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Understanding Effective Use of Big Data: Challenges and Capabilities (A Management Perspective)

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Abstract
While prior research has provided insights into challenges and capabilities related to effective Big Data use, much of this contribution has been conceptual in nature. The aim of this study is to explore such challenges and capabilities through an empirical approach. Accordingly, this paper reports on a multiple case study approach, involving eight organisations from the private and public sectors. The study provides empirical support for capabilities and challenges identified through prior research, and identifies additional insights *viz.* problem driven approach, time to value, data readiness, data literacy, data misuse, operational agility, and organisational maturity assessment.
Keywords: Big Data; Effective use; Challenges; Capabilities, Value Realisation
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1. Introduction

While the promise of value realisation from Big Data, fuelled by well-publicised examples of positive outcomes, maintains high levels of interest of C-suite executives, most companies continue to struggle to realise benefits from Big Data. Recent research shows that although most organizations have access to Big Data, they lack the capacity to use it effectively (Günther, Mehrizi, Huysman, & Feldberg, 2017). Indeed, evidence suggests that organizations struggle with effective use of Big Data and that most Big Data initiatives fail to deliver on their expectations (Partners, 2019). Despite the failures and slow progress, the potential of Big Data is significant and widely acknowledged. Mikalef, Pappas, Krogstie, and Giannakos (2018), for example, highlight that Big Data can transform economies and deliver a new wave of productive growth. To unlock this potential, there is a need to understand how Big Data can be *effectively* used, and thus what capabilities are required and what challenges need to be overcome. Challenge refers to something difficult which requires great effort and determination for organisation to achieve the effective use of Big Data. Capability refers to any system, method, resource of providing support or assistance to the effective use of Big Data. More recently, Surbakti, Wang, Indulska, and Sadiq (2019) conducted a systematic literature review of factors, including capabilities and challenges, affecting effective use of Big Data and synthesized the current body of knowledge into a conceptual framework. While this framework remains untested, it suggests that there is a large number of factors that can affect value realisation from the use of Big Data.

Prior research provides ample guidance on how to motivate use of Information Systems (Davis, Bagozzi, & Warshaw, 1989; Venkatesh, Thong, & Xu, 2012). A related stream of research has focused beyond mere Information Systems adoption and on what it takes to use Information Systems effectively (Burton-Jones & Grange, 2012). Indeed, the last decade saw the development of a substantial body of research investigating effective use of various types of Information Systems (Boudreau & Seligman, 2006; LeRouge, Hevner, & Collins, 2007; Pavlou, Dimoka, & Housel, 2008). While these studies help understand effective use of Information Systems, they do not consider Big Data systems specifically. Investigation of effective use within a Big Data context may require different factors or support mechanisms from other contexts (Mikalef et al., 2018). For example, it requires change in structure by adding dedicated teams responsible for data analytics or change in talent management of employees in data science and analytics groups and so forth.

In this paper, we focus on effective use in the context of Big Data and related systems. Compared to traditional data, Big Data is characterized by the so-called Vs (Gandomi & Haider, 2015), namely Volume (vast amounts of data generated), Variety (different type of data), Velocity (speed of data generated), Veracity (messiness of the data) and Value (turning data into useful insights). Each of these characteristics has been tackled with various degrees of success in previous research, however their collective impact presents unique challenges for organizations in terms of how to use Big Data effectively (Davenport, Barth, & Bean, 2012).

Effective use of Big Data refers to value realisation from Big Data (Surbakti et al., 2019) and is a complex phenomenon. For example, the complexity of the models and methods (*e.g.* predictive models, deep learning, *etc.*), high expectations, lack of trust and cultural issues, all affect the effective use of Big Data and are reported to be barriers for value realisation from Big Data (Davenport *et al.*, 2012). Understanding the broad range of challenges and capabilities that influence the effective use of Big Data and related systems is a necessary step towards ensuring value realisation. Accordingly, in this study, we respond to the calls for further empirical research on factors affecting effective us of Big Data in practice (Surbakti et al. (2019), by identifying, in an empirical manner, challenges and capabilities that influence effective use of Big Data. We then synthesize the empirical insights with the conceptual framework offered by Surbakti et al. (2019) to highlight confirmed and also new factors identified in practice. To do so, we conduct eight case studies with organisations in the private and public sectors that are engaged in data-intensive projects that meet the characteristics of Big Data. Our study identifies 18 main capabilities and 19 current main challenges (see Section 4). We contrast our findings by comparing them to prior literature on capabilities and challenges, and as a result we contribute an exposition of factors related to effective use of Big Data in practice, where little empirical evidence exists.

Our paper is structured as follows. In the next section, we report on the current body of knowledge as it relates to effective use of Big Data. We then explain our empirical research approach, followed by a summary of findings. A discussion of the empirical findings on the backdrop of prior research is presented next, followed by concluding remarks, and future research directions.

2. Related Work

We draw on three bodies of literature that are relevant to enhancing our understanding of challenges and capabilities of effective use of Big Data, *viz.* prior studies exploring challenges and capabilities in this context, studies on effective use of Big Data, and Big Data value realisation literature. These topics span the domains of management and also information systems research disciplines. We posit that understanding the necessary capabilities and mitigating challenges gives rise to effective use of Big Data, which results in value realisation from Big Data initiatives.

2.1 Big Data Capabilities and Challenges

Recent research on Big Data has considered two prominent theories from the management domain regarding organisational capabilities, *viz.* Resource-Based View (RBV) and Dynamic Capability View (DCV). These studies (e.g. (Braganza, Brooks, Nepelski, Ali, & Moro, 2017; Gupta & George, 2016; Mikalef et al., 2018)) indicate that Big Data capability consists of technology and infrastructure, technical and management skills, organisational support, and operational excellence. Current research also reveals that most organisations have the difficulties in getting desired outcomes from Big Data projects and that they are typically attributed to both technical and organisational challenges. Below we outline some of the major findings from recent research on Big Data challenges and capabilities.

Mikalef *et al.* (2018) conducted a systematic literature review of Big Data capabilities and argued that the value of Big Data does not solely stem from technology related capabilities but also depends on organisational capabilities. In the Big Data context, the RBV perspective highlights Big Data as a unique resource/capability that can affect better performance and innovation (Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019; Gupta & George, 2016). However, some, for example Braganza et al. (2017), argue that such a view undermines the theory's assumptions of rare, valuable, non-substitutable and inimitable resources. Braganza *et al.* (2017) argue that it is the capacity to reconfigure and transform in order to renew competences that distinguishes dynamic capabilities from capabilities per se. Relatedly, DCV has also been applied to conceptualise Big Data Analytics (BDA) as a capability that can provide competitive advantage in highly dynamic and uncertain environments (Chen, Preston, & Swink, 2015). This is because in environments where dynamism is high, the main source of competitive advantage stems from organisations being able to create or reinforce their organisational capabilities through the use of Big Data (Mikalef *et al.*, 2018).

More recently, Rialti, Marzi, Ciappei, and Busso (2019) have conducted a bibliographic and literature review on Big Data and dynamic capabilities. Their study revealed four clusters of current research papers: Big Data and supply chain management, knowledge management, decision making, business process management and Big Data analytics. In strategic management research, DCV such as organisational agility, are considered to be paramount in the search for competitive advantage (Côrte-Real, Oliveira, & Ruivo, 2017). Furthermore, Lin and Kunnathur (2019) highlight that entrepreneurial, customer, and technology orientations are three strategic orientations for the development of Big Data capability.

There is of course the flipside of the capabilities coin – there are challenges to realizing value from Big Data, stemming from technical, organizational and human resource related aspects (Sivarajah, Kamal, Irani, & Weerakkody, 2017). For example, Huser and Cimino (2016) indicate that advancing data transformation and analysis is one challenge that needs to be overcome to better exploit value from Big Data. Vidgen, Shaw, and Grant (2017) highlight challenges faced by organizations in creating value from Big Data: the need for a clear data & analytics strategy, the right people to effect a data-driven cultural change, and consideration of data and information ethics when using data for competitive advantage. Arunachalam, Kumar, and Kawalek (2018) identify six organizational challenges of adopting and using Big Data: insufficient time, insufficient resources, privacy and security concerns, behavioural issues, issues with Return on Investment (ROI) and lack of skills; and three technical challenges: data scalability, data quality and lack of techniques and procedures.

2.2 Effective use of Big Data

Effectiveness of use, as a necessary and sufficient condition for benefit attainment, has been long recognized (Delone & McLean, 2003). Prior studies have focused on developing models and theories relating to the use and effective use of Information Systems and technology. For example, TAM (Technology Acceptance Model) is one such well-tested model of information technology use (Davis *et al.*, 1989). However, to achieve designed objectives or goals, systems must be used effectively, not just used. The Theory of Effective Use (TEU) is a natural progression from studying use to the study of effective use. Burton-Jones and Grange (2012) define effective use as "*the use of a system in a way that helps attain the goals for using the system*" (p.2). While these theories, and related studies, shed light on effective use of Information Systems in a conventional enterprise setting, there is paucity of studies that consider Big Data specifically, and those few that do exist have focused on specific aspects or industry sectors. For example, Merino, Caballero, Rivas, Serrano, and Piattini (2016) explored whether data quality levels were sufficient for effective use. Accordingly, they proposed a model to assess the level of Quality-in-Use of Big Data. Several studies in the healthcare sector have explored effective use of Big Data in different contexts: in ambulatory care (Thorpe & Gray, 2015) and in the Neonatal Intensive Care Unit (Vijayalakshmi, Kumar, Gokulraj, & Malathy, 2015). The use of Big Data for organizational efficiency and effectiveness has also been investigated (Halaweh & El Massry, 2017).

More recently, Surbakti *et al.* (2019) conducted a systematic literature review of various factors, including capabilities and challenges noted above, affecting effective use of Big Data and synthesized the current body of knowledge into a framework. The framework consists of three categories, *viz.* motivational factors, operational factors and supporting mechanisms (see Figure 1). Motivational factors relate to high-level objectives of an organisation to initiate a Big Data initiative. Operational factors are those that enable an organisation to successfully execute a Big Data project, including having the correct analytics processes in place, together with appropriate data quality and data security and governance. Supporting mechanisms complement the motivational and operational factors, as they relate to human resource, organisational factors, and relevant systems and technologies that are required to realise value from Big Data use.

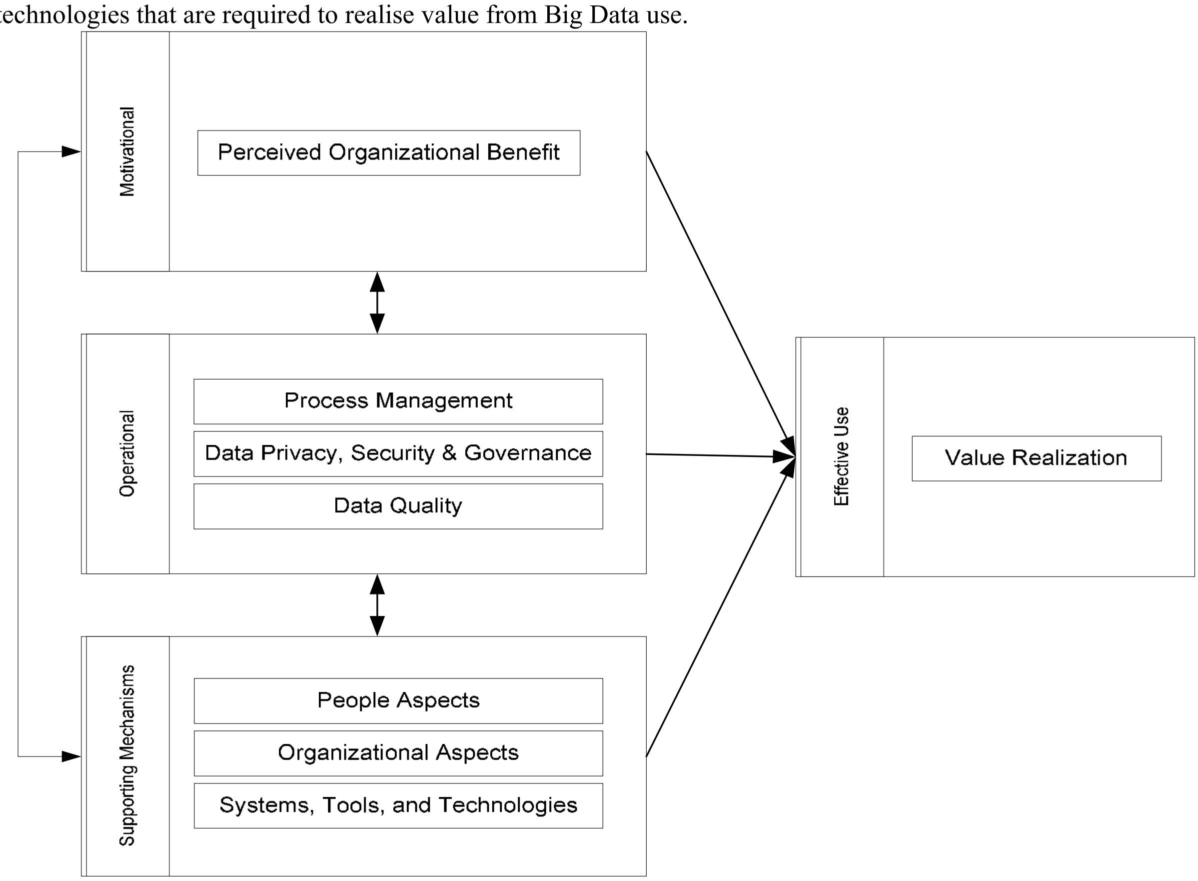

Figure 1. Framework of effective use of Big Data (Surbakti *et al.*, 2019)

In the next section, through our empirical study, we contribute to and extend the above body of knowledge by offering insights from current practice by synthesizing them with Surbakti *et al.* (2019) framework and identifying previously unknown factors.

2.3 Big Data value realisation

According to Surbakti *et al.* (2019), effective use in the Big Data context is manifested by value realisation from Big Data initiatives. Indeed, those companies that can realise value from Big Data projects often achieve competitive advantage. For example, recent reports indicate that top-performing companies have all utilised analytics to extract value from Big Data and 60% of them have successfully innovated on the basis of Big Data (Partners, 2019).

Current academic literature on Big Data value realisation remains relatively immature (Günther et al. (2017). Günther *et al.* (2017), though a literature review of value realisation studies, propose an integrated model on Big Data uses and consequences in organizations. They identify six tensions related to realizing value from Big Data in organizations, *viz.* inductive and deductive approaches, algorithmic and human-based intelligence, centralised and decentralised structure, improvement and innovation, controlled and open access, and minimising and neglecting the social risks. They also propose two socio-technical attributes, *viz.* portability and interconnectivity, which influence value realisation. Similar studies have also been conducted to identify supporting organisational mechanisms that are necessary for value realisation from Big Data (Gupta & George, 2016; Ylijoki & Porras, 2019). Lim et al. (2018) propose a nine-factor framework for organisation to represent, outline and develop the value creation process in the information-intensive service industry. They argue that the value creation process consists of 9 factors (1) data source, (2) data collection, (3) data, (4) data analysis, (5) information on the data source, (6) information delivery, (7) information user, (8) value in information use, (9) provider network of the service provider and partners. The authors call for empirical studies to assess the generalisability of their framework for other industries.

Big Data value realisation has also been examined using the service-dominant logic (Xie, Wu, Xiao, & Hu, 2016) and quality-dominant logic perspective (Wamba, Akter, & De Bourmont, 2019). Xie *et al.* (2016) discussed how Big Data interconnects companies and its customers in developing value co-creation. The authors proposed that the value realisation process in Big Data use is individual and experience centred, and identified four types of customer roles in the value co-creation process: transactional, communicational, participative, and transboundary. Meanwhile, Wamba *et al.* (2019) examined quality-dominant logic or Big Data analytics quality dynamics in Big Data use and proposed that information quality, technology quality and talent quality all have a significant impact on value creation in an organisation.

Overall, the above discussed three areas of related literature have largely emerged organically an in isolation of each other (see Table 1 for summary). Yet, they need to be considered synergistically to determine the capabilities required for effective use of Big Data, and any challenges that require mitigation.

Table 1. Summary of research

Paper	Journal	Capabilities	Effective Use	Value Realisation
Chen *et al.* (2015)	Journal of Management Information Systems		√	√
Gupta and George (2016)	Information & Management	√		
Xie *et al.* (2016)	Information & Management			√
Wamba *et al.* (2017)	Journal of Business Research	√		√
Braganza *et al.* (2017)	Journal of Business Research	√	√	
Halaweh and El Massry (2017)	Information Resources Management Journal		√	√
Günther *et al.* (2017)	Journal of Strategic Information Systems		√	√
Côrte-Real *et al.* (2017)	Journal of Business Research	√		√
Mikalef *et al.* (2018)	Information Systems & e-Business Management	√		√
Lin and Kunnathur (2019)	Journal of Business Research	√		
Ylijoki and Porras (2019)	Business Process Management Journal			√
Aydiner *et al.* (2019)	Journal of Business Research	√		√
Wamba *et al.* (2019)	Business Process Management Journal	√		√
Rialti *et al.* (2019)	Management Decision	√		
Surbakti *et al.* (2019)	Information & Management	√	√	√

3. Research Method

We conducted our study through an exploratory multiple case study approach because it allows for collection of rich descriptive data in research areas where there is lack of theory (Yin, 2017). To understand current Big Data challenges and capabilities in practice, we gathered data primarily through semi-structured interviews, supplemented with document analysis. This approach allowed us to ask for further details, probe an issue, and return to prior points to seek further clarification or input.

3.1 Case Study Setting

Private and public sectors with Big Data initiatives were selected as our case organisations. This decision was made because in these organizations Big Data was recognized as an opportunity to create value. Without a better understanding of the complex issues involved in real-word settings, the understanding of effective use of Big Data remains elusive.

Eisenhardt (1989) suggests that 4 to 10 is the ideal number of cases required to ensure some variation in the phenomenon such that the constructs can be seen in multiple situations. In our study, we recruited eight organisations to take part, as outlined below[1].

1. A large company in the resources sector, with field operations in over 25 countries. This company succeeded in implementing a Big Data solution for the purposes of cost reduction by optimising equipment maintenance.
2. A multinational financial service corporation headquartered in the USA. Their use of Big Data aimed to create credit score modelling to quantify the potential risk posed by customers.
3. A consumer-insights spin-off company, a subsidiary of a large Australian company with a large pool of customer data by virtue of their main operations. The spin-off company sells services to external clients based on the data that the company holds on their clients, and also uses the data to develop the parent company's, media and marketing campaigns, or design bespoke market research to drive their strategy.
4. A start-up company established in 2015. Its use of Big Data ranges from individual shopper and retailer level to providing in-depth, real-time, integrated shopper insights for clients.
5. An energy company established in 2015. The organisation is a technology company focused on the development of advanced, low-cost solar solutions for residential and commercial users by using Big Data analytical techniques.
6. A government department, its research and development section, and specifically its data analytics branch. The branch was given a remit in June 2016 to explore how they could use contemporary data analytics techniques to examine the large datasets in the department to create new insights that would help the department create new policies to revise the government direction.
7. A sports organisation with an internal mandate to make analytics a core function. They have done that through providing tools to everyone in the organisation empower staff to do their own analytical work.
8. An insurance company which offers customers tailor-made insurance, such as car and home insurance. Their advanced analytics team built a conversion model to determine the success of non-discretionary discounts and to predict the likelihood of converting quotes into a successful insurance policy.

3.2 Data Collection and Analysis

A total of 12 participants from the eight organisations were interviewed, as summarised in Table 2. The interviews averaged over 60 minutes in duration, with a total time of 781 minutes. Based on coding of the transcribed interviews, we found that saturation of concepts occurred within the twelfth interview, i.e. redundancy of the data was observed, and no new challenges and capabilities were identified. Our experience is in-line with (Nguyen & Burgess, 2014; Rauschnabel, He, & Ro, 2018) and the argumentation of Guest, Bunce, and Johnson (2006), who state that after twelve interviews, new themes emerge infrequently.

Table 2. Interview participants

Case	Participant	Role	Experience	Industry	Duration of Interview
A	Participant 1	Research Manager	>2 years	Resources	1h07min
A	Participant 2	Artificial Intelligence Manager	>7 years	Resources	1h30min
B	Participant 3	Risk and Information Management Manager	>3 years	Finance	1h23min
C	Participant 4	Engagement Manager	>2 years	Logistics	1h14min
D	Participant 5	CEO and Founder	>4 years	Start-Up	1h19min
E	Participant 6	Data Analyst	>2 years	Health	1h04min
E	Participant 7	Director, Health Analytics	>15 years	Health	1h18min

[1] Numbering reflects case numbers used in later sections of the paper.

Case	Participant	Role	Experience	Industry	Duration of Interview
E	Participant 8	Project Manager	>10 years	Health	1h08min
F	Participant 9	Analytics Architect	> 6 years	Sports	1h10min
F	Participant 10	Sport Scientist	>10 years	Sports	1h13min
G	Participant 11	Data Scientist	>3 years	Energy	1h15min
H	Participant 12	Head of Data & Analytics	>10 years	Finance	1h08min

Data analysis was conducted iteratively as encouraged by grounded theory methodology (Strauss & Corbin, 1998). The coding started with a process referred to as microanalysis (Strauss & Corbin, 1998). That is, a line-by-line analysis of each interview transcript to identify initial codes was carried out. We used NVivo 12[1] to organise and analyse the data to generate and label nodes/codes following the guidelines from Saldaña (2015).

The coding process was conducted using a dual coder approach. The first author coded all transcripts, which resulted in a node structure of challenges and capabilities (and their definition) and the related coding of the text. Next, two co-authors reviewed and revised the result the coding, and the related node structure, in consultation with the first author. Then, a independent second coder was provided with the node structure and transcripts and was asked to code all interviews. This coding was compared to the authors' coding and the reliability of the coding was calculated using Cohen's Kappa (Stemler, 2001), with a result of 80.2%, indicating almost perfect inter-rater agreement (Stemler, 2001). Finally, full consensus was reached through discussions among the researchers. As a result we classified 19 challenges and 18 capabilities. In the following section we present the full list of identified challenges and capabilities, and discuss most prominent (top-5) in each category.

4. Data Analysis

In this section we provide the summary of our findings on the challenges and capabilities of effective use of Big Data and discuss them against related literature. The study identified 19 challenges and 18 capabilities. Table 3 shows a list of challenges and capabilities identified in the study, ordered by the frequency of cases in which were identified in and the frequency of mentions within each case (respectively represented by the numbers indicated in brackets).

Table 3. Challenges and capabilities of effective use of Big Data

#	Challenges	Capabilities
1	IT Infrastructure (6,34)	IT Infrastructure (6,32)
2	Data Readiness (4,13)	Collaboration (6,23)
3	Data Governance (4,6)	Knowledge & Skills (5,14)
4	Data Quality (4,5)	Top Management Support (4,5)
5	Perceived Value (4,9)	Cost-Benefit Analysis (4,4)
6	Trust (3,12)	Operational Agility (3,9)
7	Talent Management (3,10)	Problem Driven Approach (3,6)
8	Knowledge and Skills (3,7)	Communication (2,12)
9	Data Misuse (3,5)	Problem Driven Approach (2,9)
10	Time to Value (3,5)	Clear Goals (2,8)
11	Problem Driven Approach (2,13	Data Governance (2,7)
12	Data Literacy (2,11)	Organisational Structure and Size (2,5)
13	Top Management Support (2,9)	Talent Management (2,5)
14	Communication (2,8)	Vendor Support (2,4)
15	Data Privacy and Security (2,6)	Data Literacy (1,4)
16	Process Orientation (1,5)	Trust (1,3)
17	Vendor Support (1,3)	Process Orientation (1,2)
18	Organisational Maturity Assessment (1,2)	Organisational Maturity Assessment (1,2)
19	Collaboration (1,2)	

4.1 Challenges of effective use of Big Data

Our study revealed that the most common challenges of effective use of Big Data are (1) implementing IT infrastructure, (2) data readiness, (3) data governance, (4) data quality and (5) perceived value. Below we provide a summary of our findings for each of these challenges, as explained by the participants of our study.

[1] NVivo 12 allows researchers to identify challenges and capabilities within data sources

Most organisations reported that implementing the requisite IT infrastructure is one of the early challenges when Big Data is first introduced. These include challenges relating to data storage given large volumes of data, as well as the need for, and support of, advanced computing power. For example, one participant indicated: *"I could extract the data a million rows a minute, but, so the kind of simulations I wanted to do in the database, so that was actually quite slow. And then if you want to say extract a customer's data for them, a year of it, it would take quite a while. So, I'm not sure that [… anonymised …] would provide the right storage choice."*. The likely challenges of implementing Big Data infrastructure have been highlighted by researches in the past. For example (Muller & Hart, 2016; Saltz & Shamshurin, 2016) argued that organisations should be equipped with IT applications that offer various decision-making tools, simulation tools, what-if analysis tools, statistical tools, and other tools, that enable the organisations to examine trends and find the best course of action for a given situation. Similarly, prior work indicates that "*Big Data initiatives require appropriate tools and technologies to help organisations integrate, analyse, visualise, and consume the growing deluge of Big Data.*" (Wamba *et al.*, 2017).

The second main challenge identified from our study is data readiness. One of our participants cited the challenge as: *"How to create a certain form of data that can be utilized by different clients and partners."* Our study thus finds empirical evidence for the arguments of Huser and Cimino (2016), who indicate that data readiness is one of the key challenges in Big Data use. Indeed, indications are that making the data ready for use accounts for up to 80% of the work of Big Data projects (Konstantinou *et al.,* 2017). Four participants in our study echoed similar thoughts, identifying data munging as the hardest and most resource intensive aspect of big data analytics. The challenge is caused by the 'messiness' of data, which is generally not ready for analytics and/or presentation to stakeholders in a format that is easily consumable.

The third main challenge identified is data governance. Our findings revealed that it is a challenge to establish data governance structures and rules to protect data from leaking or being used inappropriately. For example, as mentioned by one participant: *"Really strict data governance structures in place to protect that data from leaking out, being used inappropriately."* At the same time, six participants indicated that a large amount of effort is required to acquire data that they need in order to be able to carry out the required analysis. Indeed, data governance has been identified in prior research as an important challenge affecting Big Data project success (Abbasi, Sarker, & Chiang, 2016). Establishing effective Big Data governance that tackles the regulatory, managerial and procedural aspects of Big Data use at the same time is not a trivial task. According to Abbasi *et al.* (2016), organisations need to have dependable controls and unambiguous laws, as well as internal policies and guidelines relating to the effective use of Big Data.

The fourth main challenge is data quality. One participant, for example, indicated: *"The challenge is finding and maintaining clean data."* Our study participants indicated that handling missing data, finding and maintaining clean data, and having access to the data that they need are major challenges. Data quality was also identified as the one of the biggest challenges in the Big Data environment (Clarke, 2016; J. Gao, Xie, & Tao, 2016). These prior studies also indicate, in line with our empirical evidence, that organisations do not have a road map for standardisation or a systematic approach to data quality.

The fifth main challenge is perceived value. To illustrate, one participant indicated: *"Organisations, Management people, CEO level, they don't really understand this Big Data and they think it's a magic bullet, once I install Hadoop, once I install cloud, once I hire data scientists, boom, it's going to be a big profit."* A challenge emerges from the misconception of Big Data initiatives, where participants indicated that management viewed Big Data as a magic bullet, wherein one automatically creates significant business benefits. Our participants also indicated that perceived value is influenced by vendors, who pitch various products and tools to senior executives, as one of our participants explained: "*They make it seem like easy and straightforward to just buy their product, and within weeks the organisation will be getting returns"*. Indeed, perceived value of Big Data is seen as being one of the biggest challenges and is important to understand in highly dynamic environments because there is a general perception that Big Data is expected to increase an organisation's capacity to exploit insights (Chen *et al.*, 2015).

4.2 Capabilities of effective use of Big Data

Our study identified 18 capabilities of effective use of Big Data. The most common five include: (1) IT infrastructure, (2) collaboration, (3) knowledge and skills, (4) top management support and (5) cost-benefit analysis. Below we provide a summary of our findings for each of these capabilities identified by participants of our study.

Unsurprisingly, IT infrastructure is viewed by most organisations as an important capability for the effective Big Data projects. As mentioned by one participant: "*We created three different ecosystems that we have in our company and it's all supported by Big Data technology.*" Five organisations stressed that cloud storage and the Hadoop (Hadoop, 2011) environment in particular, as an important capability for them. The need for flexibility of IT infrastructure has previously been indicated in research as well, with Gao, Koronios, and Selle (2015) arguing that it is important to be able to easily adjust to use case requirements given the diversity of IT needs in Big Data projects. In addition, the use of robust platforms to handle multiple sources of data, especially unstructured data, is indicated in this study as a factor of high importance for Big Data value realisation. Prior research indicates that data platforms should evolve to provide specific support for Big Data and embrace all formats of Big Data, not just relational Big Data (Gao et al., 2015).

Collaboration is the second key capability required to ensure effective use of Big Data, as indicated by one of our study participants: *"It's all about collaboration...[especially] non-traditional partners, working with other […] agencies, working with […] the department."* In six organisations there are indications of collaboration between technical (subject matter expertise) and business staff (including C-suite executives), clients and government as an important capability required to achieve the right outcomes from the project. Three participants specifically mentioned that collaboration with the university sector and research centres is a significant capability. In prior literature, the culture of collaboration, which has a foundation of multidisciplinary teams and close interaction among team members, has been emphasized as a significant capability to tackle the complexity of Big Data projects (Wamba *et al.*, 2017). A good culture of collaboration is reflected in a group of people with different functional expertise coming together to complement their skills and work toward a common goal – *e.g.* business professionals working effectively with data analysts and IT professionals to gain insights from data (Halaweh & El Massry, 2017).

The third main required capability is knowledge and skills. For example, one participant reported that: "*The team was trying with many different algorithms, and at the end they finally chose to have gradient boosting method because that was the most robust algorithm and [it was] explainable."* According to our participants, the knowledge and skills needed to accomplish analytical, scientific or technology-related duties, as well as other tasks relating to Big Data tools or processes, are an essential technical capability. The key is to utilise them correctly, especially in the context of analytics. Some specific knowledge and skills mentioned are those relating to understanding legal aspects and governance, privacy principles, decision science, as well as specific sector and product knowledge. According to prior research, people's knowledge and skills (analytical, technical, and interpretation of analytical results) are critical factors in Big Data projects (Sivarajah *et al.*, 2017).

The fourth main factor related to capability is top management support. According to one participant: *"Previous secretary of the head of department giving a mandate to demonstrate data analytics to this branch, so we were always very keen to work with the various policy areas in the department to try and understand what it was they're trying to achieve and then go away and see where we could try to bring some analytic techniques and methodologies to deepen that evidence."*. Three organisations reported that they have executives who sponsored Big Data initiatives and managers who developed or facilitated access to reliable and easy to use systems to support data management. Participants indicated that it is important for management to have the willingness to provide necessary resources and authority for projects, and to have confidence in success of projects, while also actively promoting Big Data analytics solutions, valuing data and engaging in data driven decision making. For example, one organisation assigned a project sponsor (from executive team) to their Big Data initiatives. The importance of top management support in the context of Big Data initiatives has been emphasized by prior research. For example, Halaweh and El Massry (2017) indicated that it is the role of top management to ensure that Big Data is seen as a number-one priority in the organisation, and to ensure the necessary resources are provided for projects relating to Big Data.

The fifth main capability is cost-benefit analysis. Cost-benefit analysis has been indicated in our case organisations in in the context of justifying feasibility of Big Data initiatives, as highlighted by one participant: "*So, the cost-benefit analysis was set … so that 2 million of lost savings [could be recovered].*". This organisation conducts cost-benefit analysis before starting any Big Data initiatives, approving the project only if net value is positive. According to our case organisations, a cost-benefit analysis needs to be performed to measure the potential long-term benefits of adopting Big Data to support data-driven decision making and communicate findings to non-technical stakeholders by determining what net value can be gained. Indeed, our findings align with those of Skourletopoulos *et al.* (2017), who, through a case study approach, identified that cost-benefit analysis has to be used to determine to what degree well-defined business goals are realised in a Big Data project. The components of the associated costs include adoption of Big Data technologies, maintenance of these technologies, and employee training (Gao et al., 2015).

5. Empirically Explained Framework for Effective Use of Big Data

Braganza *et al.* (2017) conducted empirical studies to develop and refine the archetype Big Data process. In their work, they call on researchers to provide empirical studies to provide evidence of the capabilities required to support such a process. While the framework provided by (Surbakti et al., 2019) is conceptual in nature and based on a synthesis of literature, through our study we are able to contribute to empirically explaining the conceptual framework of effective use of Big Data, thereby also informing the capabilities required to support the Big Data analytics process. As shown in Figure 1, the original framework consists of 3 categories of factors (which can encompass capabilities and challenges), with an underlying seven themes, which together are posited to impact effective use of Big Data. The seven themes further consist of a total of 41 factors (Surbakti *et al.*, 2019). Through our study, we have been able to find empirical support for 25 of the 41 factors included in the framework. In particular, we found that: talent management, change management program, organisational structure and size, collaboration, communication, top management support, clear goals, IT infrastructure, vendor support, knowledge and skills, trust, employee engagement, data quality, process orientation, perceived value, cost-benefit analysis, data privacy & security, and data governance, all overlap with the framework and in some way impact effective use of Big Data. In addition, our study has also identified seven new factors, *viz.* problem driven approach, time to value, data readiness, data literacy, data misuse, operational agility, and organisational maturity assessment, which impact effective use of Big Data. These factors have not yet been recognised in prior literature on capabilities and challenges relating to Big Data, therefore we explain them briefly as follows.

- *Problem driven approach* refers to focusing on a specific business problem as a goal of carrying a Big Data project instead of following a data-driven exploratory approach (Gudivada, Rao, & Grosky, 2016). However, anecdotal evidence suggests that Big Data users may be inclined to not develop hypotheses or use cases, and instead explore the data for insights bottom-up in a "fishing" approach (Vanauer, Böhle, & Hellingrath, 2015). This practice is noted to be problematic according to our study, and by others: for example, decisions may be based on spurious correlations and the prognosis of output without a confidence level (Vanauer et al., 2015). Many have observed this shift to hypothesis-free knowledge and insight discovery (Mayer-Schönberger & Cukier, 2013), however, such analysis may not be suitable for all settings. Data-driven analysis requires more resources: more time for discovery, and thus more data scientists; more tools to utilise, and carries a higher risk of failure (Cao, 2018). The appropriateness of each approach needs to be further explored given a specific setting.
- Time to value refers to the time that elapses between the initial investment and when the organisation achieves tangible business value of Big Data initiatives (Harvey, 2017). There are some initial indications in literature that organisations struggle with time to value of Big Data. When Big Data initiatives managers were asked to prioritise their goals for their Big Data analytics efforts, survey respondents ranked "reduce project time to value" as the number one priority (Harvey, 2017).
- Data readiness refers to the fitness of data for an intended purpose (Belkin & Patil, 2016). It is common for many organisations today to collect data without question (Allen, 2018). Unfortunately, many organisations treat data readiness as a one-off task. For instance, they purchase new technology, collect the data and possibly never revisit the data. Data readiness is a process. Organisations have to keep working to keep data ready.
- Data literacy refers to the ability to understand and use data (Khan, Kim, & Chang, 2018). In early 2000, data literacy was regarded as a synonym for statistical literacy, which refers to the knowledge and skills that enable data users to understand, evaluate and communicate statistical data. In recent years, the term data literacy has emerged as a term of data analytics and data science perspective in this Big Data era (Schuff, 2018). Our study revealed that data literacy has emerged as a skill required for realising value from Big Data.
- Data misuse refers to deliberately inappropriate use of data (Gudivada et al., 2016). Being able to access or collect data does not mean that a business is allowed to use that data. For example, there are many web sites that prohibit the collection and use of crawled data – when web crawlers are used to gather such data they may breach the terms of use. Researchers have reported that cases of Big Data misuse are common (Gudivada et al., 2016). Martin (2015) suggest that organisations need to take ownership of their data sources and also need to be transparent about their data supply chain and data partnerships.
- Big Data-driven operational agility is the ability of a firm to rapidly adapt operational processes to market and environmental changes through Big Data use (Sena, Bhaumik, Sengupta, & Demirbag, 2019). The recent body of knowledge about operational agility research remains largely theoretical, and further study is needed to understand how IT-enabled operational agility is cultivated in complex and emergent organisational models for Big Data and analytics (Tan, Pan, & Zuo, 2019).
- Organisational maturity assessment refers to assessment of the level of the organisation's readiness and experience in relation to people, processes, and technologies related to achieving Big Data project objectives (Comuzzi & Patel, 2016). Using organisational Big Data maturity assessment is an important first step in understanding where/if the organisation is currently leveraging Big Data and to identify where to start. It also helps organisations to create structures around their Big Data capabilities (Halper & Krishnan, 2013). Moreover, using a Big Data maturity assessment model allows an organisation to assess its maturity level and prescribe a feasible maturity level achievable in a reasonable time horizon (Comuzzi & Patel, 2016).

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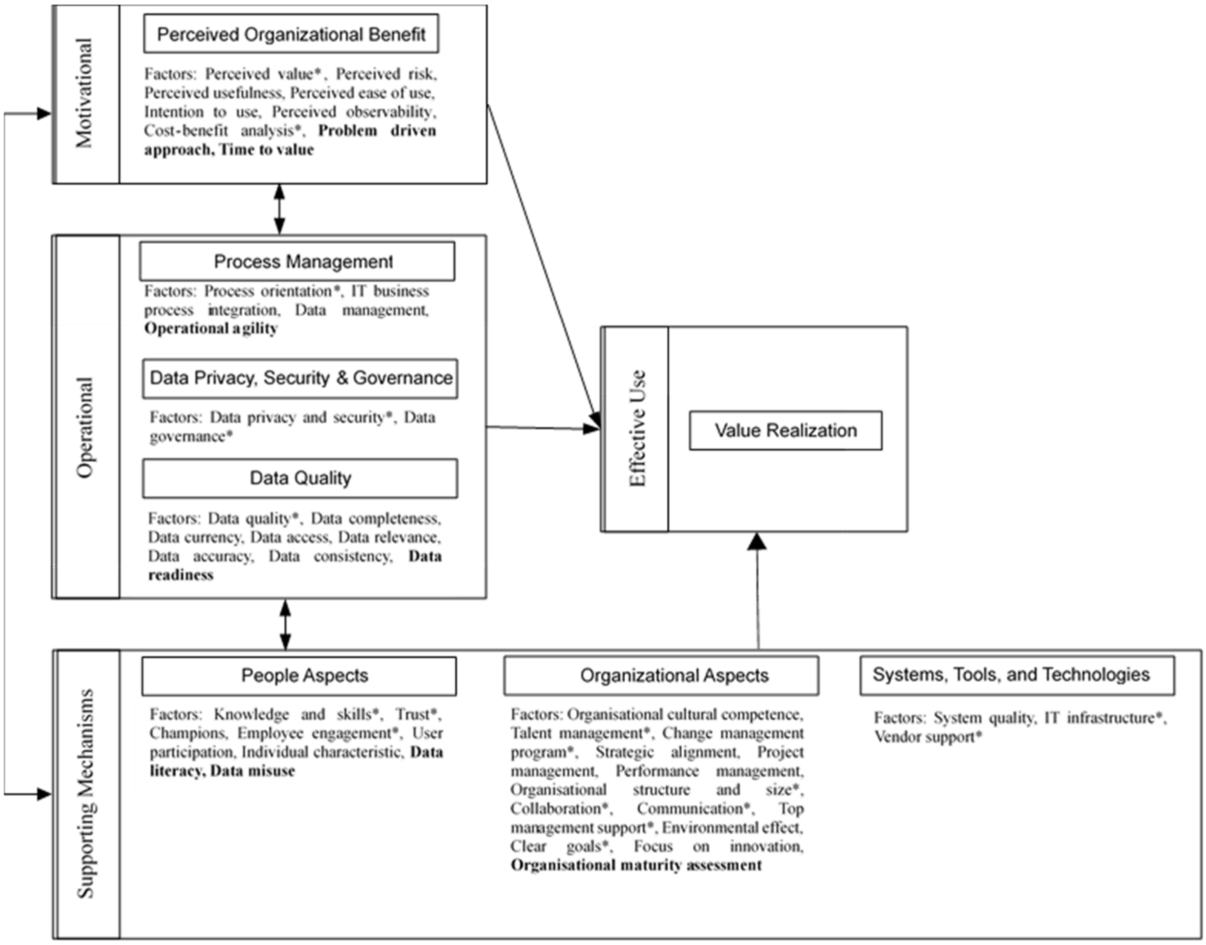

Figure 2. Empirically explained framework of effective use of Big Data

The empirically explained factors are marked in Figure 2 by an asterisk, and newly identified factors, which align with the existing seven themes, are indicated in bold. In the following discussion we respecify the framework on the basis of the new results, followed by a discussion of future research.

The theme of factors relating to organisational motivation by Surbakti *et al.* (2019) consists of 7 factors: perceived value, perceived risk, perceived usefulness, perceived ease of use, intention to use, perceived observability, and cost-benefit analysis. Our study confirmed perceived value and cost-benefit analysis, whereas problem driven approach and time to value are additional factors that emerged from our empirical study. Our findings, across all eight cases, indicate that the studied organisations started their Big Data initiatives through on problem-driven or deductive approach. This finding provides further insight for current research, where debates have ensued about whether an inductive or deductive approach to Big Data analytics is most appropriate. Some scholars indicate that inductive approaches lead to new and unforeseen insights (Madsen, 2015). On the other hand, some argue that deductive approaches provide the focus required to derive useful insights from Big Data (Gao et al., 2015). Some, e.g. Bholat (2015), propose to balance inductive and deductive approaches to data collection and analysis. Our empirical results provide support for the deductive, problem-driven, approach in terms of increasing effective use and therefore realising value from Big Data initiatives.

In the operational theme of factors, our empirical study found that the effective use of Big Data is impacted by six factors: process orientation, operational agility, data governance, data privacy and security, data quality and data readiness, with operational agility (mentioned by 3 cases) and data readiness (mentioned by 4 cases) being a new addition to the framework on the basis of our data analysis. Prior research indicates that there are five common reasons why an organisation's data is not ready for use: it is not accessible, not maintainable, not sizeable, not understandable, and not clean (Allen, 2018).

In the support mechanisms theme of factors, our re-specification of the framework consists of themes: people aspects, organisational aspects and systems, and tools and technologies, which are unchanged from Surbakti *et al.*'s (2019) original framework. It is the underlying factors, however, where the changes lie. In the people aspects theme, our study found support for knowledge and skills, trust, employee engagement factors, and also identified new factors of: data literacy and data misuse. We also verified talent management, change management program, organisational structure and size, collaboration, communication, top management support, and clear goals factors, our study also identified a new factor, namely organisational maturity assessment in organisational aspects theme. Last, our study confirmed the IT infrastructure and vendor support factors in the systems, tools and technologies theme of the initial framework. There are some factors for which we did not find empirical evidence in our study, for example, system quality, strategic alignment, performance management, which require further study. Recent research provides further evidence of the influence of this category on effective use of Big Data, for example, Halaweh and Massry (2015) argue that top management support, IT infrastructure, and a change management program are essential to any Big Data project's success, and that people's knowledge & skills (analytical, technical, and interpretation of analytical results) are critical factors in Big Data projects (Gao et al., 2015; Grublješič & Jaklič, 2015; Sivarajah et al., 2017).

Overall, the main contributions of our study are the empirical identification of challenges and capabilities and the above re-specification of the framework for effective use of Big Data, which is both empirically (though our study) and theoretically (through Surbakti et al. (2019) review) informed. Our study has provided empirical support for 25 factors (challenges and capabilities) that affect effective use of Big Data, however we note, as discussed in the conclusion section, that due to a small number of cases we do not exclude the remaining 21 factors from the framework, and instead call for further empirical research to provide broader explanation in a variety of settings. Indeed, the body of knowledge on effective use of Big Data and related systems remains scarce and more empirical insights are required.

Three directions are suggested for future related research. While we considered successful (i.e. value-realised) cases of Big Data initiatives, future studies could involve cases of Big Data project failures to identify what factors emerge in those settings and how they relate to the framework shown in Figure 2. Another fruitful direction for future research is a larger scale empirical explanation of challenges and capabilities, or a collection of such explanations in a variety of settings (e.g. start-ups, small vs large organisations, etc). Finally, a large-scale survey of organisations who do and do not have Big Data initiatives could uncover additional factors that are not possible to exhaustively explore through a qualitative research approach.

6. Conclusions

In the era of Big Data, it is not its use but its effective use that will enable organisations to realise value from their Big Data investments. The concept of effective use has garnered increasing attention from the research community over the last decade, but has yet to make inroads in the context of the specific challenges that are presented by Big Data and related systems. Based on initial conceptual studies of effective use in the context of Big Data, our motivation in this paper was to provide empirical insights into the capabilities that enable effective use of Big Data, and the challenges that need to be overcome to realise its value.

Accordingly, in this study we report on a series of eight case studies with public and private sector organisations that have engaged in successful Big Data projects. Our results identify eighteen capabilities and nineteen challenges that relate to effective use of Big Data in organisations. Furthermore, our findings contribute to an empirical explanation of a conceptual model of effective use of Big Data, which was earlier developed by Surbakti *et al.* (2019). Through our study we have been able to provide empirical support for 25 of the 41 'factors' (challenges or capabilities) identified in the literature by Surbakti *et al.* (2019). In addition to this empirical explanation, our empirical study followed the previous research agenda and identified additional insights, *viz.* problem driven approach, time to value, data readiness, data literacy, data misuse, operational agility, and organisational maturity assessment, which were previously not reported in literature, and thus allowed us to propose a revised model of effective use of Big Data.

Our study is not without limitations. Coding in qualitative research is a concern, which we have mitigated through the use of a dual coder approach to reduce bias in the analysis of our data. A qualitative approach has been interpreted for the use of small sample sizes; hence generalisability of qualitative research findings may be questionable. It is acknowledged that the study has used small sample sizes, but the individual perspectives of each participant are unique to the research context because the characteristics of the participants are varied from CEO to data analyst. Further empirical research is needed to determine whether the other factors for which we have not seen empirical support are relevant in the Big Data context, or whether theoretical saturation has not yet been reached through eight case studies. Furthermore, a significantly larger study could also allow researchers to explore whether differences in challenges and/or capabilities exist in different contexts (e.g. small vs large organisations, public vs private sectors, etc).

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