Shamim, Saqib, Zeng, Jing, Syed, Shariq Muhammad and Khan, Zaheer (2019) *Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view.* Information & Management, 56 (6). ISSN 0378-7206.

1 **Role of big data management in enhancing big data decision-making capability and**

2 **quality among Chinese firms: A dynamic capabilities view**

3 **Abstract**

4 This study examines the antecedents and influence of big data decision-making capabilities

5 on decision-making quality among Chinese firms. We propose that such capabilities are

6 influenced by big data management challenges such as leadership, talent management,

7 technology, and organisational culture. By using primary data from 108 Chinese firms and

8 utilising partial least squares, we tested the antecedents of big data decision-making

9 capability and its impact on decision-making quality. Findings suggest that big data

10 management challenges are the key antecedents of big data decision-making capability.

11 Furthermore, the latter is vital for big data decision-making quality.

12 **Key words:** Big data management; dynamic capabilities; big data decision-making capability;

13 decision-making quality; China

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1. Introduction

The dynamic capabilities (DCs) view suggests that organisations should be capable of renewing and recreating their strategic capabilities to meet the requirements of changing environments (Teece et al., 1997; Teece, 2007; Linden & Teece, 2018). Investments alone are not enough to create competitive advantages; organisations also need to develop capabilities that rival firms cannot easily imitate (Gupta & George, 2016; Teece, 2014; Pisano, 2017). In the current data-driven digital economy, organisations strive to harness big data power to make better decisions (George et al., 2014; Janssen, van der Voort, & Wahyudi, 2017). Developed economies endeavour to capture value through big data; for example, big data are an integral part of the industry 4.0 plan devised by Germany to ride the fourth industrial revolution (Shamim, Cang, Yu & Li, 2017). Similarly, companies based in emerging economies, including Chinese firms, are also utilising big data to create value (Zeng & Glaister, 2018). However, firms need to develop the relevant capabilities needed to exploit the power of big data (Wamba et al., 2017; Zeng & Glaister, 2018). Alongside unprecedented opportunities, big data also present novel complexities (Wang, Kung, Wang, & Cegielski, 2018) that require new capabilities and skills (Tambe, 2014). To develop the capabilities required to reap benefits from big data, firms need both tangible and intangible resources—e.g. human resources (HRs), culture, technology and managerial and technical skills (Chen et al., 2012; Gupta & George, 2016; Tambe, 2014).

Big data enable decision makers to decide on the basis of 'what they know' instead of 'what they think' (McAfee, Brynjolfsson, & Davenport, 2012) and also enhance their knowledge (Khan & Vorley, 2017). The term 'big data' refers to data sets that are very high in velocity, volume, and variety, which makes them incompatible with traditional techniques and tools

1   (Elgendy & Elragal, 2014). The effective use of fast moving and large-scale data sets can

2   transform the decision-making approach taken by organisations (Janssen et al., 2017).

3   The quality of data-driven decisions does not solely depend on the data themselves but is

4   also linked to the strategies employed for data collection and analysis. Analysing the

5   relationships hidden in data sets requires experts from different disciplines with diverse skills

6   and capabilities (Janssen & Kuk, 2016; Janssen et al., 2017; Tambe, 2014). Janssen et al. (2017)

7   further argued that the involvement of multiple organisations in the process results into a

8   chain of activities known as a big data chain, which involves the steps and transfer points of

9   data collection, data preparation, data analysis and decision making (Janssen et al., 2017).

10   Data quantity and quality can be affected by a number of actions—for example, removing

11   noise, converting the data into machine-readable forms, and linking different data sets

12   (Kitchin, 2014)—which also influence the quality of big data decision making (Janssen et al.,

13   2017). However, most of the studies in the existing literature address the big data analytics

14   capabilities (e.g., Gupta & George; Wang et al, 2018; Miah, Vu, Gammack & McGrath, 2017),

15   while relatively little attention is given to designing a comprehensive construct of big data

16   decision-making capabilities. Big data decision making is a broader concept than big data

17   analytics (Janssen et al., 2017).

18   The use of big data for better decision making presents some major management

19   challenges for example, attracting the right people with the right skills (Gamage, 2016;

20   Tambe, 2014). McAfee et al. (2012) argued that overcoming such challenges—including

21   leadership, talent management, availability of technology, and company culture—is very

22   important to reap the benefits linked to the use of big data in decision making, which,

23   however, is not the ultimate desired outcome despite these factors being important in

promoting it. The actual main desired outcome of this process is the achievement of decision-making quality. Janssen et al. (2017) argued that the factors influencing big data decision-making quality are contractual and relational governance, big data analytics capabilities, knowledge exchange, collaboration, process integration and standardisation, routinising and standardisation, flexible infrastructure, big data source quality, and decision-maker quality. These factors have the potential of affecting the activities in a big data chain (Janssen et al., 2017).

This study investigates the influence of big data management challenges—which include leadership, talent management, technology, and company culture—on big data decision-making capabilities. Furthermore, it also examines the effect of big data decision-making capabilities on decision-making quality.

This study addresses a number of gaps in the existing literature. Although the existing literature has identified the influencers of big data decision-making quality, it has not answered the question of how firms can enhance their big data decision-making capabilities. The existing literature has not answered how, in the context of big data decision making, DCs can be influenced by managerial factors (e.g., Martin & Bachrach, 2018). Furthermore, the existing research has limited itself to the construction and investigation of big data analytics capability constructs, and sparse research has been conducted on broader concepts like big data decision-making and management capabilities, in general. The antecedents of big data decision-making capabilities need to be investigated because big data decision-making quality depends not only on data quality but also on a number of other key factors such as talent management, leadership and organisational culture involved in the process. Furthermore, and consistent with the resource based and DCs views, the appropriate management of

1   resources is important to develop and reconfigure DCs. Finally, the impact of big data

2   decision-making capabilities on decision-making quality requires sound conceptual

3   underpinnings and quantitative examination because this area of research is in its infancy.

4   Based on the above discussion, this study is aimed at answering the following research

5   question: "How can management practices enhance big data decision-making capabilities,

6   and how can big data decision-making capabilities lead to decision-making quality?" To

7   answer this question, empirical data were collected from Chinese firms who were increasingly

8   using big data for value creation. China was selected for this empirical investigation by reason

9   of it being the world's largest digital market, with most Chinese firms being actively engaged

10   in value creation through big data (Zeng & Glaister, 2018; Zeng & Khan, 2018). As many

11   Chinese firms were successfully competing against foreign competitors like Amazon, Google,

12   and eBay (Zeng & Glaister, 2018), it made sense to investigate the management issues

13   presented by big data in the Chinese context (Zeng & Glaister, 2018). The collected data were

14   analysed using partial least square (PLS) and the findings support the hypotheses of the big

15   data management challenges related to leadership focus, talent and technology

16   management, and organisational culture being the key antecedents of big data decision-

17   making capabilities, which, in turn, influence decision-making quality.

18   The findings of this study, thus, contribute to the existing body of knowledge by providing

19   important insights on how organisations can enhance their DCs in the context of big data

20   decision making by using managerial factors. This study is the first to establish a link between

21   management practices (leadership focus, talent and technology management and

22   organisational culture) and big data decision-making capabilities. The development of a

23   comprehensive construct of big data decision-making capabilities is also a major contribution

of this study, as the extant studies limited themselves to the discussions of big data analytics

capabilities. Furthermore, this study's examination of the association between big data

decision-making capabilities and decision-making effectiveness and efficiency is also a novel

contribution.

2. Theoretical background and Hypotheses Development

The theory of DCs is basically an extension of the resource-based view of organisations (Teece,

Pisano, & Shuen, 1997). The resource-based view suggests that a firm's heterogeneous

resources determine its sustainable competitive advantages (Barney, 1991; Barney et al.,

2011) . However, in today's turbulent and dynamic environments, this theory is challenged,

which encourages scholars to extend the resource based view to the DCs one (Gutierrez-

Gutierrez, Barrales-Molina, & Kaynak, 2018; Hitt, Xu, & Carnes, 2016; Teece et al., 1997). DCs

refer to a firm's ability to integrate, reconfigure, and build the competencies required to

respond to rapidly changing business environments (Teece et al., 1997; Linden & Teece,

2018). The DC approach emphasises the development of management capabilities and of

difficult-to-imitate combinations of functional, organisational, and technological skills (Teece

et al., 1997). The resource-based view invites the use of managerial practices to create new

capabilities (Wernerfelt, 1984), while the DCs view suggests the use of management

strategies to renew competencies according to changes in the environment. In the latter view,

the term 'capabilities' emphasises the key role played by management and leadership in the

adaptation, integration, and reconfiguration of organisational skills, functional competencies,

and resources in order to remain compatible with a changing environment (e.g., Schoemaker,

Heaton, & Teece, 2018). The DCs view urges scholars to focus on how organisations develop

and renew their capabilities to respond to environmental changes. It also argues that a firm's

managerial and organisational processes influence the development of its DCs (Teece et al., 1997).

Following the DCs view, this study considers leadership focus on big data, talent and technology management for big data, and culture development, as managerial and organisational practices suited to influence big data decision-making capabilities. In changing business environments, firms strive to become more data oriented, and consider big data decision-making crucial for their performance (McAfee et al., 2012). Big data are rapidly changing the ways in which firms make decisions as, in the big data era, different decision-making capabilities are needed to make quality decisions (Janssen et al., 2017). The DC framework is also used in the existing literature to discuss big data analytics capabilities (Wamba et al., 2017). This study investigates the antecedents of big data decision-making capabilities under the framework of DCs.

Although, in much of the existing research on big data, its potential impact has been explained through the DC lens (Dubey, *et al*., 2018; Erevelles, Fukawa and Swayne, 2016), many aspects of the institutions that influence a firm's DCs of harnessing value from big data remain unexplored. For instance, in 2017, the Chinese government released a state council paper intended as the hub of artificial intelligence (AI) innovation and to foster the development of a US$1 trillion AI industry by 2030 (Financial Times, 2018). With its sheer size and scale—1.4 billion internet users, significant investment, coupled with tech giants such as Alibaba, Tencent, and Baidu—China is rapidly closing the AI gap with the US. This unique institutional environment raises some important questions on the DCs of firms of harnessing AI that are fuelled by big data within this institutional context.

2.1.   Big data decision-making capabilities

Based on Janssen et al. (2017), this study defines big data decision-making capabilities as a firm's ability to make high quality big data-driven decisions by effectively managing a big data chain. Zeng and Glaister (2018) also provided important and in-depth insights into heterogeneous big data capabilities; however, their study is more relevant to value creation from big data. Conversely, Janseen et al. (2017) specifically discussed the factors affecting big data decision-making quality. The effective management of a big data chain requires firms to build up their big data management and analytics capabilities and capacity (Chen & Hsieh, 2014). The data processing literature also shows that a firm's capability to process information can affect its performance (Premkumar, Ramamurthy, & Saunders, 2005) and that big data processing and analytics capability are likely to influence a firm's capability of making quality decisions (Akter et al., 2017; Janssen et al., 2017).

In order to effectively manage a big data chain and to make quality decisions, firms need contractual and relational governance, big data analytics capabilities, knowledge exchange, collaboration, process integration, routinising, flexible infrastructure, quality data sources, and decision-maker quality (Janssen et al., 2017). Contractual governance refers to the formalisation of agreements with big data providers aimed at enhancing data quality. Relational governance, which includes the communication and exchange of knowledge for the understanding and processing of data, ensures trust among organisational entities. To create a big data chain and overcome fragmentation, collaboration is needed among different actors that are part of the big data-driven decision-making environment—i.e. big data providers, big data analysts and decision makers, among other factors. The integration of processes and tasks is also important to reduce the cost of big data and of their related

analytics. The activities involved in a big data chain need to be part of organisational routine, as this will improve data velocity. Infrastructure flexibility also facilitates data handling and processing. Data accuracy, related to the value of the data provider, is also required to avoid making wrong decisions, which prove to be very costly. Furthermore, to enhance quality data-driven decision-making capabilities, decision makers should have the ability to interpret the outcomes of big data analysis and understand their implications (Janssen et al., 2017).

2.2. Big data management challenges

The use of big data itself cannot yield its maximum benefits until firms overcome the related managerial challenges—i.e. leadership focus, harnessing talent and technology management and company culture (McAfee et al., 2012)—which are even bigger contributing factors than the technical ones. Following the resource-based view, Gupta and George (2016) also emphasised the need for human and technological resources and culture to reap the benefits of big data. McAfee et al. (2012) discussed these management challenges, which are presented in more detail below, specifically in the context of big data decision-making.

2.2.1. Leadership focus on big data

As an effective way of providing direction to organisational members (Dessler, 2002), leadership plays a critical role in the development and reconfigurations of DCs (Nonaka, Toyama & Konno, 2000; Schoemaker et al., 2018). The contingency theory of leadership also suggests that leaders can achieve the desired outcomes by appropriately selecting their leadership style (Robbins, Judge, Millett, & Boyle, 2013). The existing literature also acknowledges the impact of leadership on different organisational and behavioural outcomes—for example a leadership focus on knowledge management positively influences it within an organisation (Donate & Sanchez de Pablo, 2015; Shamim, Cang, & Yu, 2017).

1 Leaders can also influence the tendency towards information analysis by adopting suitable

2 leadership behaviours (Shamim, Cang, & Yu, 2016). Leadership is an important influencer of

3 DC development, which is usually achieved through interactions and complementarities

4 among processes, individuals and structures (Felin, Foss, Heimeriks, & Madsen, 2012). Koryak

5 et al. (2015) also argued that leadership is crucial for the development of DCs in a firm.

6 Particularly, DCs are associated with a leadership proclivity towards change, the perception

7 of opportunities to productively change existing routines and resources and the willingness

8 and ability to implement such changes (Kor, Mahoney & Michael, 2007). The managerial

9 cognition of leaders is also critical for the development of DCs suited to cope with changing

10 environments (Helfat & Peteraf, 2015). A leader's attention to strategic matters and the way

11 in which they are outlined and communicated affect the use of resources and decision-making

12 (Dutton & Jackson, 1987; Kor & Mesko, 2013). The development of DCs requires leaders' time,

13 attention and resources (Bingham, Eisenhardt & Furr, 2007).

14   Scholars have noted that addressing the managerial challenges related to big data use

15 starts with leadership (McAfee et al., 2012). In the big data era, firms are successful not only

16 because they have access to more and better data but mainly because they employ leadership

17 teams who have a clear vision and set clear goals. The use of big data does not remove the

18 need for leadership vision and human insight, which are still needed to affect the ways in

19 which organisations make decisions (McAfee et al., 2012). This study investigates the

20 association between leadership and big data decision-making capabilities, which is a gap in

21 the existing literature. The path goal theory of leadership suggests that, to achieve the desired

22 outcomes, leaders should adapt their styles and behaviours according to the work

23 environment and the desired outcomes themselves (House, 1971). There is empirical

24 evidence of leaders controlling their work environment and achieving the desired goals and

behavioural outcomes by adapting their leadership style according to the needs of the situations (Shamim et al., 2017). Leadership has also been highlighted not only as a strategic factor shaping a firm's potential to generate innovation by encouraging and cultivating an appropriate environment (Nonaka and Takeuchi, 1995; Kavanagh and Ashkanasy, 2006) but also as critical in guiding the formulation and subsequent implementation of strategies in firms (Shrivastava and Nachman, 1989). In the context of China, the findings of empirical research support the role played by leadership in positively influencing employee performance and group creativity (e.g., Zhang, Tsui and Wang, 2011; Liu, et al., 2014). McAfee et al (2012) also argued that leadership can play a vital role in the big data decision-making process. In the context of developing DCs, the role played by leadership is well acknowledged in the existing literature (Nonaka et al., 2000). A leadership inclination towards big data can enhance contractual and relational governance by encouraging both inter- and intra-organisational collaboration and facilitating knowledge exchange and has the potential of influencing organisational processes (Griffin & Mathieu, 1997). Leadership can also foster big data decision-making capabilities by providing a favourable climate (Sarros, Cooper, & Santora, 2008). As many researchers have also called for contextualisation (e.g., Bamberger, 2008), we sought to examine the effect of leadership on big data and on their related decision-making capabilities in the context of China. We argue that this environment is of particular interest as it represents a strong contender to dominate the AI industry, which is powered by big data. Furthermore, in consideration of the well-established importance of role modelling and the role played by leadership focus in organisational culture development, a proclivity of leadership towards big data can influence the big data decision-making capabilities of a firm at all levels. Based on the above discussion, we propose the following:

H1. A leadership focus on big data is positively associated with big data decision-making capabilities.

2.2.2. Talent management for big data

Talent management, which is emerging as a key organisational challenge, is considered very important in a wide spectrum of firms (Collings & Mellahi, 2009; Scullion, Vaiman, & Collings, 2016; Collings, Mellahi & Cascio, 2018). Researchers have argued that, as the existing research on talent management has limited implications, the role played by talent management in different contexts and environments needs to be examined (Krishnan & Scullion, 2017; Collings et al., 2018). Keeping in view the important role of harnessing talent, McAfee et al (2012) suggested that the use of big data can be enhanced by appropriate talent management. As data are now more affordable for organisations, the complements of data analysis—e.g., data scientists—have become more valuable (McAfee et al., 2012). The increasing value of big data experts makes it extremely important for organisations to retain them (Tambe, 2014). Although a knowledge of statistics is important, the use of big data requires something more than traditional statistical skills. Big data management involves complex skills and techniques that may not be readily available in some locations (Tambe, 2014) but are generally possessed by the new generation of computer scientists (McAfee et al., 2012). The use of big data also requires the skills involved in cleaning and visualising the data, which suggests that organisations need to nurture the key talent (Angrave et al., 2015). Angrave et al. (2015) noted the important role played in a big data environment by HR professionals and talent, who are able to speak the language of business and thus facilitate leaders in formulating ways to tackle big data (McAfee et al., 2012).

1   The big data phenomenon has gained a prominent position on the agendas of business

2   managers across the globe, and companies need to reconsider their HR needs accordingly (De

3   Mauro, Greco, Grimaldi, & Ritala, 2018). The literature also acknowledges the crucial role

4   played by human capital in successful companies, particularly in the high tech sector

5   (Colombo & Grilli, 2010). This situation makes it crucial for organisations to acquire the

6   competencies needed to deal with big data. This race for securing secure the right talent to

7   deal with big data does not look likely to be slowing down for as long as the labour market

8   will remain unable to handle the exponentially increasing demand (De Mauro et al., 2018).

9   The traits required to deal with big data can be classified into two groups i.e. the

10   technological and methodological abilities suited to transform big data into business insights

11   and the capacity to transform these insights into organisational value creation, which involves

12   the right people and core business processes of an organisation (De Mauro et al., 2018). The

13   technological and methodological roles include big data tool experts, data managers and

14   strategists, data ethical managers (Miller, 2014), coders, data hackers (Davenport & Patil,

15   2012), statisticians/quantitative analysts (Davenport, 2014) and auditors (Mayer-

16   Schönberger & Cukier, 2013). Those in the second category, who transform insights into

17   business value, are the visualisation experts (Davenport & Patil, 2012; Provost & Fawcett,

18   2013), communicators (Wixom et al., 2014), project managers (Song & Zhu, 2016) and

19   business experts/advisors (Davenport, 2014; McAfee, Brynjolfsson, & Davenport, 2012b). This

20   situation makes talent management crucial. In the age of the information economy, there is

21   a global war for talent (Cascio & Boudreau, 2016), and abilities of companies to leverage big

22   data will greatly depend on the effectiveness of their talent management.

1   Literature suggests that effective talent management practices enhance the DCs in the

2   organisation (Gutierrez, Barrales, & Kaynak, 2018). The resource-based view suggests that

3   firms should use their strategic resources to achieve sustainable competitive advantages

4   (Wernerfelt, 1984; Barney et al. 2011). The knowledge-based view argues that a firm's most

5   important strategic asset is knowledge, which is linked to its employees (Shamim et al., 2017).

6   To reap the maximum benefit from employee knowledge and talent—e.g. in terms of

7   performance—firms need to enact appropriate talent management practices (Huselid et al.,

8   1997; (McAfee et al., 2012; Glaister, Karacay, Demirbag & Tatoglu, 2018), as is suggested in

9   the literature in regard to the use of big data. Janssen et al. (2017) also argued that big data

10   decision making requires quality decision makers and expert big data analysts. The latter

11   should not only perform data analysis but also deal with contractual and relational

12   governance to enhance data collaboration and knowledge exchange with in and across firm

13   boundaries, which can affect big data decision quality (Janssen et al., 2017) . However, a lack

14   of dedicated talent was perceived as the major barrier to capture value from big data

15   (McKinsey, 2016; Tambe, 2014). Although there are approximately 460,000 professionals

16   currently working with big data in China, a 1.5 million shortage in talent is forecast for the

17   next three to five years (China Daily, 2017). As many scholars have called for contextualisation

18   (e.g., Bamberger, 2008), we sought to examine the effect of talent management on big data

19   decision-making capability in the context of China. Many other countries, both developing

20   and developed, are in the race for the development of AI capabilities linked to big data; thus,

21   effective talent management is vital for organisations to reap the benefits from big data and

22   digital technologies. As data become cheaper, scientists in the domain become more valuable

23   (McAfee et al., 2012), which further increases the need for effective talent management

24   practices to hire, retain, and train employees needed at all levels to cope with the

requirements of big data analysis aimed at quality decision making. As such, effective talent management plays an important role in enhancing organisations' capabilities (Collings & Mellahi, 2009; Joyce & Slocum, 2012). These arguments lead to the following hypothesis:

H2. Talent management is positively associated with big data decision-making capabilities.

2.2.3. Technology for big data

DC theory is widely discussed in the context of technology management (e.g., Cetindamar, Phaal, & Probert, 2009), which is considered to be an important influencer of the DCs of firms (Cetindamar et al., 2009). Technological competency is fundamental in facilitating the use of big data for analysis (Lawson et al., 2013). Recent years have seen great improvements in the tools, including open source software, needed to handle the velocity, volume and variety of big data. The most commonly used tool is Hadoop, which combines hardware with open source software (McAfee et al., 2012). Big data can be gathered by many technological means—e.g. ubiquitous information sensing devices, aerial sensor technologies, software logs identification readers etc. The global technological capacity for information storage increases by almost 100% every three year (Chen & Zhang, 2014). Big data have changed the ways in which organisations handle data (Oliveira, Fuerlinger, & Kranzlmller, 2012); larger storage and higher speeds are required to gather, store and access data (Chen & Zhang, 2014). Other popular big data tools are Dryad, Apache Mahout, Jespersoft BI Suit, Pentahu Business analyst, Skytree Server, Tableau, Karmashpere Studio and Analyse and Talend Open Studio (Chen & Zhang, 2014).

Technology has a strong influence over work outcomes (Form, Kaufman, Parcel, & Wallace, 1988) and can also help to integrate tasks (Altmann, 2017). McAfee et al. (2012) also argued that big data decision making requires the use of the most effective and cutting-edge

technologies to collect, store, analyse and visualise data. In the existing literature, there are examples of the availability of suitable technologies, which enhance the capability to use other technologies. Much empirical research conducted in the Chinese context has highlighted the importance of technological capability in driving a firm's performance (e.g., Zhou and Wu, 2010; Jin and Von Zedtwitz, 2008). For example, technology-based imports enhance China's indigenous technological capabilities (Zhao, 1995), while information technology enhances the word class logistical capabilities of North American and European firms (Closs, Goldsby & Clinton, 1997). Collaborations, knowledge exchange and big data analytics, which can be facilitated by the effective use of technology, heavily determine big data decision-making capabilities. For example, knowledge exchange can be made easy through the use of Cyber Ba, which also enhances performance (Sujatha & Krishnaveni, 2018). Lawson et al. (2013) also argued that technological competency can facilitate the use of big data. Thus, it can be argued that the availability of suitable technologies for big data management can enhance the related decision-making capabilities of a firm. Sher and Lee (2004) also argued that technology enhances the DCs by facilitating the knowledge. In line with existing theoretical discussions, we argue that technology can support big data decision-making capabilities in the context of China and suggests the following:

H3. There is a positive association between technology and big data decision-making capability.

2.2.4. Organisational Culture of big data

Organisational culture, which refers to the set of norms, values, attitudes and pattern of behaviours that defines the core organisational identity (Denison, 1984), influences leadership styles, working climates, strategy formulations, management processes and

1 organisational behaviours (Laforet, 2017; Saffold, 1988). Data-driven organisations need to

2 develop a culture in which 'what we know' takes the place of 'what we think' to discourage

3 dependency on hunches and instincts (McAfee et al., 2012). It should be noted that many

4 organisations just pretend to be data driven; in such cases, executives make their decisions

5 using traditional approaches and then justify them by spicing them up with lots of data

6 (McAfee et al., 2012). This kind of culture can really hurt the essence of big data decision

7 making.

8 The existing literature, which discusses organisational culture in the context of DC theory

9 (Gnizy, Baker, & Grinstein, 2014), has the potential of influencing a firm's DCs; for example, a

10 learning culture can affect a firm's capability of marketing programme adaptation and local

11 integration (Grinzy et al., 2014). The existing literature establishes that organisational culture

12 affects behavioural and organisational outcomes (Shamim & Abbasi, 2012). Existing empirical

13 research has also highlighted the positive correlation that exists between organisational

14 culture and firm performance in China. For example, Tsui, Wang and Xin (2015) noted the

15 organisational culture differences that exist among firms with different ownership structures,

16 which lead to different firm performances and employee attitudes. Zhou and Su (2014) also

17 identified a positive relationship between organisational culture and level of creativity. In the

18 context of big data, McAfee et al (2012) also argued that organisational culture is one of the

19 main challenges for big data management. Employees will not regularly do things that are not

20 part of organisational norms (Shamim et al., 2016). The recent literature acknowledges the

21 critical role played by organisational culture in the success of big data initiatives (Gupta &

22 George, 2016). Most reasons for big data initiative failures are related to organisational

23 culture rather than to data characteristics and technological factors (Lavalle et al., 2011).

1   Organisational culture has the ability to enhance a firm's ability to benefit from big data.

2   Gupta and George (2016) also argued that a data-driven culture can influence data-driven

3   decision making at all levels of an organisation. Similarly, a relevant culture is needed to

4   motivate decision makers to become actively involved in big data activities and chains.

5   Existing literature also acknowledges the crucial role of culture as influencer of DCs (Chirico

6   & Nordqvist, 2010). Hall et al. (2001) argued that some firms develop such a culture, which

7   make their organisations very inflexible, reluctant to change and inclined to path dependent

8   traditions; hence, such firms become less favourable to new proactive strategies, which

9   ultimately hinders the development of DCs. Chirico and Nordqvist (2010) argued that

10   organisational culture influences the processes designed to acquire, exchange, transform and

11   shed internal and external resources, which leads to DCs. Scholars have noted that DCs

12   required a strong and change-oriented organisational culture (Schoemaker et al., 2018, p.4;

13   Teece, 2014). Such a change-oriented culture is vital to reconfigure the processes and adapt to

14   changing business requirements in order to sense and seize opportunities arising from the rise of big

15   data. It is in this context, Schoemaker et al. (2018: 6) indicate "to be effective, DCs need to be deeply

16   baked into an organisation's culture, since shared values guide risk-taking, experimentation, learning,

17   and failure tolerance". It is logical to argue that the promotion of a culture of collaboration,

18   knowledge exchange and data science can stimulate the related executive interest and, thus,

19   enhance big data decision-making capabilities. Based on the above discussion, the following

20   hypothesis is proposed:

21   *H4. A big data organisational culture is positively associated with big data decision-making*

22   *capabilities.*

23   *2.3.   Decision-making quality*

1   To capture its quality, this study evaluates decision making on the basis of its effectiveness

2   and efficiency, as is also suggested in the literature (Clark, Jones, & Armstrong, 2007). In the

3   current big data era, companies are trying to determine how to best leverage data for decision

4   making (Visinescu, Jones, & Sidorova, 2017). Managerial experience, integrated with business

5   intelligence tools, can enhance decision-making quality (Seddon, Constantinidis, Tamm, &

6   Dod, 2017). Decision-making quality—i.e. effectiveness—can be evaluated by the satisfaction

7   of the decision makers in the achievement of desired outcomes (Kaltoft, Cunich, Salkeld, &

8   Dowie, 2014), while decision-making efficiency considers the resources involved in it—i.e.

9   time, cost, etc. Business intelligence—e.g. through big data management—endows decision

10   makers with data, information and knowledge useful for problem solving and decision making

11   at both the individual and organisational levels (Clark et al., 2007; Visinescu et al., 2017).

12   The theory of DCs argues that the renewal and creation of new capabilities provide firms

13   with sustainable competitive advantages (Teece, 2007; Linden & Teece, 2018). A firm's

14   performance is based on making a number of correct organisational decisions by using DCs.

15   The existing literature suggests that a firm's capability to manage information affects its

16   performance, customer and process management capabilities, which ultimately determines

17   its results and effectiveness (Mithas, Ramasubbu, & Sambamurthy, 2011). It can be argued

18   that the achievement of better results and effectiveness is outcome of quality decision

19   making facilitated by information management capabilities. Similarly, big data also enable a

20   firm to decide on the basis of accurate information. This way, the big data decision-making

21   capabilities of a firm can affect its decision-making quality as is also suggested in the literature

22   (Chen, Chiang, & Storey, 2012). Visinescu et al. (2017) also found that business intelligence

23   can enhance decision-making quality, which is determined by decision-making effectiveness

24   and efficiency (Clark et al., 2007). The big data capabilities of the firm, including skills and

processes, can influence the outcome for greater value (Wade, M., & Hulland, 2004). Effective

and efficient decision making requires a good level of big data capabilities throughout the big

data chain. For example, Dutch tax organisations used the big data capabilities to improve the

tax filling and collection by detecting the pattern leading to incorrect and fraudulent tax filling.

Through big data-based decision making, they managed to reduce the cost and improve the

decision compliancy, i.e. they enhance the effectiveness and efficiency of decision making

(Janssen et al, 2017). Teece (2007) argues that reconfiguration of capabilities, which refers to

DCs, is required to maintain evolutionary fitness to avoid unfavourable path dependencies,

and also to maintain efficiency. Wamba *et al*. (2017) also considers big data-driven capabilities

as DCs and a game changer allowing improved effectiveness and efficiency because of its high

operational and strategic potential. Similarly, Yiu (2012) argued that big data enable the firms

to enhance data-driven decision making and allow to enhance the effectiveness and

efficiency. On the basis of these arguments, we propose the following hypotheses:

H5. Big data decision-making capabilities are positively associated with decision-making effectiveness.

H6. Big data decision-making capabilities are positively associated with decision-making efficiency.
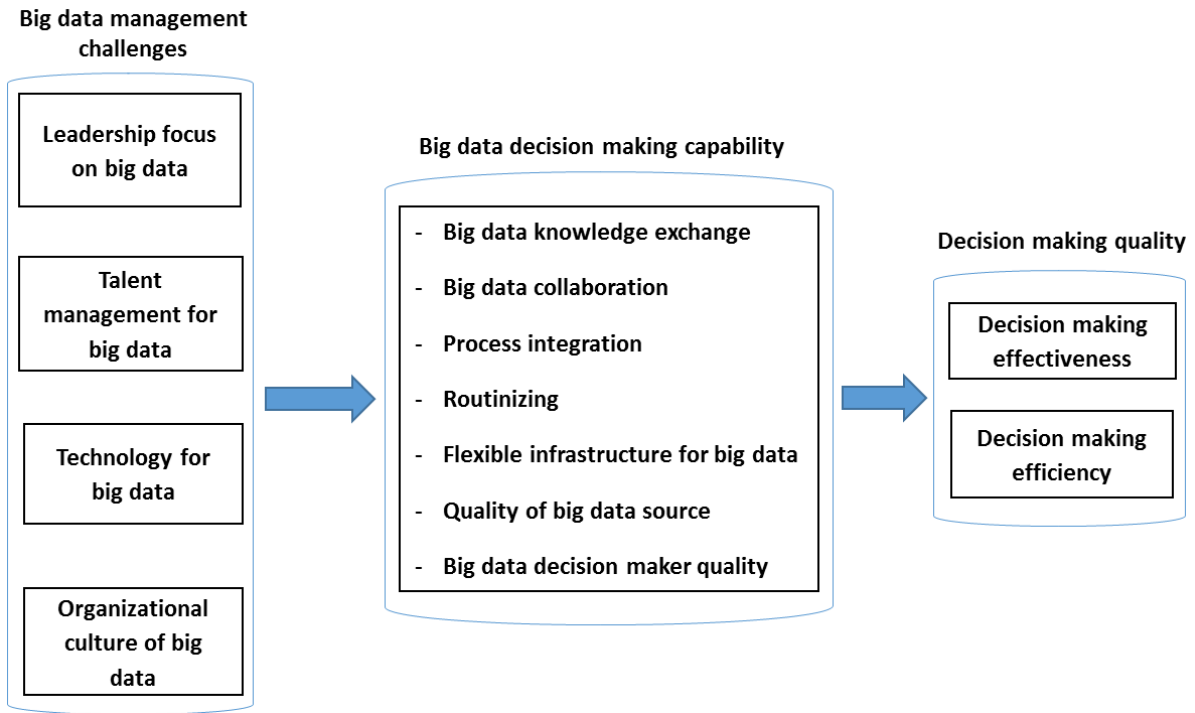
Figure 1. The conceptual framework

3. Methodology

3.1. Sample and data collection

This study followed quantitative methods of enquiry. A structured questionnaire was used to collect the data from Chinese firms that used big data for decision making. China is one of the world's largest digital markets, with many firms actively engaged in creating value from big data (Zeng & Glaister, 2018). The unit of analysis was the individual firm, and the respondents were owners or senior managers who answered questions related to their firms.

The data were collected in two rounds. The first began in October 2017 and was based on the 4th edition of the "China Big Data Enterprise Ranking", which lists the major Chinese firms using big data and was released at the 4th World Data Expo in China. We contacted more than 400 shortlisted firms—to which we had gained access through a local Chinese

consultancy firm—and distributed the questionnaire to their CEOs/Senior managers. We received 86 usable responses.

The second round of data collection took place in February 2018 during a domestic Chinese business networking event to which firm owners and senior managers had been invited to celebrate the Chinese New Year. The questionnaire was distributed to the relevant company owners or senior managers, who were asked to fill it out in their free time. This round yielded 22 usable responses, making a total of 108, each of which from a different firm.

For reasons of methodological parsimony, we strove to maintain homogeneity among the respondent firms, all of which were originally Chinese technology firms that were at least 10 years old, with employee numbers ranging from 100 to 250, and privately owned.

We undertook several steps to limit common method bias. First, we ensured the respondents about the anonymity and confidentiality of the information collected. Second, we randomised the order of items in the questionnaire, making it impossible for the respondents to identify the independent and dependent variables (Podsakoff, MacKenzie, Jeong-Yeon, & Podsakoff, 2003). Lastly, we conducted a Harman single factor test to check for common method bias; the results show that a single factor explains 40.5% of the total variance, which is not a major concern, and is unlikely to confound the interpretation of the results in this study (Donate & De Pablo, 2015).

3.2.   Questionnaire and measures

The questionnaire consisted of 53 items. Because of the lack of an established scale in the existing literature, the items to measure the variables used in this study were developed by the authors, with the exception of four, measuring decision-making effectiveness, that were

1 adopted from Visinescu et al. (2017). These variables—particularly *big data management*

2 *challenges*, and *big data decision-making capabilities*—were new concepts that had not

3 hitherto been quantitatively investigated. The items used for *big data management*

4 *challenges*—six for *leadership*, four for *talent management*, and five each for *technology* and

5 *organisational culture*—were mainly inspired by McAfee et al (2012). The items for *big data*

6 *decision-making capabilities* were mainly inspired by the exploratory study conducted by

7 Janssen et al. (2017). It is worth mentioning that these items were not directly adopted from

8 these studies, which only served as bases for the authors to develop them. In this study, the

9 relevant factors drawn from the explorations in the literature were used to design a construct

10 of *big data decision-making capabilities*. For methodological parsimony, not all the explored

11 factors were used in study; only *big data knowledge exchange, big data collaboration, flexible*

12 *infrastructure for big data, process integration, routinising, big data source quality and big*

13 *data decision maker capabilities* were rationally chosen. The *big data analytics capabilities*

14 variable was excluded from the *big data decision-making capabilities* construct because it had

15 been used as an independent capability in a number of existing studies (e.g., Gupta & George,

16 2016). *Big data contractual and relational governance* were also excluded from the construct

17 to avoid the duplication of items, as *data collaboration* was already part of the construct.

18   Both *decision-making effectiveness* and *decision-making efficiency* were each measured by

19 means of four items. *Big data decision-making capabilities* were measured by means of seven

20 factors drawn from Janssen et al. (2017)—i.e. *big data knowledge exchange, big data*

21 *collaboration, flexible infrastructure for big data, process integration, routinising, big data*

22 *source quality and big data decision-maker capabilities*.

For reasons of model parsimony and validity, *big data decision-making capabilities* were measured in two steps. In the first step, these factors were measured independently by means of five items for *knowledge exchange*, three for *collaboration*, three for *process integration*, three for *routinising*, four for *flexible infrastructure*, three for *big data source quality* and three for *decision maker quality*. After testing these factors for reliability and validity (see appendix) of, their items were transformed into a single factor to be used in the *big data decision-making capabilities* construct. Then, factor analysis was performed to ascertain construct reliability and validity. This transformation method is consistent with Shamim et al. (2017). Additionally, we controlled for firm characteristics, such as size, as large firms may possess more and better resources and capabilities for the leveraging of big data for effective and efficient decision making.

3.3. Data analysis

The data were analysed using quantitative techniques; particularly, the PLS method of applying structural equation modelling (SEM). The reliability of the factors was examined through Cronbach's alpha. The Smartpls software package was used for factor analysis, path analysis and hypotheses testing. Smartpls is especially suitable for studies using self-developed items (Shamim et al., 2017). As this study examines the self-developed constructs of big data decision-making capability, management challenges, decision-making efficiency and approaches, the PLS variance-based approach, which imposes fewer restrictions on distribution and sample size, was suitable (Chin, Marcolin, & Newsted, 2003; Shamim et al., 2017). PLS is an SEM technique that analyses the theoretical and measurement models at the same time (Chin, 1998) and is also effective in resolving multicollinearity issues (Chin et al., 2003).

1   **4. Results**

2   *4.1. Reliability and validity*

3   The reliability of the constructs was confirmed through Cronbach's alpha, which was higher

4   than 0.7 (George, 2001) for all the constructs. To test validity, we followed Fornell and

5   Lacker's (1981) approach, according to which convergent validity is established if the value of

6   the average variance extracted (AVE) is higher than 0.5 and lower than composite reliability

7   (CR). Furthermore, factor loadings should be greater than 0.65. (Fornell & Lacker, 1981). Table

8   1 shows the factor loadings, AVE and CR. The factor loadings for *big data decision-making*

9   *capabilities* ranged from 0.63 to 0.87, those for *leadership* from 0.70 to 0.84, those for *talent*

10   *management* from 0.76 to 0.82, those for *technology* from 0.71 to 0.89, those for

11   *organisational culture* from 0.79 to 0.91, those for *decision-making effectiveness* from 0.87 to

12   0.89, and those for *decision-making efficiency* from 0.78 to 0.91. The AVEs of all constructs

13   were greater than 0.5 and were lower than their CRs. On the basis of these parameters,

14   convergent validity was established.

15   **Table 1. Convergent validity**

Factors	Items	Factor loadings	AVE	CR
Big data decision-making capability	Big data knowledge exchange	0.79	0.69	0.93
	Big data collaboration	0.80		
	Process integration	0.89		
	Routinising	0.83		
	Flexibility	0.90		
	Data quality of big data source	0.70		
	Decision maker quality	0.82		
Leadership focus on big data	LDR1	0.76	0.62	0.90
	LDR2	0.81		
	LDR3	0.84		
	LDR4	0.78		
	LDR5	0.81		
	LDR6	0.70		

Talent management for big data	TM1		0.82	0.65	0.88
	TM2		0.76		
	TM3		0.81		
	TM4		0.82		
Technology for big data	TECH1		0.71	0.70	0.91
	TECH2		0.76		
	TECH3		0.89		
	TECH4		0.89		
	TECH5		0.88		
Organisational culture of big data	OC1		0.84	0.75	0.93
	OC2		0.91		
	OC3		0.85		
	OC4		0.78		
	OC5		0.92		
Decision-making effectiveness	DEFC1		0.87	0.76	0.92
	DEFC2		0.84		
	DEFC3		0.90		
	DEFC4		0.87		
Decision-making efficiency	DEFY1		0.91	0.73	0.91
	DEFY2		0.83		
	DEFY3		0.78		
	DEFY4		0.86		

1

2   Discriminant validity requires the AVE of each construct to be higher than the squared

3   correlations among them (Fornell & Lacker, 1981). The results presented in Table 2, in which

4   the AVE of each construct is given at the diagonal in italic, thus confirm discriminant validity.

5   The factor analysis, reliability, and validity testing results reflect the quality of the research

6   model. Furthermore, the values of R-squared for the dependent variables also meet the

7   minimum requirements: R-squared is 0.89 for *big data decision-making capabilities*, 0.55 for

8   *decision-making effectiveness* and 0.53 for *decision-making efficiency*. The value of chi-square

9   for the whole model is 2147.72.

10   **Table 2.** Discriminant validity

Factors	1	3	4	6	7	8	9
1.Big data decision-making capability	0.*69*						

3.Decision-making effectiveness	0.54	*0.76*				
4.Decision-making efficiency	0.51	0.27	*0.73*			
6.Leadership focus on big data	0.57	0.42	0.33	*0.62*		
7.Organisational culture of big data	0.68	0.50	0.51	0.51	*0.75*	
8.Talent management for big data	0.62	0.43	0.28	0.27	0.51	*0.65*
9.Technology for big data	0.67	0.50	0.47	0.46	0.72	0.60	*0.70*

4.2.   Path analysis and hypothesis testing

Figure 1 and Table 3 show the path analysis results, which indicate that *leadership* ($\beta = 0.20$, $p < 0.01$), *talent management* ($\beta = 0.22$, $p < 0.01$), *organisational culture* ($\beta = 0.44$, $p < 0.001$) and *technology* ($\beta = 0.18$, $p < 0.05$), all positively and significantly affect a firm's big data decision-making capability. This means that a leadership focus on these aspects can enhance a firm's big data decision-making capabilities. These findings lead to the acceptance of H1, H2, H3 and H4. The results also reveal that a firm's big data decision-making capabilities are positively and significantly associated with its decision-making effectiveness ($\beta = 0.77$, $p < 0.001$) and decision-making efficiency ($\beta = 0.71$, $p < 0.001$). Hence, H5 and H6 are also supported by the results. The P values were derived through bootstrapping.

The results presented in Table 3 also show a positive and significant indirect association of leadership ($\beta = 0.59$, $p < 0.01$), talent management ($\beta = 0.17$, $p < 0.01$) and organisational culture ($\beta = 0.33$, $p < 0.001$) with decision-making effectiveness. However, the indirect relationship of technology and decision-making effectiveness is not significant, as its t value is lower than 2. Similarly, decision-making efficiency is indirectly and significantly associated with leadership, talent management, and culture; whereas, the indirect association of decision-making efficiency with technology is not significant because of a low t value.

1
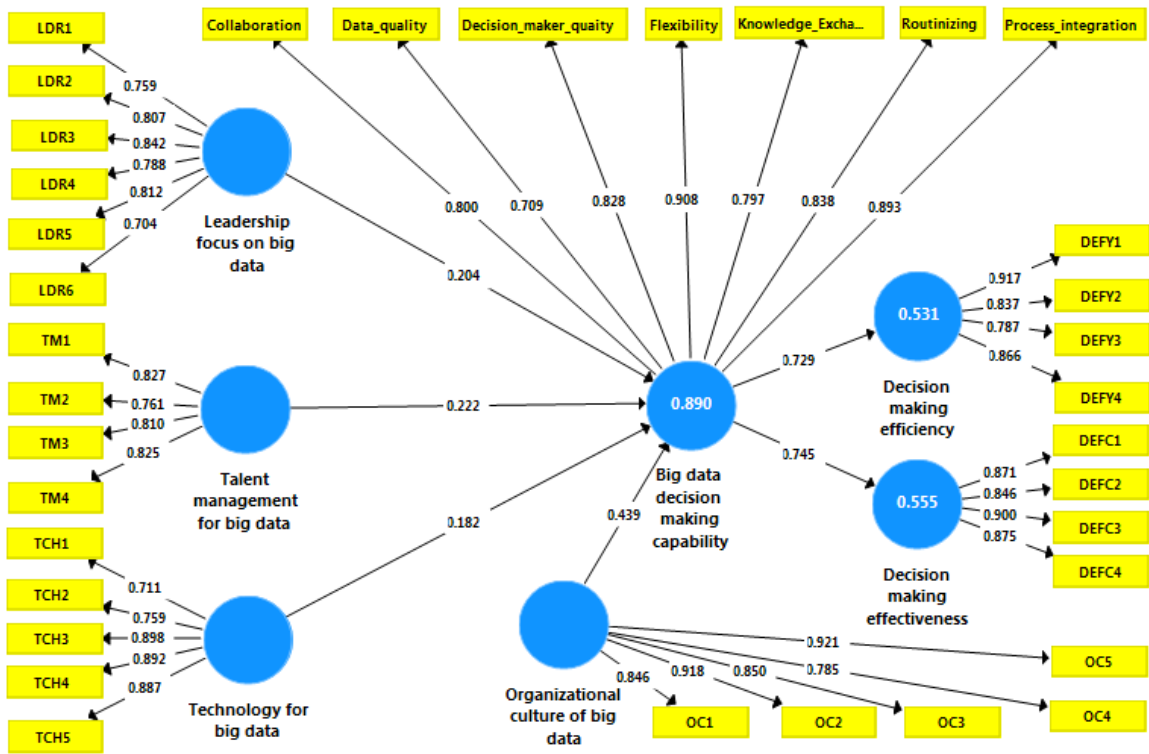
2 **Figure 2.** Path analysis

Table 3. Path analysis

Path	Direct effects		Indirect effects	
	β	T values	β	T values
Big data decision-making capability←Leadership focus on big data	0.20**	3.42		
Big data decision-making capability←Talent management for big data	0.22**	2.69		
Big data decision-making capability←Organisational culture of big data	0.44***	6.99		
Big data decision-making capability←Technology for big data	0.18*	2.00		
Decision-making effectiveness←Big data decision-making capability	0.74***	14.62		
Decision-making efficiency←Big data decision-making capability	0.73***	16.17		
Decision-making effectiveness← Big data decision-making capability←Leadership focus on big data			0.59**	3.47
Decision-making efficiency←Big data decision-making capability←Leadership focus on big data			0.49***	3.64
Decision-making effectiveness← Big data decision-making capability←Talent management for big data			0.17**	2.63
Decision-making efficiency←Big data decision-making capability← Talent management for big data			0.16**	2.79
Decision-making effectiveness← Big data decision-making capability←Technology for big data			0.14*	1.97
Decision-making efficiency←Big data decision-making capability← Technology for big data			0.13*	1.88
Decision-making effectiveness← Big data decision-making capability← Organisational culture of big data			0.33***	6.56
Decision-making efficiency←Big data decision-making capability← Organisational culture of big data			32***	6.42

1   **5. Discussion and conclusion**

2   Following the DCs view, this study used the initial work conducted by Janssen *et al*. (2017) to

3   develop a construct of big data decision-making capabilities. This study investigated how the

4   DCs development can be influenced by management practices, in the context of big data

5   decision making. As Teece *et al*. (1997) also suggested that having the resources is not the

6   main thing, effective management of resources is important to create value from the

7   resources. Especially in uncertain and turbulent environment, firm needs to reconfigure the

8   existing capabilities, and this process heavily depends on the firm's management practices,

9   which is the main argument of DCs (Gutierrez *et al*., 2016; Teece *et al*., 1997; Schoemaker et

10 al., 2018). This study investigated the big data management challenges initially explored by

11 McAfee et al. (2012) as antecedents of big data decision-making capabilities. The qualitative

12 exploration conducted by Zeng and Glaister (2018) also provided important insights to design

13 the construct of big data decision-making capabilities. However, Zeng and Glaister's (2018)

14 study was more relevant to the creation of value from big data, as Janssen et al. (2017)

15 specifically focussed on the factors affecting big data decision-making quality. Our results

16 support the assumption that leadership, talent management, technology, and organisational

17 culture are positively associated with big data decision-making capabilities. The findings of

18 this study show that leadership, talent management, technology, and organisational culture

19 have the significant association with big data decision-making capability. However,

20 organisational culture has the strongest association with big data decision-making capability,

21 and then talent management and leadership. Strength of association of technology and big

22 data decision-making capability is comparatively weaker than organisational culture, talent

23 management and leadership. It does not mean that having suitable technology is not

24 important, but it indicates the extreme importance of culture development. This finding is

1   consistent with the existing literature and also with the DCs. Literature suggests the

2   technological issues of big data are very real, but the managerial issues are even more

3   important, starting with the role of leaders (McAfee et al., 2012), who play important part in

4   culture development. DCs view also suggests that having the resources, i.e. technological

5   resource, is not enough, and it needs better management of resources to create value from

6   resources (Teece et al., 1997; Schoemaker et al., 2018). In the current big data era, firms

7   cannot be successful just because they have access to good data, but they need leadership

8   with clear vision, suitable talent management practices, and most importantly an

9   organisational culture that facilitates the use of big data. Though, this study collected data

10   from Chinese firms, however, the findings can be used in other contexts as well. As DCs view

11   has the element of reconfiguration of capabilities according to the environment (Teece et al.,

12   1997; Linden & Teece, 2018; Pisano, 2018). The finding are also applicable to other

13   economies, as they can use the main framework of management practices, and modify the

14   micro-foundations according to local context. For example, keeping the focus of leadership,

15   talent management, technology management, and culture development on big data decision-

16   making, but through more compatible strategies.   Although organisations understand the

17   importance of big data in driving significant economic value, many are struggling with how to

18   create value from the significant amount of data they already have owing to its volume,

19   velocity and variety (Lavalle et al. 2011). Our findings are also applicable to other firms who

20   are in the process of data mining and offer informative concepts and pattern that managers

21   can use to make deeper and richer assessments of the ways in which they manage data to

22   create value. Consistent with Janssen et al. (2017), our results further reveal that a firm's big

23   data decision-making capabilities enhance its decision-making effectiveness and efficiency.

24   *5.1.   Theoretical Contributions and Implications*

1   This study makes a rich theoretical contribution by using DC theory to examine the construct

2   of big data decision-making capabilities and adds to the small but growing body of research

3   aimed at understanding the process of harnessing value from big data (e.g., Zeng & Khan,

4   2018). It makes unique contributions to the existing literature in several important ways. To

5   begin, it is a first attempt to establish a link between big data management challenges

6   (leadership, talent management, technology, and company culture) and big data decision-

7   making capabilities. While there is an underlying assumption concerning the role played by

8   different factors, such as leadership and organisational culture, in affecting big data decision-

9   making capabilities, we offer empirical insights into how different organisational elements

10 can contribute to a firm's ability to create value from big data. Second, our findings offer rich

11 implications for further research on the role played by big data decision-making capabilities

12 and on big data management capabilities in general. It proposes a novel construct of big data

13 decision-making capabilities, one that can be analysed in relation to different management

14 and organisational practices in order to explore the antecedents of big data decision-making

15 capabilities. In the big data context, this study argues that management practices and

16 capabilities are more important than data science for better big data decision making. Future

17 researchers could be interested in examining how organisations can reap the maximum

18 benefit from big data decision making by adopting appropriate management practices and

19 reconfiguring their capabilities. This study extends the debate on big data capabilities, which

20 is currently limited to big data analytics. Third, this study also tested the association of big

21 data decision-making capabilities with big data decision-making effectiveness and efficiency,

22 which is a missing link in the existing literature. This is valuable for several reasons; because

23 of the volume, velocity, and variety of big data, many firms are struggling to create value from

24 the significant amount of data they already have. Our findings suggest that, through the

development of appropriate leadership, talent management, technology, and organisational culture, firms can enhance their big data decision-making capabilities, which would lead to decision-making quality. Finally, this study was conducted in the context of China, our conceptual model—linking different organisational mechanisms with a firm's big data decision-making capabilities—could also lend empirical support to the capability-building view, which could be applied to firms from other economies. The research on big data in the field of business management is still in its infancy; thus, firms from other economies could also draw from the theoretical model to improve their ability to harness value from big data.

Managerial implications

The framework proposed in this study could be used by firms to enhance their big data decision-making capabilities, which would ultimately lead to decision-making quality and data-driven decision making. While much of the existing literature places data scientists at the heart of the value creation process, we highlighted several organisational mechanisms that have an impact on a firm's big data decision-making capabilities, and subsequently lead to decision-making quality. By enhancing their big data decision-making capabilities, organisations can make knowledge-based decisions and find themselves in a better position to decide on the basis of what they know, rather than of what they think (McAfee et al., 2012). This study suggests that, to improve their decision-making quality, firms should enhance their big data decision-making capabilities by focussing their leadership on managing big data and the related talent, developing a culture of big data decision-making and acquiring technologies suitable to facilitate it. Knowledge exchange and collaboration between decision makers and data provider would also be important—together with the routinising and

integration of the big data chain, a flexible infrastructure, data source quality, and decision maker quality—to enhance big data decision-making capabilities.

In order to enhance their firms' big data decision-making capabilities, leaders should provide clear visions and goals, and encourage big data decision making. They should take great interest in the big data chain, and act as role models by using big data for decision making. Talent management activities should focus on skill enhancement aimed at big data decision making and on the hiring and retaining of big data experts. The use of a variety of cutting edge technologies for big data management would also be important. Furthermore, the development of a big data decision-making culture would be crucial, as organisational cultures influence behavioural outcomes.

5.2.   Limitations and future research areas

This study also presents some limitations and future research suggestions. It is a cross sectional study with a single data source; thus, future research could adopt a longitudinal research design and examine the variables and their associations across both developed and emerging markets. Another suggestion would involve ascertaining the generalisability of the findings of our research to different countries, including other emerging and underdeveloped economies. Our descriptive findings reflect the current situation in China; it could, therefore, be interesting to determine whether our hypotheses would be confirmed or rejected in different institutional contexts. Thus, future studies need to integrate institutions-based view with DCs and examine the value creation through big data across different range of firms such as SMEs, family-owned enterprises, business groups, state-owned enterprises and multinational enterprises. Such studies could perform a comparative analysis by examining different types of firms and their value creation approaches through big data. Because of its

quantitative research design and deductive approach, this study did not explore the phenomenon in depth; thus, future research could explore the given context in more detail through a qualitative mode of enquiry—i.e. to determine how big data management challenges enhance big data decision-making capabilities and quality. Additionally, ethnographic and experimental design-based studies would provide rich insights into the mechanisms and processes involved in creating value from big data. For reasons of methodological parsimony, this study strove to maintain homogeneity among the respondent firms. It could be interesting for future research to take into account firm level heterogeneity to investigate its moderating role in the proposed model. Lastly, future studies could examine the role of big data decision-making capabilities and quality on performance as well as on different types of innovations.

5.3.   Conclusion

This study concludes the investigation with the argument that managerial issues i.e. leadership, talent management, technology management and organisational culture are the real issues in the context of big data decision making. These management practices influences firm's big data decision-making capability, which enables the firms to make effective and efficient decisions. This study also emphasises on big data decision-making capability as DC and reflects the implications of managerial practices in the development of DC in big data-driven environments. By providing a new theoretical framework grounded in quantitative evidence, this research provides an important contribution to our knowledge of value creation from big data in emerging economies in the era of digitalised world.

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12

1 **Appendix**

2 **Table 4.** Formation of the construct of big data decision-making capability

Big data decision-making capability	**Knowledge exchange**	KEX1 KEX2 KEX3 KEX4 KEX5	0.90 0.91 0.89 0.89 0.88	0.95	0.81
	Collaboration	COL1 COL2 COL3	0.89 0.93 0.90	0.83	0.93
	Process integration	PINT1 PINT2 PINT3	0.88 0.93 0.91	0.83	0.93
	Routinising	RTN1 RTN2 RTE3	0.91 0.94 0.90	0.84	0.94
	Flexible infrastructure	FLEX1 FLEX2 FLEX3 FLEX4	0.88 0.91 0.92 0.88	0.81	0.94
	Data quality of big data source	DQS1 DQS2 DQS3	0.90 0.93 0.89	0.93	0.83
	Decision maker quality	DMQ1 DMQ2 DMQ3 DMQ4*	0.90 0.94 0.90 0.49*	0.69	0.89

3 *Eliminated items*

4 **Questionnaire for data collection**

Big data knowledge exchange							
Our employees transfer their knowledge about data	1	2	3	4	5	6	7
Knowledge about how data are collected is exchanged within the organisation	1	2	3	4	5	6	7
Knowledge about how data are used is exchanged within our firm	1	2	3	4	5	6	7
Knowledge about how data are processed is exchanged within our firm	1	2	3	4	5	6	7
The exchange of knowledge makes it easy for us to analyse data	1	2	3	4	5	6	7

Big data collaboration							
There is collaboration among big data analysts and big data providers	1	2	3	4	5	6	7
There is collaboration among big data analysts and decision makers	1	2	3	4	5	6	7
There is collaboration among big data providers and decision makers	1	2	3	4	5	6	7
Process integration							
We have the ability to integrate the processes involved in the big data chain (i.e. data collection, preparation, analysis and decision making)	1	2	3	4	5	6	7
The integration of the processes involved in the big data chain reduces the cost of big data use	1	2	3	4	5	6	7
The integration of the processes involved in the big data chain reduces the efforts necessary to analyse big data	1	2	3	4	5	6	7
Routinising							
The big data chain is a routine matter in our organisation (i.e., data collection, preparation, analysis and decision making)	1	2	3	4	5	6	7
Routinising big data activities improves big data velocity	1	2	3	4	5	6	7
Routinising big data activities helps the analysts to make real time decisions	1	2	3	4	5	6	7
Flexible infrastructure for big data							
Our big data management infrastructure is flexible	1	2	3	4	5	6	7
A flexible infrastructure helps us to enhance our ability to handle big data	1	2	3	4	5	6	7
A flexible infrastructure helps us to enhance our ability to process big data	1	2	3	4	5	6	7
Because of a flexible big data infrastructure, decision making is quick in our organisation	1	2	3	4	5	6	7
Quality of big data source							
Our big data sources provide accurate data	1	2	3	4	5	6	7
Our big data providers have a very good reputation in the industry	1	2	3	4	5	6	7
We are satisfied with the quality of the data provided by our big data sources	1	2	3	4	5	6	7
Big data decision-maker quality							

The decision makers in our organisation are able to interpret the outcomes of big data analytics	1	2	3	4	5	6	7
The decision makers in our organisation understand the implications of big data analytics outcomes	1	2	3	4	5	6	7
We employ experienced decision makers	1	2	3	4	5	6	7
The decision makers in our firm have the ability to make quick decisions	1	2	3	4	5	6	7
Leadership focus on big data							
Our leadership provides a clear vision	1	2	3	4	5	6	7
Our leadership sets clear goals	1	2	3	4	5	6	7
Our leadership encourages big data decision making	1	2	3	4	5	6	7
Our leadership shows great interest in the big data chain	1	2	3	4	5	6	7
Our leadership shows concern for the use of big data	1	2	3	4	5	6	7
Our leadership is very active in managing big data	1	2	3	4	5	6	7
Talent management for big data							
We prefer to hire employees who understand big data	1	2	3	4	5	6	7
We have the ability to recruit expert users of big data	1	2	3	4	5	6	7
We plan to enhance the big data management skills of our staff	1	2	3	4	5	6	7
We take special care in the retention of big data experts in our organisation	1	2	3	4	5	6	7
Technology for big data							
We use the latest technology to manage big data	1	2	3	4	5	6	7
Our technological competency helps us to enhance big data management	1	2	3	4	5	6	7
We use a variety of technological tools to manage big data	1	2	3	4	5	6	7
Our big data technological tools are more effective than those used by others in the industry	1	2	3	4	5	6	7
We face technological problems in managing big data*	1	2	3	4	5	6	7
Organisational culture of big data							
Our decisions are based on data	1	2	3	4	5	6	7

A dependency on hunches for decision making is strongly discouraged in our organisation	1	2	3	4	5	6	7
Depending on data is part of our organisational routine	1	2	3	4	5	6	7
We have a culture of data driven work	1	2	3	4	5	6	7
Our executives use lots of data to justify decisions they have already taken through traditional approaches*	1	2	3	4	5	6	7
Decision-making effectiveness							
I believe that we make good decisions	1	2	3	4	5	6	7
The decisions we make result in the desired outcomes	1	2	3	4	5	6	7
I am satisfied with the outcomes of our decisions	1	2	3	4	5	6	7
Our decisions improve organisational performance	1	2	3	4	5	6	7
Decision-making efficiency							
Our decision-making cost is very low	1	2	3	4	5	6	7
We spend a lot of time in making decisions*	1	2	3	4	5	6	7
We don't need a lot of people to make decisions	1	2	3	4	5	6	7
We make timely decisions	1	2	3	4	5	6	7

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