Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level

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Abstract

Drawing from the knowledge-based dynamic capabilities (KBDCs) view, this study examines the association of big data management capabilities with employee exploratory and exploitative activities at the individual level. Furthermore, it also investigates the mediating role of big data value creation in the association of big data management capabilities with exploratory and exploitative activities. The partial least square method was employed to analyse the hypotheses using data collected from 308 employees of 20 Chinese multinational enterprises. The existing literature gives scant attention to the role of big data management capabilities at the individual level. The main contribution of this study is that it conceptualises big data management as the ability to utilise external knowledge (generated from global users) under the resource constrained environment of an emerging economy. Furthermore, this study builds upon the existing literature on KBDC to explain big data management capabilities as antecedents to ambidexterity at the individual employee level.

Keywords: Big data management capabilities; big data value creation; exploratory activities; exploitative activities; MNEs; ambidexterity; emerging economies

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1. Introduction

In the last decade, digital platforms and the internet have transformed the way multinational enterprises (MNEs) develop capabilities for value creation and innovation (Brouthers, Geisser, & Rothlauf, 2016; Coviello, Kano, & Liesch, 2017; Ojala, Evers, & Rialp, 2018; Parente, Geleilate, & Rong, 2018). MNEs are now increasingly facing challenges to meet and adapt to the needs of their global users, who are connected to the firm by means of digital platforms (e.g., Facebook, Twitter, skyscanner.com, booking.com, Amazon, Alibaba, and other web-based digital platforms). Therefore, one of the core concerns of MNEs is accessing and understanding the data pertaining to their global users' needs and changing behaviours (Coviello et al., 2017, which scholars call big data. Big data refers to the data sets which are characterised by very high volume, velocity and variety (Gupta & George, 2016). For example, firms can predict customer behaviours by subjecting their online reviews to sophisticated big data text analytics (Xiang, Schwartz, Gerdes, & Uysal, 2015). To identify its customers' preferences, Netflix monitors their scrolling and browsing behaviours by collecting data on when they pause, rewind, fast-forward, etc. (Zeng & Glaister, 2018).

Existing literature also acknowledges the importance of big data's enhancement of decision-making quality (Shamim, Zeng, Shariq, & Khan, 2018) and value creation across different sectors, including manufacturing and media (Zeng & Glaister, 2018), banking (Hale & Lopez, 2017), healthcare (Wang, Kung, Wang, & Cegielski, 2018), tourism and hospitality (Li, Xu, Tang, Wang, & Li, 2018), etc. Enabled by digital technology, big data have emerged as the central tool aiding enterprises to facilitate exploitative and explorative activities (McAfee, Brynjolfsson, & Davenport, 2012). While many scholars and practitioners have emphasised the skills needed for exploitative activities, others have highlighted the importance of exploratory activities (e.g., Janssen, van der Voort, & Wahyudi, 2017; Zeng & Glaister, 2018). Central to this view is an emphasis on ambidexterity (Turner, Swart, & Maylor, 2013). Ambidexterity is defined as a firm's ability to reconcile two opposite strategies (for example, simultaneously pursuing both exploration and exploitation) within itself (O'Reilly & Tushman, 2013; Simsek, 2009). Ambidexterity is important for MNEs as it facilitates their globalisation processes. For example, companies like AB Volvo and IKEA improved their globalisation performance by being proactive in exploration and by improving their exploitation effectiveness (Vahlne & Jonsson, 2017). However, current research on management and international business lacks understanding of how management of user-generated big data impacts exploratory and exploitative activities.

Big data create unique opportunities for MNEs originating from emerging markets. Emerging market MNEs (EMMNEs) originate from an environment that is dynamic and evolving. They are also characterised by a lack of intermediaries, weak institutions, nascent innovation ecosystems and limited financial support for innovative activities from the government, which is a key institutional player (Khan et al., 2019). Such institutional immaturity is often referred to as institutional voids, and these make it very difficult for the firms in emerging economies to perform exploratory and exploitative activities (Khan et al., 2019; Wu, 2013). In such a context, sources of external knowledge becomes extremely important to pursue exploratory and exploitative activities (Khan, Rao-Nicholson, & Tarba, 2018). In this study, we view big data as an external source of knowledge creation and examine the association of big data management capabilities with big data value creation and exploratory and exploitative activities.

In the context of rapid digital transformation – whereby user data change continuously – there is a need to understand how the departments and individuals within an organisation build the capacity to renew and exploit existing capabilities and to continuously explore and integrate new ones (Turner et al., 2013; Perez-Martin, Perez-Torregrosa and Vaca, 2018). The existing literature has mainly discussed ambidexterity and big data management at the firm level; thus, a gap still exists regarding how individuals engage in the process of ambidexterity. We concur with Coviello et al. (2017), who highlighted how individuals have been left out – as black boxes – in understanding international customers of MNEs. The role played by individuals – more specifically, by employees – becomes even more crucial in the context of the international firms receiving user-generated big data through digital platforms. These enterprises are dependent upon having highly capable individual employees who can effectively and efficiently sense, interpret and make use of users' changing data. McAfee et al. (2012) also highlighted the importance of data scientists as individual employees and suggested talent management for retaining these employees. Furthermore, employee-level capabilities also play a crucial role in developing the human capital aspect of ambidexterity (Caniels & Veld, 2016; Turner et al., 2013).

The knowledge-based view (KBV) highlights the role of the individual as the prime driver in the creation of organisational knowledge (Nonaka, Byosiere, Bourucki, & Konno, 1994) and conceptualises the existence of a firm as an institution that integrates knowledge that resides within and across individuals (Grant, 1996). Employee-level outcomes of big data value creation and big data capabilities are missing links in the existing literature (Trong, Chris, & Cong, 2018). Therefore, in this study, we specifically focus on individual employees dealing with user-generated big data in international firms. This study follows the framework of knowledge-based dynamic capabilities (KBDC), which emphasise knowledge activities. The literature suggests that knowledge activities at any level initially require the willingness of individual employees (Shamim, Cang, & Yu, 2017b). Kim and Lee (2013) also argued that in order to meet increasing customer expectations, firms need to focus on knowledge activities at the individual employee level. Thus, this study applies the KBDC framework at the individual employee level by examining the association of big data management capabilities with big data value creation as well as employee-level exploratory and exploitative activities. The few relevant examples in the literature that apply KBV at the individual employee level are Shamim, Cang and Yu (2017a) and Shariq, Mukhtar and Anwar (2018). However, KBDC requires further investigation at this level. Our core focus is on the relationship between individuals' big data management capabilities, abilities to capture value from data and ambidexterity (i.e., development of explorative and exploitative capabilities) (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

Drawing from the KBDCs view, this study aims to fill these research gaps by investigating employee-level heterogeneous big data management capabilities and their influence on value creation. Furthermore, it also examines the influence of big data value creation on employee-level exploratory and exploitative activities. To examine the influence of big data management capabilities on value creation and employee ambidexterity, this study uses the framework created by Zeng and Glaister (2018) – i.e., the capabilities to democratise, contextualise, experiment with and execute data – but at the individual employee level. By investigating these issues, this study aims to answer the following research question: How do big data management capabilities influence employee ambidexterity through big data value creation? In this research, we focus on China, which provides a suitable context. China provides an example of an emerging economy in which increasing numbers of start-ups are creating disruptive digital business models and providing services to wide arrays of users through diverse platforms and virtual communities.

1.1. Theoretical background and hypotheses

1.1.1. Knowledge-based dynamic capabilities view

In the today's dynamic business environment, firms need to have the dynamic capabilities (DCs) to explore and exploit the changes in the environment (Zheng, Zhang, & Du, 2011). DCs refer to the ability to build, integrate and reconfigure competencies to address the changing business environment (Teece, Pisano, & Shuen, 1997). The DCs view is an extension of the resource-based view (RBV) (Teece et al., 1997; Zheng et al., 2011). RBV suggests that firms must leverage their unique strategic resources to have a sustainable competitive advantage (Barney, 1991; Barney, Ketchen, & Wright, 2011), and according to the firm's KBV, the main strategic asset of a firm is its knowledge, whether it be individual or organisational. KBV further argues that the basic purpose of an organisation is to create value from knowledge (Grant, 1996). Critics of RBV argue that it is not very effective in a rapidly changing dynamic environment and that it leads to the creation of the DCs view to develop the capabilities to handle the changing environment (Gutierrez-Gutierrez, Barrales-Molina, & Kaynak, 2018; Teece et al., 1997).

DCs can create an infinite loop by modifying and extending themselves. The DCs view shifts the emphasis of strategic management researchers from RBV to the ability to change and quickly develop new capabilities (Zheng et al., 2011). A DC is a learned and stable pattern of collective activities to modify the organisational processes to improve effectiveness, and learning mechanisms such as knowledge activities are the key drivers of DCs (Zollo & Winter, 2002). Synthesis of KBV with DCs leads to the KBDCs framework, which refers to the ability to acquire, generate and combine knowledge resources to sense, address and explore the dynamic environment (Zheng et al., 2011).

This study uses the KBDCs view to argue that big data management capabilities are crucial for value creation and exploratory and exploitative activities. In the current digital economy, the way firms create value is changing and requires novel capabilities (Akter et al., 2016; Braganza et al., 2017). Big data has appeared as a prominent strategic source of value creation in the modern data-driven digital economy (Jannsen et al., 2017; McAfee et al., 2012). Hence, it is crucial for firms and individuals to have the capabilities to create value from big data. The way decisions are made in an organisation is changing due to the increasingly availability, affordability and importance of data. Successful firms need to be data driven in today's business environment (McAfee et al., 2012). This study investigates how big data management capabilities (i.e., big data democratisation, contextualisation, experimentation and execution) are related to value creation and exploratory and exploitative activities. These capabilities include knowledge-related activities that involve managing access to big data through democratisation and gaining new data insights through contextualisation, both of which lead to knowledge creation. Similarly, experimentation with data execution and insight can help to illuminate data and information patterns, which leads to knowledge creation (Uriarte, 2008). Understanding and gaining insight from big data generated by global customers requires DCs (e.g., big data management capabilities). In the context of this study, big data often increase in value the more they are used. They are self-regenerative, are significantly different from traditional and appropriable physical assets and are a scarce and non-renewable resource (Glazer, 1991). Furthermore, ambidexterity is also considered to be a DC for MNEs (Vahlne & Jonsson, 2017).

Sirmon, Hitt and Ireland (2007) argued that because resources alone are not enough to create value, resource management is also required. Wamba et al., (2017) also pointed out that in order to create value from big data, it is important to possess big data management capabilities. The capability to deal with the technical aspects of big data is not sufficient to create value from it; for example, making effective decisions based on big data does not solely depend on possessing big data analytical capabilities but also management ones (Janssen et al., 2017). McAfee et al. (2012) also advocated the crucial role played by big data management factors in the process of value creation through big data.

In their exploratory enquiry, scholars suggested (Acharya et al., 2018; Braganza et al., 2017; Jabbour et al., 2019) suggested a framework for big data management capabilities suited to facilitate the process of value creation from big data. According to the authors, these are the capabilities to democratise, contextualise, experiment with and execute data. However, the researchers analysed these capabilities at the firm level, while this study focusses on individual employee-level big data management capabilities and value creation. Thus, a gap still exists in relation to examining the micro-foundations at the individual level and their effects on value creation by individual employees.

1.1. Knowledge based dynamic capabilities in emerging economy firms

Big data have become especially significant for firms in emerging economies, as they must continuously use external knowledge to identify new capabilities which in turn shape the internal capabilities of these firms to engage in the process of value creation. The existing research shows that external knowledge from international markets creates alternatives for emerging economy firms to compensate for the institutional void in the market (Khan et al., 2019). Existing research focuses more on inter-firm relationships, both horizontal and vertical, as a core source to access and develop new external knowledge. For example, Xu, Guo, Zhang and Dang (2018) found that firms in emerging economies use vertical and horizontal inter-firm relationships to source external knowledge and then leverage the benefit from relationships through entrepreneurial orientation. The research in this area takes input from variety of interdisciplinary literature including catch-up and innovation (Fu, Pietrobelli, and Soete 2011; Mathews 2006; Nuruzzaman, Singh, and Pattnaik 2018; Pandit, Joshi, Sahay, and Gupta 2018; Zeng and Williamson 2007), institutional theories (Casson and Wadeson 2018; Corredoira and McDermott 2014; McDermott and Corredoira 2009; Meyer and Peng 2005; Peng et al 2018; Xie and Li 2018), evolutionary perspectives in management (Fleury and Fleury 2014; Herrigel, Wittke, and Voskamp 2013; Guo and Zheng 2019; Kumaraswamy et al. 2012; Nguyun and Diez 2019; Xie and Li 2018), strategic management (Cooke et al 2018; Lahiri and Kedia 2009, 2011; Lahiri, Kedia, and Mukherjee 2012) and international marketing (Jean, Sinkovics, and Cavusgil 2010; Jean, Kim, and Sinkovics 2012; Sinkovics et al. 2011) among many more.

This research on innovation from emerging economy firms aims to understand how emerging economy firms, leverage their global linkages in order to catch-up with technologically advanced MNEs. For example Kumar and Puranam (2012) report the rise of Indian firms working with large MNEs from developed economies. They explain that the innovation emerging from these Indian firms may not be visible to the final consumer but is extremely valued by their long term MNE buyers. Similarly Mathews (2006) argue that the internationalisation path of the emerging economy firms is different from developed economies (Casson and Wadeson 2018; Peng et al, 2018). Whereas MNEs from developed economies exploit their firm-specific advantages in order to expand abroad (Johanson and Vahlne 1977). The internationalisation path of latecomers is shaped by their ability to access new resources through insertion (linkages) into global value chains and benefitting from the insertion (leverage, and learning) (Nuruzzaman, Singh, and Pattnaik 2018; Pandit, Joshi, Sahay, and Gupta 2018; Kumaraswamy et al. 2012; Nguyun and Diez 2019; Xie and Li 2018).

Other studies have draw upon institutional and organizational perspectives and intend to focus on the interaction of local institutions and internal strategies of domestic emerging market firms.For example McDermott and Corredoira (2009) and Corredoira and McDermott (2014) look into how the institutional and relational mechanisms enable domestic firms in Argentina to achieve product and process upgrading. McDermott and Corredoira (2009) report that upgrading of small firms is not shaped by linking to any type of network. Instead small firms should actively make effort to access 'valuable' linkages or networks. Khan et al. (2019) identified international networks as a strategy for moto-parts suppliers to source and develop exploratory innovation. Furthermore, Sinkovics, Choksy, Sinkovics and Mudambi (2019) identified conditions under which software suppliers from emerging economies increase the comfort zone of their international clients in global value chains. Existing literature on emerging economies has demonstrated that successful firms are able to source knowledge externally and continuously reconfigure their resources to build new capabilities.

The strategic management and international marketing studies focus on the antecedent and consequences of unique supplier capabilities using quantitative survey methodology. For example Jean et al (2008) draw upon transaction cost approach and resource based view to understand how suppliers can improve their performance in international B2B context. They report that advance IT capabilities (Electronic integration, Human IT capabilities, organisational complementary capabilities) contributes towards organisational processes (coordination, absorptive capacity, and monitoring) which in turn improves the operational and strategic performance of supplier in B2B context. Jean, Sinkovics, and Cavusgil (2010) report that advance IT capabilities support suppliers' ability to govern their relationship with international customers. Effective governance mechanisms help suppliers to innovate in international customer relationships and improve their overall market performance.

In this study, we depart from previous studies on DC development in emerging economies in two ways. First, instead of looking at international relationships, including international clients, partners or suppliers, we focus on user-generated data around the world. Recent literature has highlighted the role of big data in facilitating value creation and capability development in emerging economies. For example, Shamim et al. (2018) found that big data decision-making capabilities improve the decision-making effectiveness and efficiency of Chinese firms. They argued that the firms' ability to manage internal challenges shape their ability to develop big data decision-making capabilities. Similarly, Zeng and Khan (2018) argued that entrepreneurial orientation plays a significant role for Chinese firms to leverage value from big data. Verma and Bhattacharyya (2017) focused on the failure of Indian firms to derive strategic value from big data analytics due to lack of willingness of organisational members to change internally and adapt to environmental turbulence. Current literature on big data in emerging economies is scant. The existing literature limits big data capability to data that does little to explain the spatiality of the user-generated data. To date, there is not a single study that focuses on the internationalised nature of user data, which is crucial to understand the capabilities of emerging economy's MNEs at a micro-level.

Building upon the first point, we focus on the individual nature of big data management capabilities and how they enable those individuals within EMMNEs to engage in ambidextrous activities. While the majority of studies on emerging economies and big data in particular explain capability development from the perspective of the firm, an increasing number of studies focus on more micro-level dimensions of capability development, including big data savvy skills at the team level (Akhtar, Frynas, Mellahi, & Ullah, 2019). In this article, we argue that big data management capabilities are rooted in individual employees' capacity to sense and seize large volumes of global user data.

Based on the above discussion, we conceptualise the individual-level big data management capability as an integrative concept that enables continuous access, analysis and management of user-generated data around the world. In line with the previous literature, we argue that these individual-level big data management capabilities facilitate emerging economy firms to compensate for the weak institutions that encourage capability development.

1.2. Big data management capabilities and value creation from big data

According to the framework of Zeng and Glaister (2018), big data democratisation refers to the ability of the firm to integrate big data analytics with other departments within the firm to enable a wide range of data applications at any given time. While the existing research tends to put great emphasis on specific individual expertise – data scientists who have the specialised skills and knowledge to analyse big data (e.g., Davenport & Patil, 2012) – Khan and Vorley (2017) pointed out that the broad scale of big data applications at the firm level will drive value creation. Their study proposed that in a big data context, the greater the capability to democratise data and thus enable a wide range of data applications, the greater the likelihood of increasing the potential value created from big data. At the individual level, this may involve micro-level interactions among employees within and across departments to integrate big data across different domains and users. Continuous processes aimed at accessing new data and frequent interactions among individuals enable the latter to respond rapidly to changing global user needs (Moses, Kayode, & Susan, 2017).

The capability to contextualise big data refers to the ability to interpret it in order to assign meanings in specific contexts. A variety of data is available within firms (i.e., data related to consumer behaviours, market trends, changing customer needs, etc.). The capability to contextualise any clues provided by big data to gain a holistic view can be positively associated with big data value creation (Zeng & Khan, 2018). Due to the sheer volume of big data, without layers of context to explain their type or the location, time or circumstances where data are collected, they cannot generate much insight. From the perspective of digital enterprises, employees' abilities to contextualise data are crucial, as these firms need to achieve a thorough understanding of their users in the global market.

Another big data management capability is the ability to experiment with data, which encourages trial and error and nurtures an intrusive attitude towards big data. It encourages employees to frequently experiment with big data and to monitor their transformation. The data experimentation capability plays an important role in creating value from big data. This is in line with Luo and Rui (2009), who argued that ambidextrous EMMNEs have employees who continuously engage in the process of generating ideas and upgrading capabilities (Deng, 2012; Khan et al., 2018; Nicolson et al., 2016). Indeed, the differences between exploration of new possibilities and exploitation of old certainties captures some fundamental dilemmas in firm behaviour and strategies that are critical for firm survival and prosperity. Through big data experimentation, MNEs can constantly absorb new information, test ideas in real time and adjust their strategies to new opportunities.

A further relevant big data management capability is that of executing data, which refers to the ability to transform data-generated insights into actions in an agile and responsive manner that may lead to the identification of opportunities and the creation of value (Zeng & Glaister, 2018). Although many firms are able to collect a significant amount of data, they are unable to respond to the opportunities that emerge from these data in a timely manner. Without data execution, these resources cannot be transformed to create value for the firm. This study investigates the association of these capabilities with value creation at the individual employee level. On the basis of these arguments, drawing from the KBDC framework and consistent with Sirmon et al. (2007), resource management is identified as crucial for value creation. This leads to the following hypothesis:

H1. Employees' big data management capabilities are positively associated with value creation from big data.

1.3. Employees' exploratory and exploitative activities

The ability to simultaneously conduct exploratory and exploitative activities is referred to as ambidexterity. Whereas exploitative activities occur within the existing mental models, policies and organisational norms, exploratory activities are radical in nature, impacting organisational routines and existing models (March, 1991). At the individual employee level, exploratory activities include generating and implementing new ideas, developing radically innovative ways of thinking and searching for competitive solutions (Caniels, Neghina, & Schaetsaert, 2017; Gibson & Birkinshaw, 2004). In contrast, exploitative activities involve leveraging the existing knowledge base to incrementally improve efficacy and efficiency (Gibson & Birkinshaw, 2004).

Most empirical studies on ambidexterity have focussed on organisational ambidexterity (Junni, Sarala, Taras, & Tarba, 2013). Broadly, there are two distinct conceptualisations of ambidexterity: structural and contextual (Caniels & Veld, 2016). Structural solutions refer to a firm setting up dual structures, thus enabling two activities to be carried out simultaneously in different business units within an organisation (e.g., Adler, Heckscher, & Grandy, 2013). The literature suggests that organisational ambidexterity is not easy to achieve because exploratory and exploitative activities have contending goals, fight for same resources and require different capabilities (Caniels et al., 2017). Contextual ambidexterity posits that organisational settings should facilitate the simultaneous performance of exploratory and exploitative activities by individuals (Caniels & Veld, 2016). This school of thoughts utilises more behavioural and social means to integrate exploitation and exploration. Such an approach uses processes, systems and beliefs that shape individual-level behaviours in an organisation (Ghoshal & Bartlett, 1994). Thus, it focusses on the development of exploratory and exploitative activities at the individual employee level (Prieto & Pilar Perez Santana, 2012). This conceptualisation of contextual ambidexterity suggests that a high degree of ambidextrousness involves high levels of both exploratory and exploitative activities at the individual level (Cao, Gedajlovic, & Zhang, 2009). Thus, while both exploratory and exploitative activities are performed by individual employees, it focusses on the latter (Kang & Snell, 2009). The existing research on individual employee-level ambidexterity is scarce (Raisch & Birkinshaw, 2008); therefore, there has been a call for more studies on the subject (Caniels et al., 2017; Junni et al., 2013). In response to this call, this study investigates employees' big data management capabilities and value creation from big data as antecedents of exploratory and exploitative activities at the individual employee level.

The creation of value from big data can lead to the identification of new opportunities, which often leads to positive customer outcomes, such as customer willingness to pay for the product (Zeng & Glaister, 2018) and the exploration of the factors affecting customer satisfaction (Xiang et al., 2015). Big data value creation has the potential to influence exploratory activities. Furthermore, big data can facilitate the process of product development and the value added and personalisation of services to existing customers (Zeng & Glaister, 2018), which indicates the influence of big data value creation on exploitative activities.

Big data management capabilities and ambidexterity both are DCs (Shamim et al., 2018; Vahlne & Jonsson, 2017), and the literature suggests that DCs influence other DCs, creating a loop (Zheng et al., 2011). Particularly, big data management capabilities fit into the framework of KBDC, as it involves knowledge activities. Getting access to data, understanding the contextual insights, experimenting with data to understand the patterns and executing the insight gained from the analysis of data lead to knowledge creation (Uriarte, 2008), which is a prominent predictor of exploratory and exploitative activities (Khan et al., 2018). On the basis of these arguments, the following are our hypotheses:

H2. Employees' big data management capabilities are positively associated with their exploratory activities.

H3. Employees' big data management capabilities are positively associated with their exploitative activities.

H4. Big data value creation is positively associated with exploratory employee activities.

H5. Big data value creation is positively associated with exploitative employee activities.

Scholars (Rothberg and Erickson, 2017; Zeng and Glaister, 2018) explored a number of exploratory and exploitative activities as outcomes of big data value creation, such as the development of a credit score model in a firm, credit rating and review contents, a big data predictive programme suited to monitor diseases, etc. On the basis of these arguments, it is logical to assume that the creation of value from big data can facilitate the processes of exploration and exploitation among employees. The key constructs proposed, such as democratisation and contextualisation, require intensive collaboration between individual employees to drive the value creation process. As knowledge does not always transfer easily within the organisation, open discussions and knowledge sharing between individual employees can stimulate knowledge flow within the firm (Lane et al., 2006). Ambidexterity is a DC (Vahlne & Jonsson, 2017), and big data is an important strategic asset that requires pertinent management capabilities to create value (Janssen et al., 2017; McAfee et al. 2012; Sirmon et al., 2007). This means that as they have the potential of leading to value creation, big data management capabilities are also important for the enactment of exploratory and exploitative activities among employees. We assume that creating insight from data through data management capabilities is a creativity stage, which requires implementation or utilisation of data insight for value creation to convert the creativity and data insight into actual innovation, whether it be exploitative or exploratory. Creativity is limited to idea generation, and innovation requires implementation and commercialisation of creative ideas (Amabile, 1988), which means value creation. Following these logical arguments, it can be assumed that big data value creation mediates the relationship of big data management capabilities with employee exploratory and exploitative activities.

H6. Employees' big data management capabilities are indirectly and positively associated with their exploratory activities through the mediation of big data value creation.

H7. Employees' big data management capabilities are indirectly and positively associated with their exploitative activities through the mediation of big data value creation.

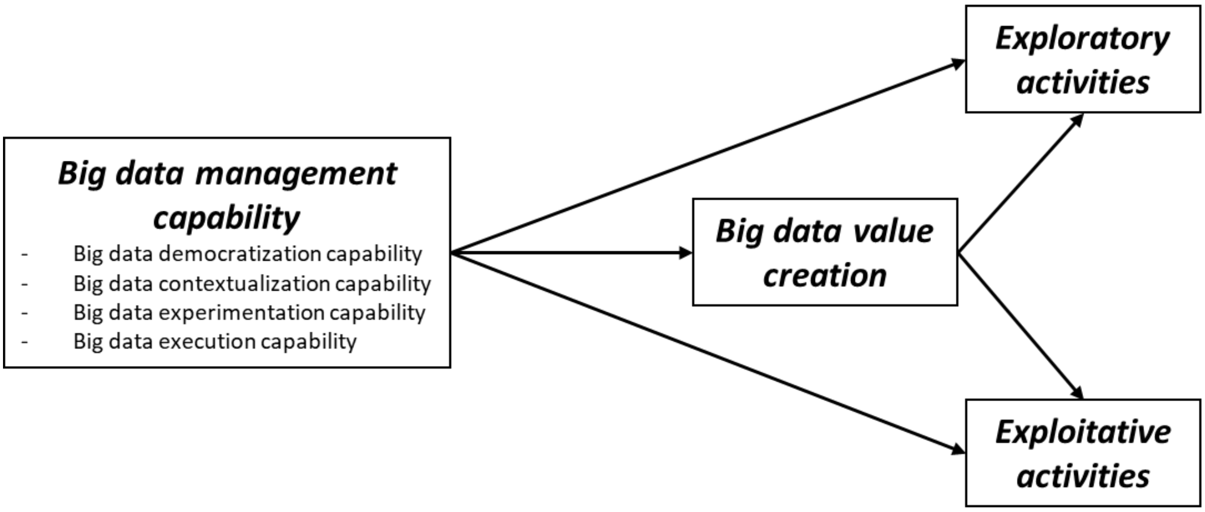

Figure 1: Conceptual model.

2. Methodology

2.1. Sample and data collection

This study adopted a quantitative method of enquiry. A structured questionnaire was used to collect data from employees of Chinese MNEs. China is one of the world's largest digital markets, with many firms actively engaged in big data value creation activities (Zeng & Glaister, 2018). The sample population for this study consisted of Chinese MNE employees who made use of big data in their jobs. For data collection purposes, this study focussed on the employees of companies involved in e-commerce activities. Such companies are very active on the internet to collect data (Doan, Ramakrishnan, & Halevy, 2011) and are heavily dependent on their ability to generate information for value creation, unlike traditional companies, which mainly depend on their physical assets to derive internal and supply side efficiencies (Parker & Van Alstyne, 2005). The value of data is also higher in these types of companies, which usually keep their data platforms open and accessible to both internal and external users (Zeng & Glaister, 2018). Finally, the selected EMMNEs had branches abroad; however, most of their global services were managed and orchestrated from the home country. It is important to note that the unit of analysis in this study was not the firms but their employees as individuals, who use big data for value creation by managing their access to data, experimentation with data, ability to contextualise data and execution of data insights.

Following the purposive sampling technique, which is suited for both quantitative and qualitative enquiries (Tongco, 2007), companies were selected to distribute the questionnaire to their employees. All the sample companies were MNEs that had originated in China and were using big data generated from international customers. The age of the companies was over 10 years, and the number of employees was over 500. The selected companies were from the sectors of online retailing, telecommunication, airline, information technology, block chain technologies and financial services, and all had global customers to generate big data.

The questionnaire was initially sent to the senior managers of the sample companies, who then distributed it to those employees who made use of big data for their jobs. Since most of the work was orchestrated in China (the home country), the questionnaire was mainly distributed to employees located there. The employees filled out the questionnaire anonymously during their free time. The data were collected in two waves between December 2017 and June 2018. The questionnaire was distributed to 756 employees, 403 of whom responded by filling it out. Of these, 308 responses were found to be usable. All the participants were between the ages of 30 and 40, had five to 15 years of work experience and held at least a bachelor degree. Furthermore, 72% of them were working at the managerial level. For methodological parsimony, we tried to maintain homogeneity among the sample.

2.2. Common method bias

To reduce common method bias, we ensured the anonymity of the respondents and the confidentiality of the information collected, and we randomised the order of the items in the questionnaire (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Data were collected in two waves to mitigate common method bias. Furthermore, the Harman single factor test was also employed to check for common method bias, and the results showed that a single factor explained 41.7% of the total variance; this is not a major concern and is unlikely to confound the interpretation of the results of this study (Donate & de Pablo, 2015). This method of reducing common method bias is consistent with the existing literature (e.g., Yang, Secchi, & Homberg, 2018).

2.3. Measures

Using the foundations of the exploratory study conducted by Zeng and Glaister (2018), this study developed the items suited to measure big data management capabilities (big data democratisation, contextualisation, experimentation and execution) and value creation at the individual employee level. The democratisation and execution capabilities were measured by developing seven items for each, the contextualisation capability was measured by means of five items and the experimentation capability was measured by six items. Zeng and Glaister (2018) emphasised big data management capabilities at the firm level; however, they also highlighted the importance of these capabilities at the individual employee level. For example, they found significant variation in the benefits that individual employees gained from the insights extracted from big data. They argued that organisations should pay attention to big data management capabilities to enable individual employees to create value from these data (Zeng & Glaister, 2018). Furthermore, KBV also highlights the prime role of individuals in knowledge activities (Nonaka, 1994). These arguments suggest that big data management capabilities should be investigated at the individual level as well. Following these suggestions, this study measured big data management capabilities at the individual level on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

For model parsimony and validity, big data management capabilities were measured in two steps. In the first step, big data democratisation, contextualisation, experimentation and execution were measured independently. After testing these factors for reliability and validity (see Appendix), these items were transformed into a single factor to be used in the big data management capabilities construct. Then, a factor analysis was performed to ascertain the construct reliability and validity. This transformation method was consistent with Shamim et al. (2018).

The scales to measure exploratory and exploitative activities were adopted from the study conducted by Mom, Van Den Bosch and Volberda (2007); these items have been used by a number of studies on employee-level ambidexterity (e.g., Caniels et al., 2017). Ten items were used to measure ambidexterity, five for exploratory activities and five for exploitative activities at the employee level. All the items were measured using a seven-point Likert scale ranging from 1 (never) to 7 (always).

2.4. Data analysis strategy

This study adopted the quantitative techniques of data analysis, particularly, the partial least square (PLS) method, which involves 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 to test the hypotheses. SmartPLS is especially suitable for studies using self-developed items (Shamim et al., 2017a). Because this study examined the self-developed constructs of big data management capabilities and big data value creation, a variance-based approach was suitable (Shamim et al., 2017a). PLS is a variance-based approach that imposes fewer restrictions on distribution and sample size (Chin, Marcolin, & Newsted, 2003). It is an SEM technique which analyses the theoretical and measurement models at the same time (Chin, 1998) and is also an effective way to resolve multicollinearity issues (Chin et al., 2003).

3. Results

3.1. Reliability and validity

The reliability of all the constructs was examined through Cronbach's alpha. The results in Table 1 show that the values of Cronbach's alpha for all the variables were higher than 0.7, which reflects good reliability and internal consistency, as suggested by the literature (George, 2011).

In order to establish convergent validity, the factor loadings for each item in the construct should be higher than 0.65, the average variance extracted (AVE) for each variable should be greater than 0.50 and the composite reliability (CR) should be greater than the AVE of the construct (Fornell & Larcker, 1981). The results in Table 1 show that the factor loadings for all the constructs were greater than 6.5, the AVEs were higher than 0.50 and the CR of each construct was greater than its AVE, thus meeting the criteria for convergent validity. Regarding big data management capabilities, the loadings ranged between 0.74 and 0.94, the AVE was 0.56 and the CR was 0.90. Big data value creation showed loadings ranging between 0.70 and 0.84, the AVE was 0.60 and the CR was 0.90. The factor loadings for employee exploratory activities ranged from 0.72 to 0.83, the AVE was 0.60 and the CR was 0.88. Finally, employee exploitative activities showed loadings ranging from 0.67 to 0.89, the AVE was 0.58 and the CR was 0.87. On the basis of these results, convergent validity was established

Table 1. Reliability and convergent validity

Factors	Items	Factor Loadings	AVE	CR	Cronbach's Alpha
Big data democratisation capability	DD1	0.71	0.64	0.92	0.90
	DD2	0.74			
	DD3	0.72			
	DD4	0.82			
	DD5	0.87			
	DD6	0.89			
	DD7	0.83			
Big data contextualisation capability	DCC1	0.67	0.55	0.85	0.79
	DCC2	0.75			
	DCC3	0.86			
	DCC4	0.70			
	DCC5	0.69			
Big data experimentation capability	DEC1	0.82	0.60	0.90	0.87
	DEC2	0.76			
	DEC3	0.88			
	DEC4	0.69			
	DEC5	0.79			
	DEC6	0.68			
Big data execution capability	DEXC1	0.71	0.56	0.90	0.87
	DEXC2	0.77			
	DEXC3	0.72			
	DEXC4	0.74			
	DEXC5	0.71			
	DEXC6	0.75			
	DEXC7	0.82			
Big data management capabilities	Big data democratisation capability	0.94	0.75	0.92	0.88
	Big data contextualisation capability	0.87			
	Big data experimentation capability	0.74			
	Big data execution capability	0.90			

Big data value creation	VC1	0.70	0.60	0.90	0.86
	VC2	0.72			
	VC3	0.77			
	VC4	0.84			
	VC5	0.84			
	VC6	0.72			
Employees’ exploratory activities	EXR1	0.75	0.60	0.88	0.83
	EXR2	0.81			
	EXR3	0.83			
	EXR4	0.72			
	EXR5	0.73			
Employees’ exploitative activities	EXP1	0.73	0.58	0.87	0.81
	EXP2	0.70			
	EXP3	0.89			
	EXP4	0.78			
	EXP5	0.67			

According to Fornell and Larker (1981), discriminant validity requires that the AVE of each construct be greater than the squared correlation among the constructs. Table 2 shows that the AVE of all the constructs satisfied this criterion. These results confirm discriminant validity.

The results of the factor analysis and of the reliability and validity tests reflected the quality of the research model. Furthermore, the values of R-squared for dependent variables also met the minimum requirements; the R-squared was 0.89 for big data value creation, 0.48 for employee exploratory activities and 0.50 for employee exploitative activities. The chi-squared value for the whole model was 7846.44.

Table 2. Discriminant validity

Factors	**1**	**2**	**3**	**4**
1. Big data management capabilities	**0.75**			

2. Big data value creation	0.68	**0.60**		
3. Employee exploratory activities	0.47	0.47	**0.60**	
4. Employee exploitative activities	0.46	0.49	0.43	**0.58**

3.2. Path analysis and hypotheses testing

For path analysis and to test the hypotheses, the PLS method was employed. Firstly, the direct association of big data management capabilities with big data value creation and employees' exploratory and exploitative activities was examined. Then, big data value creation was entered into the model as a mediator. Mediation was analysed using Baron and Kenny's (1986) approach. The path analysis results are summarised in Figure 2 and Table 3. According to the results, big data management capabilities were positively associated with big data value creation ($\beta = 0.83$, $p < 0.001$), employees' exploratory activities ($\beta = 0.69$, $p < 0.001$) and employees' exploitative activities ($\beta = 0.68$, $p < 0.001$). Furthermore, big data value creation was also positively and significantly associated with employees' exploratory ($\beta = 0.39$, $p < 0.01$) and exploitative ($\beta = 0.46$, $p < 0.001$) activities. These findings support H1 through H5.

After examining the direct associations, big data value creation was entered into the model as a mediator to analyse the indirect relationship of big data management capabilities with employees' exploratory and exploitative activities through the mediation of big data value creation. According to the results presented in Table 4, big data management capabilities were indirectly and significantly associated with exploratory ($\beta = 0.36$, $p < 0.01$) and exploitative ($\beta = 0.43$, $p < 0.001$) activities through the mediation of big data value creation. However, this mediation is partial, because after entering big data value creation as a mediator, the direct relationship of big data management capabilities and exploratory activities was reduced from $\beta = 0.69$ to $\beta = 0.32$, but the association was still significant at p <

.05. Similarly, after entering the mediator, the direct association of big data management capabilities and employee exploratory activities was reduced from β = 0.68 ($p < 0.001$) to β = 0.25 ($p < 0.05$), but the association was still significant, which indicates partial mediation. These findings support H6 and H7.

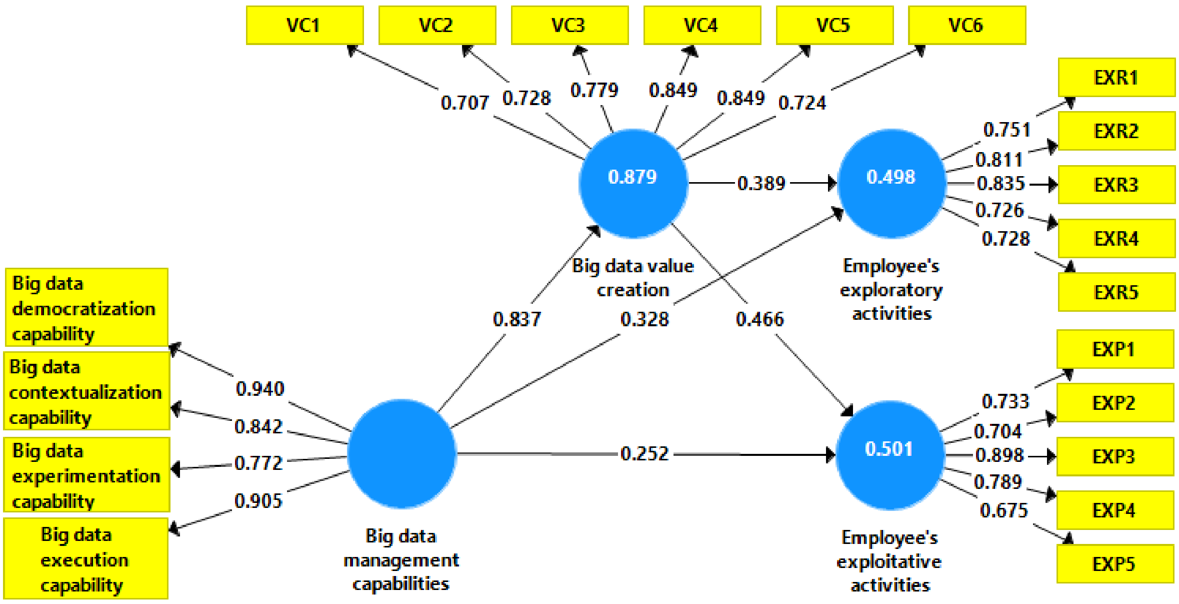

Figure 2. Path analysis.

Table 3. Path analysis

Path	Direct Effects β/t-value	Indirect Effects β/t-value	Total Effects β/t-value	Hypotheses	Results
Big data value creation ← Big data management capabilities	0.83***/107			H1	Supported
Exploratory activities ← Big data management capabilities	0.69***/17.10			H2	Supported
Exploitative activities ← Big data management capabilities	0.68***/16.02			H3	Supported
Exploratory activities ← Big data value creation	0.39**/2.79			H4	Supported
Exploitative activities ← Big data value creation	0.46***/3.81			H5	Supported
Exploratory activities ← Big data value creation ← Big data management capabilities	0.32*/2.39	0.36**/2.75	.69***/16.40	H6	Supported
Exploitative activities ← Big data value creation ← Big data management capabilities	0.25*2.08	0.43***/3.79	.68***/16.04	H7	Supported

4. Discussion and conclusion

Utilising the KBDC view, this study examined the association between big data management capabilities, big data value creation and employee ambidexterity. This study used the foundations of Zeng and Glaister (2018) to analyse big data management capabilities and big data value creation. Furthermore, it extended their initial exploration by adding exploratory and exploitative activities as outcomes in the model. The quantitative findings of this study are consistent with the qualitative exploration conducted by Zeng and Glaister (2018). The results support the positive association of big data management capabilities with big data value creation. However, unlike Zeng and Glaister (2018), this study analysed these issues at the individual employee level. The results also support the positive association of big data value creation with employee exploratory and exploitative activities. Furthermore, the direct and indirect effects of each of the big data management capabilities on both exploratory and exploitative activities were found to be significant. Big data management capabilities and big data value creation were found to be positively associated with both exploitative and exploratory activities; thus, it can be argued that big data management capabilities and big data value creation can increase employee ambidexterity.

4.1. Theoretical contribution

In terms of its theoretical contributions, this study extends the literature on the KBDCs view of the firms by discussing big data management capabilities in this framework. It is one of the very few to provide an understanding of the individual micro-foundations through which the employees of EMMNEs build ambidexterity. We argue that this is important because employees' big data management capabilities and ambidexterity are crucial for EMMNEs to manage the demands of global users. Institutional voids in emerging economies make big data an important and alternative source of knowledge creation which leads to exploratory and exploitative activities. However, it requires a certain level of big data management capabilities.

We particularly extend the knowledgebase and DC perspective on emerging economies by introducing the concept of big data management capabilities as the ability of employees to continuously access, analyse and manage large volumes of data from global users. The current literature on emerging economies mainly focuses on international relationships as a key source of external knowledge. This paper changes the narrative of the literature on emerging economies in two ways. First, this paper focuses on the volume and depth of global users' data as a core external source of knowledge. Second, this paper unpacks the individual-level perspective on integrating knowledge and transforming it into capabilities that lead to individual ambidexterity. Furthermore, this is the first quantitative study to examine big data management capabilities – including big data democratisation, contextualisation, experimentation and execution capabilities – in relation to both value creation and employee ambidexterity in the context of China.

This study delivers four contributions to the theoretical and empirical research on ambidexterity. First, the current body of research on ambidexterity focuses on firm and business unit-level ambidexterity. Although some scholars have explicitly argued that 'ambidextrous organizations need ambidextrous senior teams and managers' (O'Reilly & Tushman, 2013), conceptual and empirically validated understanding about what is ambidexterity at the individual level of analysis and variation in individuals' ambidexterity is still underdeveloped (Raisch & Birkinshaw, 2008). Studies of firm level heterogeneity assume, for example, that significant variation occurs at the firm level of analysis, whereas individual are more or less homogenous or randomly distributed across firm. Although some studies provide valuable examples of ambidextrous behaviour (e.g., O'Reilly & Tushman, 2004), scholars would benefit from further conceptualisation at the individual level of analysis. This paper therefore proposed four related characteristics of individuals' capabilities in an attempt to understand their value creation activities from big data.

Second, our paper furthers theoretical and empirically validated understanding about variation in individuals' ambidexterity by developing and testing hypotheses on the direct effects of the four capabilities and value creation from big data. Both empirically validated and theoretical insight on the combined effect of the different characteristics of these value creation capabilities are scarce in the literature on ambidexterity (e.g Rivkin & Siggelkow, 2003). This gap is highlighted by previous scholars (e.g., Shamim et al., 2018; Zeng & Glaister, 2018) who accentuated the importance of big data in driving the firm's competitive advantage. Observation from individual level of analysis can unveil level of heterogeneity that are currently underreported and under-theorized. This paper therefore contributes to a burgeoning literature that highlight the crucial but often neglected role of individual employees in contributing to ambidexterity of the firm

Third, this study extends the literature on the KBDCs view of firms by discussing big data management capabilities in this framework. This study also adds to the ongoing discussion on the levels of DCs by examining them at the individual employee level. Teece (2007) argued that DCs enable business enterprises to create and deploy intangible assets. The foundations of DCs are distinct skills, processes, procedures, organisational structures, decision rules and disciplines (Teece, 2007). Augier and Teece (2009) highlight that individual such as employees and managers play distinctive role in sensing opportunities, orchestrating asset recombination and bringing about continuous organizational renewal. By exploring the role of individual who serve as critical agent to operationalize the dynamic capability process will provide important theoretical and practical insights into the theory of strategic management, and to dynamic capability in particular. Fourth, this paper tests the hypotheses based on a sample of 308 participants working at big data companies in China, the country that currently generates the most value from big data. This will generate great insights for other emerging economies in manage big data to drive ambidexterity of the firm.

4.2. Managerial implications

This study has important practical implications. The framework examined can be used to enhance employee exploratory and exploitative activities. In order to harness big data for value creation and employee ambidexterity, firms should devise strategies aimed at developing big data management capabilities among their employees. For example, organisations may use human resources practices suited to enhance big data democratisation, contextualisation, experimentation and execution capabilities, which, in turn, would lead to value creation and ambidexterity. Similarly, organisations could also focus on big data management capabilities in their recruitment and selection processes. The existing literature also suggests that data science alone is not able to harness the power of big data; big data management capabilities are also needed (Janssen et al., 2017). These capabilities can present companies with several business imperatives, in other words, they can enhance the ability for data-driven decision making, which would enable managers to decide on the basis on what they know as opposed to what they think (Janssen et al., 2017; McAfee et al., 2012). Literature also suggests that management proclivities towards big data can strengthen value creation through big data; for example, a combination of the right leadership, talent management, culture and technology is important for big data value creation (Shamim et al., 2018). The results of this study suggest that big data value creation mediates the relationship of big data management capabilities with exploitative and exploratory activities. It is important for managers not to limit their efforts to the collection, experimentation and analysis of big data. Implementing data insight and taking action to gain commercial benefits is extremely important for achieving innovative outcomes. For example, big data can be used for decision making. The literature suggests that managers usually do not make decisions based on data, but rather they use relevant data to justify their decisions (McAfee et al., 2012). Big data management capabilities should be used to their full potential by creating value through big data.

In the context of emerging economy's MNEs in particular, big data can help organisations to foster their globalisation processes through ambidexterity. Since the go global strategy was initiated by the central government of China in 1992, Chinese enterprises have been increasingly active in outward foreign direct investment. Especially during the recent economic slowdown in China, many Chinese companies have started looking abroad. According to the World Investment Report (United Nations, 2018, p. 185), Chinese enterprises increased offshore investment from $27 billion in 2000 to $1.5 trillion in 2017. In spite of the vast investment flowing out of China, more than $250 billion in overseas investments made by Chinese enterprises have failed since 2005, according to the China Global Investment Tracker (*Global Times*, 2015). Rao-Nicholson, Khan, Akhtar and Merchant (2016) advised that the key for enterprises to succeed in foreign direct investment is organisational ambidexterity. Ambidextrous organisations have the ability to simultaneously engage explorative and exploitative innovation (March, 1991). Increased internationalisation of value chain activities can be enhanced by developing better capabilities in big data management and analysis. Through the analysis of different forms of raw and structured data, big data management capabilities facilitate value creation. For example, big data can be used to generate new knowledge (Khan & Vorley, 2017), which is an exploratory activity. Similarly, organisations can and should exploit their existing resources by analysing big data to understand consumer behaviours. For example, firms can use customer reviews to gain a better understanding of customer preferences (Xiang et al., 2015). However, all these exploratory and exploitative activities and value creation require big data management capabilities.

This study also suggests that data themselves cannot create value without data management capabilities. It validates the argument that resources themselves do not make a difference, but the capabilities to manage these resources do (Sirmon, Hitt, Ireland, & Gilbert, 2011). Our investigation shows that employees differ in their ability to extract value from big data. Particularly, employees with greater capability to democratise, contextualise, experiment with and execute data insights are in a better position to create value out of big data. Thus, organisations should focus on developing these capabilities at both the individual and organisational level. Organisations should adopt suitable leadership styles, talent management, technologies and culture in order to enhance big data management capabilities. The existing literature also acknowledges the important role of these management tools to enhance capabilities related to value creation from big data (Shamim et al., 2018). Shamim et al. (2018) examined the role strategic level capabilities such as leadership, talent management, culture, and technology management to harness big data in Chinese manufacturing businesses, which is an example of emerging economy context. However, strategic management literature suggest that operational level capabilities are crucial to achieve the desired outcomes of strategic level capabilities (Witcher & Chau, 2010).

Big data democratization, contextualization, experimentation, and execution are the operational level capabilities, so firms need to enhance these capabilities at both individual and organizational level.

4.3. Limitations and future research area

This study has some limitations. One of its limitations is that it used a cross-sectional research design. However, necessary measures were taken to reduce common method bias (i.e., randomising items, collecting data in two different waves and employing statistical techniques). This study highlights the influence of big data management capabilities on big data value creation and on employees' exploratory and exploitative activities. Understanding how to enhance big data management capabilities at both the employee and organisation levels requires specialised research. Initially, a qualitative enquiry could be fruitful in exploring the factors affecting big data management capabilities. Furthermore, as the scope of this study was limited to Chinese MNEs, future research should also consider other developing and underdeveloped economies to enhance understanding and generalisability. Additionally, investigating the moderating effect of demographic factors – which are used by several studies as control variables – is an important research direction which should be considered in future studies. Following Donate and de Pablo (2015) in regard to methodological parsimony, this study did not fully include the control variables, which could be considered in future research. Another interesting line of enquiry for future on this topic is to investigate big data management capabilities at strategic and operational level. Following the strategic management literature strategic level capabilities influence operational level capabilities, and operational level capabilities facilitates the strategic level capabilities to achieve the desired outcomes (Witcher & Chau, 2010). Along with investigating the relationship of big data capabilities with value creation, scholars should also explore the ways to enhance these capabilities through different management practices such as data governance. Particularly contractual and relational governance is also suggested by Jannsen et al. (2017). Knowledge in these areas is thin and need specialized research.

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1 Appendix

Big data democratisation capability							
1. I have the ability to access big data when it is needed at any given time.	1	2	3	4	5	6	7
2. I have the ability to understand big data where it is needed.	1	2	3	4	5	6	7
3. The sheer volume of big data creates problems for me to deal with.*	1	2	3	4	5	6	7
4. I can convince senior management to give me access to more databases.	1	2	3	4	5	6	7
5. I have the ability to understand the data of other departments.	1	2	3	4	5	6	7
6. I can use a wide range of big data applications.	1	2	3	4	5	6	7
7. I have the ability to break down data barriers.	1	2	3	4	5	6	7
Big data contextualisation capability							
8. I have the ability to interpret big data.	1	2	3	4	5	6	7
9. I can identify contextual clues in big data.	1	2	3	4	5	6	7
10. Based on the data, I can see the connection between individual customers and their everyday lives.	1	2	3	4	5	6	7
11. Based on the data, I can understand the scenarios that drive customers to make decisions.	1	2	3	4	5	6	7
12. It is difficult for me to understand the context of big data.	1	2	3	4	5	6	7
Big data experimentation capability							
13. I conduct experiments with big data to monitor changes.	1	2	3	4	5	6	7
14. I have the ability to come up with new methods to test big data.	1	2	3	4	5	6	7
15. Trial and error with the data is a routine matter for me.	1	2	3	4	5	6	7
16. For me, data are a scary set of numbers.*	1	2	3	4	5	6	7
17. I do not know how to start experimentation with data.*	1	2	3	4	5	6	7
18. I prefer not to mess with the data.*	1	2	3	4	5	6	7
Big data execution capability							
19. I can transform big data insights into actions.	1	2	3	4	5	6	7
20. I often use big data to perform my duties.	1	2	3	4	5	6	7
21. I respond to the data in a timely manner.	1	2	3	4	5	6	7
22. When I observe any abnormality emerging from the data, I react to the situation in real time.	1	2	3	4	5	6	7
23. I monitor market trends/customer activities through data tools based on historical and real-time data.	1	2	3	4	5	6	7
Big data value creation							

24. Exploiting the large volume of internal data for business growth is easy for me.	1	2	3	4	5	6	7
25. My data analysis findings often lead to the identification of new business opportunities.	1	2	3	4	5	6	7
26. I often explore new ways to increase customer willingness to use/pay.	1	2	3	4	5	6	7
27. Based on the data, I often propose future product improvements.	1	2	3	4	5	6	7
28. My data analysis often facilitates innovation processes in the firm.	1	2	3	4	5	6	7
29. My understanding of contextual clues in big data help me to gain a holistic view of customers.	1	2	3	4	5	6	7
Exploratory activities							
30. Searching for new possibilities with respect to products/services, processes or markets	1	2	3	4	5	6	7
31. Evaluating diverse options with respect to products/services, processes or markets	1	2	3	4	5	6	7
32. Focussing on the strong renewal of products/services or processes	1	2	3	4	5	6	7
33. Activities requiring some substantial adaptability	1	2	3	4	5	6	7
34. Activities requiring me to learn new skills or knowledge	1	2	3	4	5	6	7
Exploitative activities							
35. Activities which clearly fit into existing company policy	1	2	3	4	5	6	7
36. Activities which serve existing (internal) customers with existing services/products	1	2	3	4	5	6	7
37. Activities on the conduction of which I am clear	1	2	3	4	5	6	7
38. Activities primarily focussed on achieving short-term goals	1	2	3	4	5	6	7
39. Activities which I can properly conduct by using my present knowledge	1	2	3	4	5	6	7

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