewise, Kshetri (2014) argues that human expertise is needed to solve problems for which the conditions are unknown, such as unforeseen environmental conditions. Moreover, Shollo and Galliers (2015) describe how business intelligence stakeholders—interviewed in a study on the role of business intelligence in knowledge creation—agreed that data should be supplemented with human experience, common sense, and contextual knowledge that are hard to capture by data. Indeed, some scholars contend that too much reliance on algorithms by decision makers may lead to a loss or replacement of such relevant knowledge, particularly when it is not clear how algorithms arrive at certain results, patterns, and decisions (Markus, 2015; Newell and Marabelli, 2015). Aaltonen and Tempini (2014) observed in their case study at a mobile network operator that constructing an audience from network data, which can be sold to advertisers, largely depends on data exploration by human operators. Their study shows that, albeit building on algorithmic calculations, humans need to develop strategies to gain insights from big data beyond a number of stable metrics. For such reasons, Jagadish et al. (2014, p.8) argue that big data analytics processes "will be designed explicitly to have a human in the loop".

Both types of intelligence have strengths and weaknesses, and in many cases, still augment each other (Abbasi et al., 2016). Therefore, it is proposed that organizations need to devise ways to meaningfully balance them (Ekbia et al., 2015). To this end, scholars have started to explore the interaction between algorithmic and human intelligence and how this leads to valuable insights. Madsen (2015), for example, focused on how project leaders working with digital social analytics interact with the technological features of a data environment. Likewise, Shollo and Galliers (2015), in their study at a financial institution, considered the interplay between analytics systems and users, and how this interaction facilitates organizational knowing. Aaltonen and Tempini (2014) observed how both data-driven technologies and humans played a role in analyzing network data, and Stein et al. (2013) have paid specific attention to human agents and their interactions with data-driven classification systems in arriving at relevant insights. Power may play a role at this level, too, as those individuals with the ability to make sense of and effectively integrate insights into their practices may be more influential in decision making (Shollo and Galliers, 2015), and shape how organizations leverage the potential of big data (Bhimani, 2015).

In sum, scholars considering big data at the work-practice level debate how different actors work with and gain potentially valuable insights from big data. Although a number of studies have based their argumentation on empirical evidence (e.g., Aaltonen and Tempini, 2014; Madsen, 2015; Namvar and Cybulski, 2014; Shollo and Galliers, 2015; Tamm et al., 2013), many theoretical arguments are provided at this level. Additionally, it is questionable whether the debates at the work-practice level are unique, as we can see some of their roots in the IS literature. Specifically, the debate around human and algorithmic intelligence seems as old as the field of machine learning. Indeed, Simon (1968, p. 623) emphasized the importance of information processing systems and the inclusion of "human members of organization who constitute the other half of the system". Likewise, the general role of technologies in automating and "informating" the workplace has been addressed in earlier studies, as well as the related distinction between "smart people" and "smart machines" (Zuboff, 1985). This might mean that it remains to be seen whether big data actually leads to changes in work practices that differ from what other technologies such as knowledge management systems have already brought about. As of yet, it remains unclear under what particular conditions organizational actors are able to generate insights through inductive or deductive approaches, or a combination of both. Nor is it clear what specific contributions human and algorithmic intelligence add to the creation of insights in different situations (e.g., stable and routine practices versus emergent and temporal situations).

3.2. Organizational level: Developing organizational models

We identified two debates at the organizational level regarding how organizations develop big data capability structures and change their business models to realize value from big data.

3.2.1. Centralized and decentralized big data capability structures

Many capabilities are proposed in the literature that enable accessing, tracking, collecting, managing, governing, processing, and analyzing big data for data-driven decision making and implementation purposes (Işik et al., 2013; Jia et al., 2015; Jiang and Gallupe, 2015; Kung et al., 2015; Wang et al., 2014). To develop such capabilities, organizations need to find ways to effectively "develop, mobilize and use" the technical and human resources (Peppard and Ward, 2004, p. 182) related to big data. Specifically, organizations face questions regarding not only how to acquire or develop technical and human resources (Brinkhues et al., 2015; Tambe, 2014), but also how to structure them in teams or departments.

On the one hand, the development of analytics *competency centres* has been considered an effective approach to centralize resources in order to deal with the shortage of analytical skills (Davenport et al., 2010 in Sharma et al., 2014). A competency centre is "a centralized unit housing expertise in business analytics and providing a service to business units" (Sharma et al., 2014, p. 436). Such centralized structures may decide on the roles, processes, and governance related to data intelligence (Knabke and Olbrich, 2015). For example, the Bank of England initiated an "Advanced Analytics Division with the objective of establishing a centre of excellence for the analysis of Big Data" and a "Data Lab" for data storage, manipulation, visualization and analysis of granular, unstructured data that employees can visit (Bholat, 2015, p. 2). Moreover, in a study on how information is governed by organizations experiencing data growth, interviews with executives from different organizations imply that centralization eases the adoption of data governance, whereas decentralization makes it difficult to govern data across organizational units and departments (Tallon et al., 2013–14). Likewise, a recent study on IT innovation diffusion asserts that big data itself is, in essence, not *decentralizable* due to security issues; the notion that big data is a key resource to be overseen by one Chief Data Officer; increased communication costs; the need for synergistic collaborations and central buy-in, and the need for expensive complementary technologies, skills, and knowledge (Miranda et al., 2015).

On the other hand, although the idea of centralized capability structures seems promising, their effectiveness has also been questioned (Tamm et al., 2013). Specifically, they may not "connect very well to business units" and make it difficult "to convert their insights into value through competitive actions by business units" (Sharma et al., 2014, p. 436). Centralized structures potentially limit communication with and the involvement of different business stakeholders in big data projects (Sharma et al., 2014). Such interaction is, however, acknowledged as being important to big data value realization. For example, results from a survey among business intelligence users, developers, and managers confirmed that different perceptions of these stakeholders have to be taken into account when initiating metadata management for big data analytics (Dinter et al., 2015). Moreover, one of the success factors in big data projects is the combination of different skills in multidisciplinary teams (Gao et al., 2015), particularly for the purpose of business-analyst engagement (Sharma et al., 2014). In a study on the use of business intelligence for decision making, business intelligence stakeholders expressed concerns regarding this engagement and highlighted the importance of close communication in order to arrive at shared understanding between stakeholders (Namvar and Cybulski, 2014). Even though decision makers are increasingly expected to be able to perform their own analytics (Tamm et al., 2013), they often still require the help of analysts to explain results and meanings (Namvar and Cybulski, 2014). In the age of big data, "analysts must now truly engage business" (Olbrich, 2014, p. 3), which implies the need to place data analysts close to the business (Chatfield et al., 2015).

When designing for analytics, organizations may assess the synergistic benefits of centralized capability structures, as well as recognize the need for specific expertise associated with decentralizing (Sidorova and Torres, 2014). Hybrids between centralized and decentralized structures have been suggested as a viable compromise (Tallon et al., 2013–14). For example, in a research facility, policies on information governance were set centrally, whereas independent researchers were allowed to hire their own staff to deal with issues such as storage administration (Tallon et al., 2013–14). Another example of what can be considered a hybrid is described in a case study on how analytics contributes to business value at a US-based technology firm that has an offshore central analytics division with several departments catering to specific business needs (Krishnamoorthi and Mathew, 2015). The study describes how business divisions were free to find analytics services elsewhere, yet had the ability to lean on the analytics division when the need surfaced.

3.2.2. Big data-driven business model improvement and innovation

There is some considerable acknowledgement in the literature of data being a potential key resource of organizations' business models (e.g., Abbasi et al., 2016; Struijs et al., 2014). Business models "are reflections of the realized strategy" (Casadesus-Masanell and Ricart, 2010, p. 204) and representations of how organizations create and appropriate value (Teece, 2010). Whereas startup organizations are taking advantage of low barriers to entry and are able to more easily set up new data-driven business models (Loebbecke and Picot, 2015), for incumbent organizations, this means having to rethink their existing business models and how these may be affected by big data (Gillon et al., 2014).

One way of using analytics is by accessing new data sources and techniques, and consequently acting to improve existing processes in terms of efficiency and effectiveness (Ghoshal et al., 2014; Woerner and Wixom, 2015). For example, IBM has implemented a database system to link its employees, which it uses "to improve knowledge sharing and efficiency around the organization" (Gillon et al., 2014, p. 291). This approach implies that organizations can leverage big data while generally continuing to function in the same manner, only more effectively and efficiently: "incremental enhancements to established business models through increased digitization and big data analytics may replace less efficient business models (and thereby companies) in the long run" (Loebbecke and Picot, 2015, p. 151).

Organizations also *innovate* their business models when big data leads them to *inter alia* develop whole new value propositions, target different customers, or interact with customers in different ways. This was the case at the mobile network operator at which Aaltonen and Tempini (2014) performed their case study on how actors make sense of big data. The organization realized it could construct an advertising audience from its network data, which it could subsequently sell to advertisers as a new value proposition. Moreover, Netflix is a fashionable example of an organization that overruled its traditional business model and moved from a disc rental model to a streaming model, now even producing data-driven content (Lycett, 2013). Specifically, Netflix now offers media streaming to customers, constructs dynamic recommendations based on users' behavioral patterns, and uses data to inform content for its productions. Other examples include Nike, which has moved from being solely a shoe manufacturer to a digital platform owner for data-driven fitness services, and The New York Times, a traditional newspaper that has invested in data experimentation and is now using data to engage readers in a digital environment (Gillon et al., 2014). These examples illustrate that organizations innovate their business models to monetize data or insights by selling and trading them, or by enhancing customer experiences through new value propositions (Woerner and Wixom, 2015). In other words, big data allows organizations to radically alter their business strategies (Bhimani, 2015) and to move into new industry contexts (Woerner and Wixom, 2015).

Studies show that, in capitalizing big data through business models, improvement and innovation approaches can be mixed and even happen in sequence. For example, a 4-stage big data maturity model has been proposed, suggesting that organizations should first reach functional excellence and are only able to reach business model transformation in the last stage (Tiefenbacher and Olbrich, 2015). Ekbia et al. (2015) consider the matter from a technological perspective and emphasize the relevance of systems such as Hadoop in their discussion on continuity versus innovation, as those systems are able to simultaneously work with both big data and more traditional data. Additionally, the extent to which organizations adopt big data (Agrawal, 2015) and are able to innovate is said to depend on the industry and the size of the organization (Ekbia et al., 2015; Gillon et al., 2014). Specifically, moving from one stage of big data maturity to another requires the development of capabilities (Tiefenbacher and Olbrich, 2015) for which mainly large organizations have the resources (Gillon et al., 2014).

In sum, at the organizational level, scholars debate what appropriate organizational models can be developed to create and appropriate value from big data. Yet, the literature appears scarce as to how this is achieved in practice. Whereas examples of centralized capability structures are given (e.g., Bholat, 2015), it is often not clear how these structures are put in place, how they interact with business units, or how they produce value. While some scholars emphasize the importance of more decentralized structures, few examples of such structures are discussed. In passing, it should be noted that the debate around centralized and decentralized control, facilities, and functions has a long history in the IS field and can be expected to continue regardless of the specific technological developments (King, 1983).

Additionally, business model improvement versus innovation seems to be a rising topic of discussion (Loebbecke and Picot, 2015; Woerner and Wixom, 2015), but such trajectories are generally not (yet) empirically studied. Specifically, the business model is often not the unit of analysis in longitudinal studies. This may not be surprising, as limited evidence exists thus far in terms of cases where there have been improvements in or innovations to business models based on big data (Gartner, 2013).

3.3. Supra-organizational level: Dealing with stakeholder interests

Beyond organizational boundaries, relevant stakeholders include: universities and research institutes (Struijs et al., 2014; Ekbia et al., 2015), governments (Chatfield et al., 2015; Kim et al., 2014), data providers (Greenaway et al., 2015), users, and customers (Constantiou and Kallinikos, 2015; Ekbia et al., 2015; Kennedy and Moss, 2015). We identified two debates in the literature concerning how organizations manage data access, and how they deal with stakeholder interests such as ethical concerns and regulation.

3.3.1. Controlled and open big data access

It is proposed that in order to benefit from big data, organizations rely on effective data exchange with their network of partners (Malgonde and Bhattacherjee, 2014) and engage in practices of data disclosure and screening to do so (Jia et al., 2015). In this respect, different inter-organizational governance modes have been identified, depending on the extent to which access to data is controlled or open (Van den Broek and Van Veenstra, 2015).

Organizations can be reluctant to share or exchange data with network partners (Kennedy and Moss, 2015) due to, for example, privacy and security concerns (Chatfield et al., 2015), or when data analytics is considered a source of competition and sharing endangers the organization's unique strategic position (Jagadish et al., 2014; Greenaway et al., 2015; Van den Broek and Van Veenstra, 2015).[7] For such reasons, organizations tend to control data access, which can be pursued in a number of ways. For example, ownerships and rights can be explicitly determined through market mechanisms such as formal contracting and selling, where data can be sold as raw data or traded for other products (Woerner and Wixom, 2015). Moreover, access to data and algorithms can be controlled in a hierarchical fashion where command lies with a dominant organization (Van den Broek and Van Veenstra, 2015). For instance, in a study on inter-organizational data collaborations across industries, the case of a retailer illustrated how one dominant organization can control data access by implementing a review board to deal with access requests (Van den Broek and Van Veenstra, 2015). On the receiving end, organizations can control data access by choosing to collect data from specific channels only, that is, those that are considered most valid, reliable, and robust (Madsen, 2015).

[7] See also, Marabelli and Newell, 2012; Trkman and Desouza, 2012.

Open modes of access are emerging in which data are made publicly available to organizations and consumers. Commercial organizations and governments can choose to open up data to, for example, stimulate innovation (Van den Broek and Van Veenstra, 2015) and provide transparency (Kennedy and Moss, 2015). For instance, the Bank of England, as part of its "One Bank Research Agenda", has committed to "opening up to the public previously proprietary data sets in order to crowd-source solutions to challenging policy questions" (Bholat, 2015, p. 2). Similarly, local governments in the US "have implemented open data portals to share its big data with citizens and businesses" (Chatfield et al., 2015, p. 2). In essence, when potentially everyone has access to data, as is also typically the case for social data, coordination in terms of production and sharing happens beyond organizational control (Constantiou and Kallinikos, 2015; Van den Broek and Van Veenstra, 2015). In these open modes of access, the data are structured by the IT infrastructure that "sets the rules for data production" (Madsen, 2015, p. 6). Yet, it is speculated that such infrastructures can be (deliberately) modified, thereby affecting the reliability and quality of data that are not provided or owned by the organization using them (Madsen, 2015), and potentially impeding their replicability (Ekbia et al., 2015). For example, social media organizations may not be transparent about how the data they make available through their interfaces are prepared or selected (Madsen, 2015).

Some evidence suggests that networks can be formed in which data are accessed through both open and controlled modes. For example, platforms can be leveraged to simultaneously control data access (e.g., selling to members only) and open up data (e.g., giving away for free) (Van den Broek and Van Veenstra, 2015). Organizations can also choose to share data based on trust rather than formal contracts (Van den Broek and Van Veenstra, 2015).[8] Communication and clear agreements between network partners are generally considered crucial in data collaborations (Kim et al., 2014). Moreover, consumers, users, and publics that are both data sources and recipients of data-based products are becoming increasingly active (Bhimani, 2015) and should be considered legitimate network participants as well (Constantiou and Kallinikos, 2015; Ekbia et al., 2015; Zuboff, 2015; Kennedy and Moss, 2015). As a consequence, organizations will also have to deal with the legal and ethical consequences of sharing and using data. For example, they may have to explicitly ask for user consent for sharing data. This raises another debate at the supra-organizational level.

3.3.2. Minimizing and Neglecting the Social Risks of Big Data Value realization

Whereas organizations consider big data as a *source* of value, *realizing* such value often also raises social risks (Clarke, 2016). For example, the practice of combining personal data sources can reveal very personal and sensitive information that is at risk of being released (Alshboul et al., 2015; Ekbia et al., 2015; Newell and Marabelli, 2015; Van den Broek and Van Veenstra, 2015). Similarly, the current trend to offer personalized products and services to customers based on big data analytics raises many concerns related to privacy, identity theft, illegal discrimination, unjust classification (Alshboul et al., 2015; Clarke, 2016; Ekbia et al., 2015; Markus, 2015), and even "exploitation of the vulnerable" (Newell and Marabelli, 2015, p. 6). Moreover, even though surveillance of individuals by governments and other organizations may lead to improved public control and safety, measures of surveillance also impede individuals' feelings of freedom, privacy, and autonomy (Newell and Marabelli, 2015). These examples show that, apart from regulation and legislation, organizations often have to deal with public expectations and ethical considerations in the process of realizing value from big data.

For industries in which organizations deal with highly sensitive data, such as healthcare, (Jagadish et al., 2014), or in which organizations deal with considerable governmental influence, such as education (Cech et al., 2015), regulations are strict and limit big data collection and use (Kim et al., 2014). Organizations can take extensive measures to comply with such industry regulations and avoid the risk of reputational damage resulting from illegal or unethical data use (Van den Broek and Van Veenstra, 2015). For example, to ensure that data access, sharing, and use are legally compliant and ethically responsible, organizations can control data access; implement risk management (Gao et al., 2015); carefully determine data purposes and advocate transparency (Van den Broek and Van Veenstra, 2015; Kennedy and Moss, 2015); explicitly ask user authorization (Kim, 2015); request user consent for sharing data; offer users control (Greenaway et al., 2015), and adopt strict governance practices (Tallon et al., 2013–14). In their interviews with individuals having data governance responsibilities, Tallon et al. (2013–14) found that organizations consistently put effort into developing data policies regarding, for example, data retention, security, and disposal. Indeed, some organizations consider the debates on privacy and ethics around big data as an opportunity to differentiate themselves from competitors on the basis of their privacy propositions (Greenaway et al., 2015).

In some cases, however, organizations pursue data-driven goals at the expense of users' privacy by choosing to minimally adhere to their rights, or even deliberately ignoring them (Van den Broek and Van Veenstra, 2015; Greenaway et al., 2015). For example, organizations can keep their policies secret or prevent customers from having a say in how their data are collected and shared (Greenaway et al., 2015). As in the case of an insurance company in which the privacy of clients was offset against scientific and societal goals (Van den Broek and Van Veenstra, 2015), organizations can specify in their terms of agreement and contracts that data are shared for certain purposes, yet not explicitly ask for user consent. Some organizations are criticized for taking considerable advantage of situations where regulation and legislation around big data lag behind (Zuboff, 2015), as is the case, for example, in developing countries (Kshetri, 2014). Opportunistic organizations collect and exploit data (Ekbia et al., 2015) until resistance is encountered or they face legal action (Greenaway et al., 2015). This has

[8] See also, for example, the special issue of The Journal of Strategic Information Systems on Trust in the Digital Economy (Sambamurthy and Jarvenpaa, 2002), and subsequent articles, such as, McKnight et al. (2017) and Xu et al. (2016).

been described as meaning that "many of their rights appear to come from taking others' without asking" (Zuboff, 2015, p. 83). As unethical big data collection and use might result in massive resistance when it becomes known to those affected (Clarke, 2016), organizations on this side of the debate consider privacy concerns as a problem rather than an opportunity (Greenaway et al., 2015).

Other organizations are attempting to find a middle ground in this debate. For example, some organizations choose to collect data for their own purposes, but do not sell these data on, or allow individuals to "opt out" on services heavily relying on personal data (Greenaway et al., 2015). In some cases, however, finding a balance is particularly difficult. This is especially the case when organizations are aiming to create social value, such as conducting big data-driven surveillance to improve public security, but are simultaneously compromising on other types of social value and privacy rights (Newell and Marabelli, 2015). As has been argued, "[t]here is a fine line between collecting and using big data for predictive analysis and ensuring citizens' rights of privacy" (Kim et al., 2014, p. 81). Questions arise such as to what extent are users willing to give up privacy in exchange for utility (Goes, 2015), what are the acceptable levels of intrusion, and how to find the right balance between infringement and big data value, especially when organizations do not know in advance what the data can be used for (Abbasi et al., 2016; Struijs et al., 2014).

To summarize, at the supra-organizational level, several stakeholders, including organizations, their competitors, partners, and customers, can mutually benefit from data being shared and combined. Data governance, that is, the arrangements around policies, procedures, and formal control, generally plays an important role when multiple stakeholders are involved (Van den Broek and Van Veenstra, 2015). Although questions concerning what arrangements to make with regard to data sharing, and how to deal with stakeholder interests in strategic partnerships, have traditionally been key issues (Konsynski and McFarlan, 1990), big data raises many additional concerns acknowledged by scholars. Whereas most of the discourse on big data has up till now revealed an optimistic tone, discussions around legal and ethical concerns such as data ownership and privacy mitigate this optimism. Many legal and ethical discussions revolve around the social risks when certain actors in an ecosystem (typically organizations) exert and exploit power over others (typically individuals) through big data analytics (Greenaway et al., 2015; Zuboff, 2015). However, thus far, empirical IS studies have barely touched upon how organizations deal with legal and ethical concerns in acceptable and innovative ways.

3.4. A critical analysis of the literature

Our review shows that the current literature is still at a nascent stage in terms of explaining how organizations realize value from big data. A number of notable papers focus on "paths to value" from big data, both from a theoretical (Sharma et al., 2014) and an empirical perspective (Gao et al., 2015; Seddon et al., 2017; Tamm et al., 2013). Moreover, several positive relations have been proposed between analytics-related capabilities and social and economic value (e.g., Chasalow and Baker, 2015; Côrte-Real et al., 2014; Krishnamoorthi and Mathew, 2015), mediated by several factors such as data-driven and analytical culture (Cao and Duan, 2014; Duan and Cao, 2015; Kulkarni and Robles-Flores, 2013); leadership commitment and user involvement (Kulkarni and Robles-Flores, 2013); the decision environment (Işik et al., 2013); enterprise architecture maturity (Van Hau Trieu, 2013), and the fit between tools, tasks, and people (Ghasemaghaei et al., 2015). Yet, the literature can still reasonably be characterized by its many speculations and opinions. As such, this calls for further empirical studies that carefully examine how organizations actually realize value from big data in practice. Specifically, future research needs to empirically examine how different actors within organizations work with big data in practice, how organizational models are developed, and how organizations deal with different stakeholder interests to realize value from big data. We suspect that organizations take different positions on each of the debates, depending on a range of factors, such as industry context and organizational size (Gillon et al., 2014). This calls for more empirical approaches that look at *when, if, and how* the opposing positions of each debate are relevant for organizations.

What position organizations take on each of the debates, and therefore how organizations realize value from big data in practice, also depends on what the technology *enables*. Therefore, we need to critically examine which features of big data influence such value realization.

4. Portability and interconnectivity as socio-technical features of big data

To deepen our theorization of how organizations realize value from big data, we critically ask: *What are the potentially unique features of big data that influence how organizational actors work with big data, develop organizational models, and deal with stakeholder interests in practice?* This critical reflection is intended to help us to better contextualize value realization with regard to big data use.

Much of the literature stresses the opportunities afforded by big data technologies by referring to the so-called 3 Vs: volume, velocity, and variety (Laney, 2001).[9] Since the conception of the 3 Vs, other scholars have added veracity (i.e., how much noise is in the data) (Goes, 2014), granularity (Aaltonen and Tempini, 2014; Yoo, 2015), and many other features[10] that have largely been associated with the technological functionality of big data. Although we do not overlook big data's technological features, we also take the organizational context into account, thereby answering a call for a more

[9] See, for example, http://whatis.techtarget.com/definition/3Vs.

[10] See also, Kitchin and McArdle (2016) for an overview of big data's ontological characteristics.

socio-technical characterization of big data (Markus and Topi, 2015). Drawing on the six debates discussed in the previous section, we formalize two socio-technical features that shape how organizations realize value from big data: *portability* and *interconnectivity*. We next discuss how portability and interconnectivity can be identified from the debates. Appendix C, Table C.2 provides grounding for this assessment.

With *portability* we refer to *the possibility to transfer and remotely access digitized data from one context of application to be used in other contexts* (e.g., Lycett, 2013; Tallon et al., 2013–14). For instance, a transportation company that has been collecting geographical data from vehicles navigating through cities can sell these data to organizations dealing with road maintenance to find locations that require repairs. As such, data that have been collected within one context can be assigned a whole different meaning when they are used by organizations in other contexts. Portability, thus, seems crucial in the context of big data where the focus is on leveraging large volumes of varied data from many sources, considerably beyond organizational boundaries (Zuboff, 2015). In essence, organizations "now have access to essential data needed to solve problems or gain insights that was not possible to collect before" (Woerner and Wixom, 2015, p. 60), as data can be transferred and remotely accessed across technological platforms and organizational boundaries.

At the work-practice level, portability allows analysts and decision makers to remotely access data or transfer these data to platforms, tasks, and institutional settings, without having a prior plan for collecting and using such data (e.g., Constantiou and Kallinikos, 2015). Human intelligence may still be needed to make a selection from these new data sources (e.g., Shollo and Galliers, 2015). At the organizational level, portability enables analysts and decision makers across the organization to perform their own analytics (e.g., Tamm et al., 2013), potentially in a decentralized fashion. Portability also facilitates the development of business models based on selling (partial) data sources (e.g., Woerner and Wixom, 2015), as data can be transferred to contexts of potential customers. At the supra-organizational level, portability allows for open systems of sharing and accessing data across organizations (e.g., Malgonde and Bhattacherjee, 2014; Van den Broek and Van Veenstra, 2015), while enabling potentially harmful practices such as sharing sensitive, personal data (e.g., Greenaway et al., 2015).

With *interconnectivity* we refer to the *possibility to synthesize data from various big data sources* (e.g., Malgonde and Bhattacherjee, 2014). In essence, sophisticated technologies (Chaudhuri et al., 2011) increasingly allow actors to integrate heterogeneous sources of data and extract insights from their combination. This enables organizations to go beyond the pre-existing templates of tapping isolated data sources by correlating and combining them in new ways (e.g., Lycett, 2013).

As synthesized data are "greater than the sum of its individual parts" (Bholat, 2015, p. 4), interconnectivity typically enables analysts and decision makers at the work-practice level to arrive at more insights by exploring connections (e.g., Shollo and Galliers, 2015). Moreover, whereas the ability of algorithms to connect data for finding patterns is supposedly superior to that of humans (e.g., Madsen, 2015; Van der Vlist, 2016), human creativity may also be important to connect and link data, leading to new insights being formed (e.g., Aaltonen and Tempini, 2014; Seddon et al., 2017). Thus, interconnectivity enables finding connections in data through the interplay between human and algorithmic intelligence. At the organizational level, the debate around centralization hinges on the feasibility of synthesizing data sources that are spread across various organizational departments (e.g., Miranda et al., 2015; Tallon et al., 2013–14). In addition, interconnectivity enables whole new value propositions as in, for example, the case of Netflix, where user data are now combined to inform the content of their new series (Lycett, 2013). At the supra-organizational level, interconnectivity empowers new partnerships and collaborations across organizations (e.g., Van den Broek and Van Veenstra, 2015), but also requires having to deal with public concerns. For example, correlating different data sources such as health and financial records may yield (re)identification of private, sensitive information (e.g., Ekbia et al., 2015; Van den Broek and Van Veenstra, 2015).

The opportunities created by both portability and interconnectivity influence how organizational actors work with big data, develop organizational models, and deal with stakeholder interests. Thus, future research needs to critically examine how they are exploited by organizations in practice. For example, a growing body of literature suggests that big data yields more *emergent* insights (e.g., Aaltonen and Tempini, 2014; Constantiou and Kallinikos, 2015), as portability and interconnectivity allow for patterns and ideas to *emerge* rather than being inscribed or even foreseen in advance. Yet, the literature also acknowledges that insights may not actually emerge if those who are actively using and making sense of big data are biased by fixed, extant mindsets, their current daily routines, and historical values and norms (e.g., Namvar and Cybulski, 2014; Sharma et al., 2014). This, then, calls for research that empirically shows how, at the work-practice level, analysts and decision makers are biased (Pachidi et al., 2014), and under what conditions portability and interconnectivity indeed yield more emergent insights in practice.

Additionally, organizations can develop organizational models, standards, principles, and policies such that portability and interconnectivity are optimized within and between different organizations (Konsynski and McFarlan, 1990). However, optimizing within a certain network of partners can impede organizational units to connect with other entities that are not able to comply with the standards, principles, and policies that are in place, even though they might be valuable strategic partners. This provides an interesting paradox: on the one hand, mechanisms (e.g., standards, principles, policies) should be stable enough to allow for portability and interconnectivity within and between organizations, while on the other, the "rules of the game" need to be continuously revisited. Future research can usefully focus on how organizations deal with this paradox.

Furthermore, collecting and synthesizing data from many different contexts is a complex process involving many different stakeholders. This makes it difficult for organizations to ensure that the data they collect and combine are of high quality (Clarke, 2016; Gao et al., 2015). A lack of quality can have severe consequences for organizations and society, especially when these data are translated into faulty actions (Clarke, 2016; Gao et al., 2015). For example, when the data are not reliable, timely, complete, or precise enough (Clarke, 2016), this can lead to decisions based on wrong insights or affect the quality of data-driven products and services (Hazen et al., 2014). Thus, future research is needed to empirically study how, across different contexts, organizations create effective strategies for ensuring data quality is "good enough" (Işik et al., 2013), while exploiting the socio-technical features of big data.

5. Cross-level interactions and alignment

We have shown that two features of big data—portability and interconnectivity—influence how organizations realize value from big data. However, so far, to convey our message, we have considered each of the levels of analysis and their debates in isolation. To further advance our understanding of big data value realization, we should also move beyond these individual levels and examine how work practices, organizational models, and stakeholder interests *interact across the various levels*.

The vignette below helps to illustrate that organizations may fail to realize value from big data when work practices, organizational models, and stakeholder interests are not aligned, despite extensive efforts at one single level.

Vignette: How a lack of alignment raises challenges to realize value from big data.

This illustration revolves around a European postal service organization, active in the business-to-business market, that delivers addressed mail for business clients such as banks and utility companies. Recognizing that the mail industry is shrinking due to digitization, some of the organization's managers and executive team members regarded big data initiatives as a good opportunity to innovate their business. As part of a data-driven strategy, the organization's goal was to sell addresses of potentially relevant households to business clients who aimed to increase the effectiveness of their advertising. Specifically, sales team members sat together with business clients to identify a number of specific household characteristics (such as households with a certain income or type of family composition), based on which addresses were selected and sold. Realizing value from this data-driven initiative however proved to be quite challenging in practice. We describe three challenges:

1. **Limited by stakeholder interests:** Throughout the years, the organization had been collecting large amounts of data about mail orders (e.g., type of mail, sender, number of items, receivers). Due to the nature of these data, analysts at the work-practice level found they could create profiles of every household in their country. However, it quickly became clear that, because the data had been collected for efficiency purposes more than anything else, the organization was by contract not allowed to use them for any other purpose. In fact, the data were not owned by the organization, but by their business clients. As a result, analysts and decision makers at the work-practice level could not use them to develop profiles of households or enrich their insights.
2. **Underestimating the development of organizational models:** The organization acquired a data-driven startup that had been collecting data on socio-demographics, real estate, and other data about households from many different sources. The organization believed it would thereby attain the capabilities needed to implement the data-driven strategy. The decision to acquire appeared to be influenced largely by supra-organizational drivers, as the organization needed to access data from elsewhere and was pressured by a shrinking market. However, managers and executive team members had difficulty seeing where and how the acquired capabilities would fit (or not fit) with the existing organizational structure. As a consequence, failing to integrate the startup within the existing structure resulted in isolated practices, controversies, and unclear roles at the work-practice level.
3. **Limited by a dominant, traditional business model:** Those who were in charge of selling data-driven propositions at the work-practice level found it difficult to make sense of the data. Specifically, in this case, sales team members had to interpret data characteristics in their conversations with clients, and were expected to arrive at a relevant selection of addresses together with their clients. However, sales teams had traditionally been selling contracts for high volumes of mail to business clients. Being framed by this traditional business model with a focus on volume, they struggled to sell data-driven propositions and as such generate revenue from the data.

We propose that it is imperative for organizations to continuously *realign* work practices, organizational models, and stakeholder interests to realize value from big data (cf., Karpovsky and Galliers, 2015; Wilson et al., 2013). Following this line of reasoning, we suggest a number of propositions that explain how work practices, organizational models, and stakeholder interests interact. We explain each of these propositions below, and accordingly, we discuss what this implies for future research on the topic (summarized in Table 1).

We first discuss the interaction between work practices and organizational models. In particular, we expect that gaining insights from big data at the work-practice level should parallel the development of appropriate structures and business models. Failure to do so may limit big data value realization by organizations. For example, by combining different data sources in new ways, analysts and decision makers at the work-practice level can arrive at innovative insights that initiate a whole new line of business (Woerner and Wixom, 2015). These insights may not be transformed into value through

Table 1
Propositions on potential cross-level interactions.

Proposition	Implications for future research
Work-Practice ←→ Organizational	
Proposition 1a: To realize value from big data, insights gained at the work-practice level need to be paralleled by the development of appropriate organizational models. *Proposition 1b: When collecting and analyzing big data at the work-practice level, analysts and decision makers are constrained by dominant organizational models.*	– How do organizations develop new data-driven business models while managing the old? – How do organizations create flexible organizational models to facilitate interdisciplinary work at the work-practice level? – How do organizations create synergy between work practices and organizational models through, for example, de-coupling and re-coupling?
Organizational ←→ Supra-Organizational	
Proposition 2a: Whether and how organizations are able to deal with stakeholder interests depends on their organizational models. *Proposition 2b: Integrating external big data resources into organizational models creates new challenges around dealing with different stakeholder interests.* *Proposition 2c: To realize value from big data, organizations need to consider the interests of different stakeholders while developing organizational models.*	– How do different organizational models facilitate dealing with stakeholder interests? – How do organizations deal with the challenges created by outsourcing or acquiring big data resources? – How do organizations accommodate flexibility in their organizational models, such that they can deal with emerging stakeholder interests?
Supra-organizational ←→ Work-Practice	
Proposition 3a: Insights gained from big data at the work-practice level raise new stakeholder interests that limit big data value realization. *Proposition 3b: When collecting and analyzing big data, analysts and decision makers are constrained by stakeholder interests and the mechanisms set to deal with those interests.*	– How to secure stakeholder interests at the work-practice level? – What types of ethical and legal training should be given to those who analyze the data? – Which actors should be included at the work-practice level in order to be able to deal with different stakeholder interests? – In which contexts do different actors succeed or fail to gain valuable insights from big data?

organizations' existing business models, but may require the development of entirely new business models (Parmar et al., 2014). In that case, in parallel with developing new data-driven business models, established organizations may need to depart from their existing ways of doing business, dominant logics, and traditional cultures (Rezazade Mehrizi and Lashkarbolouki, 2016) that are at odds with new big data products and services. This calls for future research that not only focuses on how organizations identify new data-driven business opportunities, design new data products (Davenport and Kudyba, 2016), and develop innovative business models based on big data, but also on how big data and analytics drive the *transition* to new models (Parmar et al., 2014). In this respect, we highlight the importance of methodological approaches that capture the process of business model innovation from "the inside" at the time of their occurence (Besson and Rowe, 2012; Tsoukas and Chia, 2002). Strategy-as-practice, for example, provides a powerful lens for studying such a process, as it allows researchers to "zoom in" on how actors work with big data, and how their day-to-day practices shape an organization's strategy (Jarzabkowski and Spee, 2009; Whittington, 2006, 2014) and business model to create and appropriate value from big data.

The literature also showed that, when approaching big data, analysts and decision makers at the work-practice level are constrained by dominant organizational models. For example, actors can be constrained by their structural and organizational boundaries (Sharma et al., 2014). This calls for the inclusion of different roles and perspectives to arrive at new, yet valuable insights (Jagadish et al., 2014; Gao et al., 2015). Thus, future research is needed to consider how organizations can create flexible organizational models to facilitate cross-disciplinary interaction at the work-practice level. Additionally, it might be that emergent insights can only be supported when at the organizational level, big data is not merely force-fitted to the current business model but is also leveraged to innovate the business model. For example, inductive approaches may be better supported when organizations first de-couple work practices from their existing businesses, and re-couple them to the existing business later to benefit from the available resources (Doz and Kosonen, 2010; Sund et al., 2016). This calls for future research that focuses on how to create synergy between work practices and organizational models. For example, when would be the best time to de-couple an initiative from an existing business and when or how should organizations re-couple? What does this require in terms of management skills, culture, and resources?

The second interaction is between organizational models and supra-organizational stakeholder interests. First, whether and how organizations are able to deal with stakeholder interests depends on their organizational models. For example, organizations are better able to control data exchange with external stakeholders when data are centrally governed, by some central entity (Tallon et al., 2013–14). Conversely, organizations may find it easier to promote data sharing with external parties when different business units are given more autonomy over their analytical capabilities. Future research can usefully study how, across contexts, different organizational models facilitate dealing with stakeholder interests.

Second, integrating external resources into organizational models creates challenges around dealing with different stakeholder interests. Specifically, when organizations are not able to develop big data resources (e.g., for dealing with interconnectivity and portability) in-house, they may choose to outsource analytics practices to external parties (Gao et al., 2015; Jagadish et al., 2014), or even merge with or acquire data-driven organizations to integrate with their own business

(Fogarty and Bell, 2014).[11] Outsourcing, however, creates additional challenges regarding intellectual property and ownership, especially when knowledge is simultaneously shared with other clients (Fogarty and Bell, 2014). Moreover, organizations may still have to develop their own skills when big data becomes an important part of their strategy (Gao et al., 2015). Mergers and acquisitions can also be challenging, for example, when acquired organizations have different organizational cultures and mindsets than the acquiring party (Weber et al., 1996). Thus, future research is needed that looks beyond formal processes of outsourcing, and mergers and acquisitions, and considers how organizations align and create productive interactions between external teams, routines, cultures, and technologies with the traditional ones, especially when strategic differences exist.

Additionally, we expect that even when insights from big data are developed in parallel with the development of appropriate organizational models, organizations may fail to realize value when they are unable to deal with stakeholder concerns (Clarke, 2016). Thus, strategy makers need to consider the interests of different stakeholders while developing organizational models. The literature shows that in some cases stakeholder concerns emerge only after organizations have already collected and combined massive amounts of data to incorporate in their business model (Zuboff, 2015). This calls for future research on how to accommodate flexibility in the development of organizational models, in order to be able to deal with emerging stakeholder interests.

The third interaction is between supra-organizational stakeholder interests and work practices. In particular, insights at the work-practice level may raise new stakeholder interests that should be dealt with in new ways, for example, through new regulatory frameworks, policies, or governing mechanisms. For instance, analysts can arrive at market-related insights at the work-practice level that are highly confidential and should not be disclosed. As a consequence, managers can choose to control data access to prevent competitors from arriving at the same valuable insights (Van den Broek and Van Veenstra, 2015). Insights gained can also be ethically and legally sensitive, urging organizations to control them and raising questions about how to secure stakeholder interests at the work-practice level (Tallon et al., 2013–14). Future studies can explore who (e.g., legal experts as well as data analysts) should be involved in data analysis at the work-practice level, and how they should be deployed, in order to prevent ethically and legally questionable work practices. This also raises questions about how those who analyze big data should be educated and trained to ensure timely and proactive compliance with legal and ethical considerations, even when legal frameworks are still lacking behind (Zuboff, 2015).

Conversely, we expect that analysts and decision makers at the work-practice level are also constrained by supra-organizational stakeholder interests when approaching big data for valuable insights, making decisions related to big data use, and acting on insights. For example, these actors may not be willing or allowed to use or combine different data sources (as in our vignette example), because it is not clear who has ownership over the data or what the privacy implications of combining those sources might be. When creating social value is an important objective for organizations, this influences actors' ethical mindsets regarding data collection and analysis: in exploring and accepting insights for decision making, actors are limited by what is considered ethically and legally responsible. As frameworks, norms, and values differ in different contexts (e.g., industry sector or country), we call for comparative case studies to examine how actors succeed or fail to gain valuable insights from big data in different contexts.

In Fig. 3, we propose a model that synthesizes the insights presented in the literature and particularly focuses on cross-level interactions.

6. Limitations and avenues for future research

In our study, we were limited by the methods used. Specifically, although we captured a rich set of papers from the IS domain, further interesting and complementary insights can be found in related fields (e.g., Wamba et al., 2015). Moreover, we do not claim to be exhaustive and call for empirical studies that focus on identifying additional debates as well as other features of big data that yield social and economic value in practice. Additionally, while selecting papers that have "big data" in their title, abstract, keywords, or body helped us to gain a better insight into the research and findings related to this topic, we filtered out studies that do not use this exact wording. Our literature review thus explicitly addresses the field of "big data", while it might be questionable whether in the near future the phenomenon will continue to be addressed with the same label. Further research is needed to address each of these limitations.

Additionally, one may argue that portability and interconnectivity can also be considered socio-technical features of more traditional data, rather than specifically "big" data. However, it seems that the debates on big data value realization that we identified have become more explicitly relevant, because portability and interconnectivity have been intensified in the case of big data. In other words, it is the scope and degree with which organizations are exploiting the opportunities created by portability and interconnectivity that have fueled the six debates. Yet, whether portability and interconnectivity are *unique* features of big data and raise specific challenges to big data value realization should be validated by future research.

We recognize the need for empirical research on the societal consequences of big data use by organizations. Although this is beyond the scope of our study—as we focused specifically on organizational changes, drivers, and actions in the process of realizing value—some of the (mostly theoretical) studies have begun to explore such consequences (e.g., Newell and Marabelli, 2015; Kennedy and Moss, 2015; Zuboff, 2015). Future research is needed that empirically validates societal consequences and links them to organizational actions. For example, how does realizing value from big data alter power

[11] For a broader consideration of sourcing issues, see for example, Lacity et al. (2009, 2017).

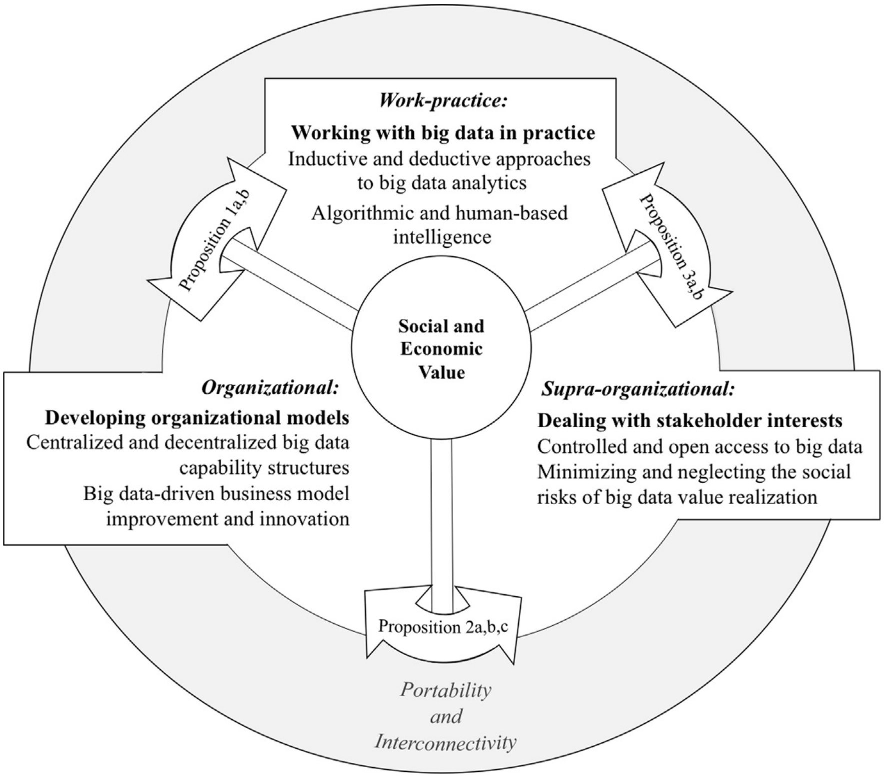

Fig. 3. Integrated model of big data value realization.

relations between different organizations, governments, groups, and individuals (Kennedy and Moss, 2015; Zuboff, 2015)? In general, studies on big data value realization should in our view take power relations more explicitly into account, especially when studying the way organizations strategize with big data (cf., Marabelli and Galliers, 2017). Relatedly, an ethical concern that is gaining increased interest is the performative power of big data and algorithms (Yoo, 2015), as well as the political significance of such performativity (Flyverbom, 2016; Newell and Marabelli, 2015; Zuboff, 2015). Algorithms are not only able to analyze individuals' behavior, but also actively guide and shape behavior through prediction and personalization (Yoo, 2015). Yet, the data on which decisions are made only represent fractions of reality (Flyverbom, 2016). This calls for future studies taking more explicitly into account the agency of big data and algorithms.

IS researchers acknowledge that strategizing for and realizing value from technological advancements are complex, emergent, and dynamic processes that involve many social dimensions and increasingly reach beyond organizational boundaries (Galliers, 1995; Marabelli and Galliers, 2017; Merali et al., 2012). In line with this, we found that it is imperative for organizations to continuously realign work practices, organizational models, and stakeholder interests in order to realize value from big data. We argue that approaches that build on process thinking (Langley, 2007) are particularly useful for studying big data value realization when they combine different levels of analysis and, as such, allow researchers to trace how work practices, organizational models, and stakeholder interests evolve over time. In addition, we contend that empirically studying big data value realization calls for interdisciplinary research, and potentially, mixed methods (cf. Mingers, 2001).[12] For example, to study when inductive approaches at the work-practice level are best supported by higher levels, researchers can draw on theories from the fields of psychology and sociology. Moreover, to study the power attributed to algorithmic intelligence and how this affects organizations and society might urge researchers to familiarize themselves with theories from the field of ethics, but also incorporate knowledge and ideas from computer science and artificial intelligence.

In conclusion, the current literature on big data value realization is characterized by a limited number of empirical studies and some repackaging of old ideas. We identified six debates central to how organizations realize social and economic value from big data that require attention from future research. Additionally, we identified two features of big data—portability and interconnectivity—that influence how organizations realize value from big data in practice. Finally, we argue that realizing value from big data is the result of continuous interaction between work practices, organizational models, and stakeholder interests, and call for empirical research on cross-level interactions and alignment. Based on future empirical evidence, we as scholars may be able to judge to what extent big data value meets its expectations, both for organizations seeking to strategically benefit from big data, and society as a whole.

[12] For a consideration of alternative IS research approaches, see for example, Galliers et al. (2007).

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Appendices. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jsis.2017.07.003.

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