Value creation through Big Data in Emerging Economies: the role of Resource Orchestration and Entrepreneurial Orientation

Jing Zeng

Kent Business School

University of Kent, UK

Email: J.Zeng@kent.ac.uk

Zaheer Khan*

Kent Business School

University of Kent, UK

***Corresponding author: Email: z.a.khan@kent.ac.uk**

Abstract

Purpose – The purpose of this paper is to examine how managers orchestrate, bundle, and leverage resources from big data for value creation in emerging economies.

Design/methodology/approach – The authors grounded the theoretical framework in two perspectives: the resource management and entrepreneurial orientation. The study utilizes an inductive, multiple-case research design to understand the process of creating value from big data.

Findings – The findings suggest that entrepreneurial orientation is vital through which companies based in emerging economies can create value through big data by bundling and orchestrating resources thus improving performance.

Originality/value – This is one of the first studies to have integrated resource orchestration theory and entrepreneurial orientation in the context of big data and explicate the utility of such theoretical integration in understanding the value creation strategies through big data in the context of emerging economies.

Keywords: Big data, Resource Management, Resource based view, Entrepreneurial Orientation, Value Creation, emerging economies

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1. Introduction

Recently, big data has attracted increasing interest due to its potential to enhance organizational performance and its vital role in knowledge management (George *et al*., 2014; McAfee and Brynjolfsson, 2012; Khan and Vorley, 2017; Rothberg and Erickson, 2017; Zeng and Glaister, 2018). Big data refers to extremely large amounts of both structured and unstructured data sets that may be analysed computationally by means of techniques that are characterised by high volume, high velocity and high variety, which traditional data processing technology is unable to store, capture, and analyse (Chen *et al*., 2012; McAfee and Brynjolfsson, 2012; Schonberger and Cukier, 2013; Laney, 2001).

Many organizations are exploring ways of deploying and harnessing such large-volume data to create and capture value (Davenport, 2013; Waller and Fawcett, 2013; Wamba *et al*., 2017). This information resource may eventually overshadow physical resources (e.g., capital and labour) as the main driving force that re-shapes the competitive advantage of a firm (Bharadwaj *et al*., 2013; Davenport, 2013; Chen *et al*., 2012; Davenport and Patil, 2012; Koutroumpis and Leiponen, 2013; George *et al*., 2014). The importance of big data has recently drawn great attention from management scholars, leading to a small but growing stream of literature on the factors influencing big data decision making quality (e.g., Janseen, Van der Voort and Wahyudi, 2017; Frisk and Bannister, 2017; Perez-Martin, Perez-Torregrosa and Vaca, 2018); managerial capability to drive big data value creation (e.g., Zeng and Glaister, 2018); big data analytics from health care, marketing and supply chain perspective (e.g., Wang and Hajli, 2017; Erevelles, Fukewa and Swayne, 2017; Dubey *et al*., 2018b); big data and business strategy alignment and performance (Akter *et al*., 2016; Wamba *et al*., 2017; Dubey *et al*., 2018a; El-Kassar *et al*., 2018; Prescott, 2014).

However, relatively few studies have sought to understand how managers transform resources to create value (e.g., Adner and Helfat, 2003; Helfat and Winter, 2001; Helfat *et al*., 2007; Ndofor *et al*., 2011; Sirmon *et al*., 2007; Sirmon *et al*., 2011). The exceptions are those relatively few studies that have sought to understand this process by emphasizing the resource management process (e.g., Sirmon *et al*., 2007) and accentuating the dynamic capability of the firm based on '*asset orchestration'* (e.g., Helfat, *et al*., 2007). Sirmon *et al*. (2011) later extends our understanding of the resource-related management literature by providing a holistic and complementary view that addresses explicitly how managers' actions/capabilities to transform resources lead to value creation. The existing research on big data conducted by management scholars has predominantly relied on the dynamic capabilities approach to explain the potential impact of big data (e.g., Dubey, *et al*., 2018a; Erevelles, Fukawa and Swayne, 2016; Opresnik and Taisch, 2015; Zeng and Glaister, 2018; Braganza *et al*., 2017). However, additional theory development is required to add richness to our understanding of how managers orchestrate resources in dynamic environments—such as those associated with big data and analytics—to improve organizational performance (Helfat and Winter, 2011; Hefat *et al*., 2007; Sirmon *et al*., 2011; George *et al*., 2014).

Despite the contributions made by the existing studies, however, relatively limited research has examined how value can be generated from big data in different contexts; the case in point being emerging markets, which may not possess the key skills needed for bundling and orchestrating big data-related resources for value creation strategies. The existing research noted that relevant big data analytics skills are mostly confined to developed economies—such as the California bay area—and are not readily available (Tambe, 2014). Companies may find it difficult to mobilize resources during the process of big data-related resource orchestration. One potential way through which managers can mobilize and orchestrate big data resources for value creation can be through the development of an entrepreneurial orientation (e.g., Lumpkin and Dess, 1996, 2001; Covin and Lumpkin, 2011).

Scholars from the field of entrepreneurship have examined corporate performance by paying closer attention to a company's underlying entrepreneurial orientation (EO). An EO refers to a company's strategic orientation that captures entrepreneurial behaviours in terms of risk taking, proactiveness, and innovativeness (e.g., Lumpkin and Dess, 1996; Wiklund, 1999; Rosenbusch, Rauch and Bausch, 2013). An EO can be one of the important links in explaining how a company can bundle and orchestrate the resources for value creating strategies (e.g., Sirmon *et al*., 2011). Thereby, an EO can explain, in part, the managerial processes that enable some companies to stay ahead of the competition; this is because an EO facilitates company action based upon early signals from its internal and external environments (Lumpkin and Dess, 1996). So far, the existing research on big data has applied a dynamic capabilities-based approach to explain the impact of big data on performance; yet, the way organizations orchestrate and bundle resources can be complex in changing environments. Thus, an EO can play a vital role in turning big data-related resources into knowledge assets by bundling and orchestrating big data-related knowledge for value creation (Lumpkin and Dess, 1996; Covin and Lumpkin, 2011).

This is the context in which the present article aims to understand how companies based in emerging economies generate value from big data and improve their performance. The study adds to the limited research that has examined the potential performance implications of big data in emerging economy contexts. Understanding how managers orchestrate, bundle, and leverage resources from big data in emerging contexts has wider implications for research on big data and its implications for corporate performance in different settings (e.g., Akter *et al*., 2016; Jabbour *et al*., 2017; Wamba *et al*., 2017) .

This study makes three key contributions to the existing literature on big data and its implications for company performance. First, we bring resource orchestration into the domain of big data and identify an EO as one of the key factors through which companies bundle and orchestrate the knowledge assets arising from big data. The existing research highlighted that resources themselves may not create value for companies; companies need to have internal practices and methods suited to putting resources into innovative value creating strategies. Entrepreneurial orientation is one such method by which companies can improve performance through big data.

Second, this study provides important insights in terms of empirically demonstrating the value of integrating resource orchestration and entrepreneurial orientation in explaining the performance implications of big data. This is an important contribution as most of the existing literature on resource orchestration is conceptual in nature (Sirmon *et al*., 2007, 2011). Additionally, we provide important insights from the important emerging economy of China and show how managers bundle and orchestrate resources and create value from big data. This is one of the first studies to integrate resource orchestration theory and EO in the context of big data and to empirically support the arguments it puts forward by examining case studies from China.

2. Conceptual Development

2.1 Resource orchestration and value creation through big data

The resource-based view (RBV) suggests that resources, on their own, may not be sufficient to create value, but that companies need to put in place an appropriate organization in order to take advantage of hard to imitate value creating resources (cf. Barney, 1991, 2001). Sirmon *et al*. (2007) defined resource management as the comprehensive process of *structuring*, *bundling,* and *leveraging* company resources with the purpose of creating value for customers and competitive advantages for the company itself. The resource management process involves the three sub-processes of *structuring*, *bundling*, and *leveraging*.

Structuring contains those processes by which companies acquire, accumulate, and divest themselves of those resources that are affected by the environmental context. 'Acquiring' refers to purchasing resources from strategic markets. 'Accumulating' denotes the internal development of resources. 'Divesting' pertains to the assessment—crucial for a company— of its existing resources, ridding itself of less-valued ones to generate the slack and flexibility needed to acquire and accumulate others of higher value (Sirmon and Hitt, 2003; Sirmon *et al*., 2007; Uhlenbruck *et al*., 2003).

Bundling includes: ‘stabilizing’, by which companies make minor incremental improvements to existing capabilities; ‘enriching’, which entails extending and elaborating current capabilities; and ‘pioneering’, which involves creating new capabilities.

Leveraging refers to the processes used to exploit a company’s capabilities and take advantage of specific market opportunities. According to Sirmon *et al*. (2007), effective cross-market leveraging capabilities include mobilizing, coordinating, and deploying. ‘Mobilizing’ refers to the capabilities required to form requisite capability configurations. ‘Coordinating’ involves integrating capability configurations. ‘Deploying’ involves physically using capability configurations to support the chosen leveraging strategy formed by the coordinating sub-process. Sirmon *et al*. (2007) further noted that, while each process and its sub-processes are important in themselves, they need to be synchronized in order to optimize value creation.

The process of resource management is referred to as *managerial capabilities* (Kraaijenbrink *et al*., 2010). Scholars have examined the managerial actions that affect resource management which in turn affect firms' performance (Ndofor *et al*., 2011; Morrow *et al*., 2007; Sirmon *et al*., 2010), and the relationships that exist among resource management processes (Holcomb et al. 2009; Kor and Leblebici, 2005; Sirmon *et al*., 2011). These empirical studies have produced some important results. For example, Holcomb *et al.* (2009) indicated that the effects of managing resources are contingent on the quality of the resources held and on the synchronization of the processes used to manage them.

In parallel with research on the development of resource management, Helfat *et al.* (2007) put forward a related logic that focused on the asset orchestration emerging from the dynamic capability literature. Dynamic capability is an extension of RBV by highlighting explicitly the role of managers when they "purposefully create, extend or modify [the company's] resource base" to create value to achieve sustainable advantage (Amit and Schoemaker, 1993; Eisenhardt and Martin, 2000; Teece *et al.*, 1997; Winter, 2003). The recent work by Helfat and colleagues (Adner and Helfat 2003; Helfat *et al*., 2007) elaborated the concept of dynamic capability by accentuating the manager's capabilities and decisions in influencing company's performance regardless of the environment in which it operates. The asset orchestration, proposed by Helfat *et al.* (2007), consists of two primary processes: search and selection, and configuration and deployment. The search/selection process refers to a manager's capability to identify assets and design organisational structures for the company and create business models to capture opportunities. The configuration/deployment process entails the coordination of co-specialized assets in order to nurture innovation. Helfat *et al*. (2007) argue that achieving a 'fit' between these dimensions is a primary function of effective management. Essentially, dynamic managerial capabilities are largely created by adding new knowledge to the company's current knowledge stocks (Adner and Helfat, 2003).

Sirmon *et al.* (2011) further extended RBV and their previous work (Sirmon *et al.*, 2007) on resource management by bridging two related frameworks: resource management and asset orchestration. Resource orchestration was subsequently proposed, explicitly articulating managerial actions aimed at orchestrating resources in ways that help companies create a competitive advantage (Sirmon *et al*., 2011). Further research focusing on resource orchestration, highlighted by Sirmon *et al*. (2011), could serve as a catalyst for related research on the flow of knowledge within an organization.

The research being conducted in the area of resource management and asset orchestration is promising and encouraging; however, our understanding of how managers orchestrate a company's resources could be enhanced by applying it to a big data context. This is the case for two reasons. First, big data, as an information asset, is a non-rivalrous resource due to its self-generative nature (Glazer, 1991). Therefore, making a distinction between non-rivalrous and rivalrous resources and understanding the value creation process based on the former could provide a more robust explanation for resource orchestration networks. Second, to date, very few empirical studies have explicitly incorporated resource orchestration into the heart of their inquiries (e.g., Chirico *et al*., 2011; Chadwick *et al*., 2015; Ndofor *et al*., 2011; Wales *et al*., 2013). For the most part, these studies deductively tested the relationship between managerial actions in relation to the connection between resources and performance (e.g., Ndofor *et al*., 2011; Wales *et al*., 2013; Chadwick *et al*., 2015; El-Kassar and Singh, 2018), or in family-run company contexts (Chirico *et al*., 2011). Furthermore, the underlying methods and managerial actions for the orchestration of resources are neither well theorized nor empirically proven. Thus, there is a great opportunity to understand how big data-related resources are orchestrated and leveraged in different contexts (Akter *et al*., 2016; Dubey et al., 2018b; Jabbour *et al*., 2017; Prescott, 2014; Wamba *et al*., 2017). Such examination will provide not only important insights, but also a theoretically rich understanding of resource orchestration in the context of big data.

2.2 Entrepreneurial orientation and the Orchestration of Big data-related knowledge assets

Resources, on their own, may not create value; companies need to have internal managerial processes, structures and strategies in place to take advantage of resources and capture value from difficult to imitate resources (Barney, 1991; Eisenhardt and Martin, 2000). Due to its (EO) three set of characteristics of innovativeness, proactiveness, and risk taking (e.g., Wiklund, 1999; Covin and Lumpkin, 2011), an EO can be one of the important internal company-specific processes that can bundle and orchestrate knowledge assets originating from big data for pursuing innovative opportunities for the development of competitive advantage (Covin and Lumpkin, 2011; Prescott, 2014; Wamba *et al*., 2017).

The existing studies have examined the direct relationship between individual sets of resources and company performance, however there has been relatively limited research focus on understanding how managers can effectively utilize those resources for value creation (Helfat, 2000). Since EO is often associated with a company’s strategic actions in capturing specific entrepreneurial aspects of decision-making styles, methods, and practices, it is perceived by entrepreneurship scholars as one of the key capabilities that can explain the differential performances of companies (Lumpkin and Dess, 1996; Covin and Lumpkin, 2011). Applied to the resource orchestration framework, an EO may shed light how management can utilize and coordinate resources—such as big data-oriented ones—to improve performance (Simsek, Heavey and Veiga, 2010; Wales *et al*., 2013).

Resource bundling and orchestration in a big data environment is vitally important for achieving sustainable performance (e.g., Prescott, 2014; Dubey *et al*., 2018a; Wamba *et al*., 2017). Due to its characteristics in terms of managerial practices and methods, an EO may play an important role in the orchestration of the resources, as managers will prepare the company to generate value from big data; this is because an EO "*provides the mobilizing vision to use firm resources. By directing the use of resources, EO not only provides an objective, but also helps identify the resources necessary to support the objective*" (Chirico *et al*., 2011:311), as it refers to the "*strategy making practices, management philosophies, and firm-level behaviors that are entrepreneurial in nature*" (Anderson, Covin and Slevin, 2009:220). Thus, drawing insights from two sets of frameworks, an EO offers a complementary and integrated understanding of managerial actions in creating value from big data. Our objective, hence, is to add richness to current theory by extending the logic and ideas of resource orchestration to a company's harnessing of big data (e.g., Akter *et al*., 2016; Dubey *et al*., 2018b; Jabbour *et al*., 2017). In the following section, we elucidate our context, data collection, and analysis procedures.

3. Context and Research methods

Due to the paucity of research on resource orchestration and EO in the context of big data, we adopted an inductive, multiple-case research design that allows a 'replication' logic (Yin, 2003) and in which cases are treated as experiments that confirm or refute the inferences drawn from others (Yin, 2014; Eisenhardt, 1989). This process typically creates opportunities to triangulate the information collected, augment external validity, and help guard against observer bias, and yields more robust, generalizable theory than single cases (Eisenhardt and Graebner, 2007; Ketokivi and

Choi, 2014; Miles and Huberman, 1994; Pagell and Wu, 2009; Yin, 2003). Following Mohr's (1982) suggestion for process research, this research key focus was on understanding the causal dynamics of a particular setting.

3.1 *Research setting*

The research setting for this study was the high-velocity internet two sided platform industry, which enables direct transaction or value creation over web-based virtual platforms by linking markets from different groups of users, and extracts a significant proportion of its revenue from such transaction (Zeng and Glaister, 2016). This industry is attractive for this study because data are its core product. Rather than largely relying on physical assets to drive efficiency, the internet platform industry largely depends on their ability to generate information/data—mainly knowledge-based assets that enable/facilitate the interaction between different groups of users in order to create value (Parker and Van Alstyne, 2005). Consistent with theoretical sampling, we selected companies in which our focal phenomenon of value creation from big data was likely to occur. Specifically, as suggested by Rouse and Daellenbach (1999), we focussed on selecting the key performing companies from a single industry to improve the potential for generalizability of our research findings. Following the advice proposed by Block and McMillan (1985), four companies were selected that were closely matched in terms of starting conditions, availability of resources, and company development as factors associated with competitive advantage (Lieberman and Montgomery, 1988) and entrepreneurial growth (Aldrich, 1999; Naman and Slevin, 1993). This research design also enabled the emerging conceptual insights from one case to be evaluated against comparative evidence from the others (Yin, 2003). Table 1 describes the four cases used in this paper. We stopped at four cases because we were near or at a saturation point and were also reaching the limits of the amount of data that could be processed in one study (Yin, 2003; Pagell and Wu, 2009).

[Insert table 1 about here]

3.2 *Data collection*

For each company, we traced the process of value creation from big data through both primary and secondary data sources. The primary sources were semi-structured interviews conducted with individual informants. We selected our informants from different departments that were involved in the data analysis and data execution process and from different hierarchical levels, ranging from top management executives to individual data analysts. The main benefit of this approach was that it ensured exposure to different perspectives to compensate for any individual informant personal bias and lack of knowledge, and to enable the cross-checking of the information provided by different informants (Huber and Power, 1985). We employed semi-structured interviews as they afforded us the flexibility to probe informants for details and provide as wide a scope as possible while ensuring that we still covered the issues relevant to our research question (Yin, 2003). The semi-structured interviews were conducted in Chinese, ranged from 60 to 150 minutes long (but occasionally took as long as 3 and half hours), were recorded (if allowed by the interviewees), and were transcribed verbatim within a week by a professional transcribing and translating service provider.

Following Pettigrew's (1990) suggestion for case based research, although we approached the organizational field with theoretical constructs in mind, we did not impose them. We carefully considered how the evidence gathered from both primary and secondary data could inform existing theory or constructs, such as resource orchestration and entrepreneurial orientation (EO). We examined how the data informed our understanding of 1) the process of creating value from big data and 2) the mechanisms that drive and facilitate the process.

Our exploratory interviews, in a semi-structured format, were conducted with informants from the top management executive level of each company as they had 'interpretational' roles (Bennis and Nanus, 1985; Smirich and Morgan, 1982) and 'visibility' of the object of the inquiry (Pettigrew, 1990). The interview protocol involved by asking about the respondent's background and the company's big data strategy. The informant was then asked to describe the process of value creation from big data and to identify the key mechanisms that facilitated/hindered this process. After the initial top management interviews, we conducted semi-structured interviews with staff from various departments, and then with individual data analysts. The interviews began with a request to describe the company's big data strategy and the informant's personal background. Each informant then described his/her interaction with the big data team, and the key mechanism that facilitated or hindered the process of value creation from big data. Thus, a general view of the mechanisms affecting the process of value creation from big data within the company emerged. Following the methods of inductive research, these questions were supplemented with others that seemed fruitful to pursue during the interview. In total, 36 interviews were conducted. In order to ensure the credibility of the data, we followed the suggestions made by Eisenhardt and Graebner (2007) and adopted a 'courtroom questioning' style, by which the informants were encouraged to provide concrete examples to support their commentary and concentrate on facts and events, rather than on their interpretations of them. Complete anonymity was promised in order to encourage the participants to give candid responses.

Secondary data were also collected to triangulate and gain a complete and accurate picture (Yin, 2003); these included reports and strategic memos produced by the companies for the period between February 2008 and March 2013, and extensive archives—including newspapers, internet sources, and corporate materials published between March 2000 and July 2014.

3.3 Data analysis

As is typical in inductive research, we first built individual case studies using the data gathered from both the interview transcripts and archival materials. We then wrote a case study for each site, emphasizing the themes that were supported by the different data collection methods and confirmed by several informants (Jick, 1979). This was an iterative process in which we revisited the data as important features of the mechanisms within each case emerged. We read the cases independently to form our own views of each case and in order to identify the theoretical constructs, relationships, and longitudinal patterns within each case independently and with respect to our research question. Although we noted the similarities and differences with other cases, to maintain the independence of the replication logic (Eisenhardt, 1989), we only started further analyses after we had completed all the case write-ups.

Once the individual case studies were complete, we conducted a cross case analysis to look for similar constructs and themes in the cases (Eisenhardt and Graebner, 2007; Ketokivi and Choi, 2014; Pagell and Wu, 2009). We started by comparing cases in order to seek common themes and refine the unique aspects of each particular case. We then used replication logic to further refine these initial relationships by frequently revisiting each case in order to compare and contrast the specific constructs, relationships, and logics. With each iteration, we used new permutations of case pairs to refine the conceptual insights. Any discrepancies and agreements in the emergent theory were noted and investigated further by revisiting the data. We followed an iterative process of cycling among theory, data, and literature to refine our findings, relate them to existing theories, and clarify our contributions. The propositions were induced following Eisenhardt's (1989) guidance on building theory from case studies. After a tentative proposition had been developed, we revisited each case to see whether the data confirmed the proposed relationship. We went back and forth between our data and proposition, relying on the existing literature to further sharpen the insights yielded by the inductive process (Eisenhardt, 1989). We also presented our analysis at a peer workshop and to our informant in order to induce alternative explanations. The feedback we received was taken into consideration when drafting the final conceptual framework. We display additional selected quotes in Table 2 to illustrate and document the robustness of our claims.

[Insert table 2 about here]

4. Findings and analysis

What emerged from our data were insights that linked value creation from big data with a set of mechanisms. For all companies, making sense of the high volume, high velocity, and high variety data itself was central to the challenge of creating value from it. We found that, to address this challenge, companies differed in their approaches to create value from big data.

Through our examination of the data, we developed a framework that capture the value creation process from big data (please see figure 1)

Insert figure 1 about here

In the next sections, we elaborate on these insights and describe their grounding in the data.

4.1 *Resource coordination for data exploitation*

Prior research suggested that the analytical skill and knowledge of data scientists contributes greatly to a company's opportunities for value creation from big data (e.g., Davenport and Patil, 2012). Yet, our data suggests that the presence of a data scientist or a group of data scientists is a necessary but insufficient condition to cope with high volume, high velocity, and high variety data. We found evidence that, while some companies rely heavily on data scientists or data departments to exploit big data, others focus more on bridging the knowledge gap and building coordination networks between the data department and the rest of the company.

Serong provided a compelling illustration of this pattern. Serong had initially set up a data team focusing on data mining. However, the outcome was barely satisfactory, as one informant pointed out:

“*We have a set of statistics and report from them (data team) on a regular basis. It was useful to a certain extent. They are data analysts, not marketer, not product developers so they could not see much connections and potential as marketers or product developers do*”.

Following such observation, Serong encouraged the data team to build close collaborative relationships with other departments. Such collaborative interaction stimulated a great flow of knowledge across different departments.

“*People from different background and discipline see data and correlations from different perspective. For example, data analysts from computer science background would miss or overlooked some correlations and patterns that would matter greatly from marketing and product design perspective. Getting them working together to fully appreciate the meaning from the data is crucial*”.

Information gathered from other informants and archival data also supported such collaboration.

A similar example can be found from Targar. A consistent pattern across all Targar informants highlighted the importance of broadening the data mining boundaries beyond the individual team/department.

For example, one informant indicated:

“*Unless you have a clear set of questions in mind when you interrogate data, you can easily get lost given the significant volume of data we have. And because we have so many data, you can also easily get correlations that make no sense at all. So we talked to people from different departments, to understand what is bothering them that can be solved by the data we have, what data or information do they need to make their job better and easier*”.

This view was often echoed by other informants, who ascribed great significance to cross-department collaboration. We also noted that Targar had opened up its platform to external partners to develop value-added applications based on the datasets available on their platforms. A senior director from Targar commented:

> "*We were sitting on huge amount of data that was not being used to its full potential. We only have limited resources here and by opening up our dataset on our platform really connect our data with many 'a-ha' moment. They* [the external partners] *never failed to impress us with their creative ideas*".

Similarly, many informants highlighted that opening up their data to third-party developers had resulted in the establishment of a distinctive resource network within their network innovation systems.

We observed quite different patterns in the other cases. Yogy, for instance, did not mention such cross disciplinary collaboration. Yogy informants expressed rather frustrating views on benefiting from big data.

> "*They always sit behind closed doors and we never know what is going on there. We do regularly get reports and instructions from the top* [the managers] *in terms of what to do based on the data they* [the data team] *crunched but sometimes it just seemed rather pointless and a waste of time. Yes, they are good at numbers, but do they understand business, or do they understand our jobs?*"

The findings suggest that the managers from Yogy had often had high expectations in terms of the data department generating value from big data. One informant from the data department explained:

"*We are under a lot of pressure to deliver results, but our attention is limited given how much data we have crunch. And data crunching is not just a one-off, it changes especially given how many real time data we have. It should be about the instant flow and connection with other teams. We feel quite isolated her*e".

Similar patterns were observed across another case company—Gray. The data team was often described as "*living in their own world*". The informants often expressed a low level of confidence in the role of big data holding strategic importance for their companies. One informant commented:

"*It is a big hype. We implement changes that were requested from the top from the analysis reported put together by the data team, some of the requests did not make much sense and we never got to fully understand it. I wish a bilateral dialog could be built*".

Why does resource coordination between different departments facilitate the process of value creation from big data? One reason may be that those who lack familiarity with customers (Shane, 2000; Von Hippel, 1988) and knowledge of ways to serve the market (Shane, 2000) find it difficult to recognize solutions to meet customer needs and to formulate effective strategies to introduce and sell new products/services. Therefore, by working in isolation, data scientists are unable to discover patterns and correlations related to customer behaviour. This was illustrated by the following quote:

"*Given the volume of the data we have, it is easy to get random correlations. We need people with different backgrounds and knowledge of the market to truly appreciate and understand these correlations and patterns. You cannot achieve this by getting them to work separately*".

Based on our findings, without such coordination, an organization is less capable of discovering and exploiting new opportunities emerging from big data. Many scholars highlighted that team members' willingness and ability to share hard-to-find specialized knowledge with other team members (bringing expertise to bear) were crucial to firm's performance (Majchrzak et al., 2000; Kanawattanachai and Yoo, 2007). From the above evidence, we argue that resource coordination as a result of cross department collaboration provides a company with an increased ability to discover and exploit any opportunities emerging from big data. This leads to our first proposition:

Proposition 1: *Resource coordination between different departments is positively related to opportunities for discovery and exploitation from big data which leads to value creation.*

4.2 Entrepreneurial orientation and value creation from big data

The findings indicate that our sample companies varied in their approaches to create value from big data. Some believed that employing skilled data scientists was critical to success. Others valued data scientists but ascribed more importance to capitalizing on big data by encouraging entrepreneurial activities at the company level (Covin and Lumpkin, 2011).

One good example was provided by Serong. The main focus of Serong was to encourage its employees to be curious about data and to experiment with it. One informant had this to say about his understanding of the key aspects of creating value from big data:

> "*We wanted people to take ownership of the data, not to think that data analysis is the experts' job and responsibilities. They don't need to get to the technical side of it, but rather to think creatively about how we can tell a good story with the data we have, what kind of impact it will have on our customers*".

Creativity and experimentation were perceived as great approaches to complement the technical data crunching. For example, Serong introduced a “Magic Data Cube” initiative to inspire employees at the company level to generate projects based on the big data. One informant from data team described:

> “*Data are like a magnifying glass to understand the market, its trends and our customers. There were many interactions between us* [the data department] *and the rest of the company; what data they needed to tell a story and what data we had to support that. They can see things differently and come up with great creative ideas which we would never have thought of*.”

Similar entrepreneurial examples can be found from Targar. Many informants highlighted the value of real time data and the importance of a company’s ability to extract information from real time operational data. The faster a company can harness insights from real time data, the greater its advantage in driving its value creation opportunities, as “*top down command-control structure will not work well in this sense*”

One informant commented:

> “*By the time you get through the different layers of approvals, you already missed the time and opportunity to respond to these data. The top down structure has to change to cultivate and support the entrepreneurial activities at the front line level*”.

Our informants further accentuated a risk-taking approach in relation to data management. This was explained by the following observation:

> “*With the insights coming from the data, you don't have to go all out. You can manipulate the scale to which you want to test your ideas. Initially, the scale is quite small, so the risk is low; then, you can gradually scale it up based on how data reacts*”.

Such entrepreneurial activities were perceived as being essential in driving a company's value creation opportunities from big data.

These findings support the notion of entrepreneurial orientation in maximizing value from big data. The data suggest that the companies with a greater level of entrepreneurial orientation were in a better position to take advantage of the opportunities offered by big data. The literature has consistently identified three dimensions of an EO: *innovativeness* in engaging in creativity and experimentation, thereby departing from established practices and technologies (Lumpkin and Dess, 1996); *proactiveness* in opportunity-seeking, being forward-looking to stay ahead of the competition (Lumpkin and Dess, 1996); *risk-taking*, being willing to commit large amounts of resources to projects in which the cost of failure could be high or the outcomes unknown (Miller and Friesen, 1978). The underlying assumption is that an EO provides organizations with a basis for entrepreneurial decisions and actions for capturing innovative opportunities (e.g., Lumpkin and Dess, 1996; Wiklund and Shepherd, 2003; Covin and Lumpkin, 2011).

By contrast, such entrepreneurial actions were barely mentioned by Gray and Yogy. For example, Gray emphasized the technical side of big data and the importance of the data department in contributing to a company's value creation opportunities from big data. When asked about the involvement of other departments in value creation opportunities from big data, one informant from the top management team described:

> "*Of course, they are given the data analysis report—sometimes from us, sometimes directly from the data team. It is a chain of action and they can act on what needs to be done*".

When asked the same question, an informant from a different department stated:

> "*We do receive regular reports and tasks from them* [the top management and the data team], *some of them are useful but most of them are not contextual, there is no story behind it. I wish that we could get more involved in this process*".

We observed very similar patterns in Yogy. The Yogy informants described the process of generating insights from big data as being too technical; therefore, the involvement from other teams/departments was limited. Some of the interviewees stated:

> "*We just follow the direction and act on what needs to be done*".

When asked about experimentation and risk-taking, an informant responded:

> "*They focus too much on the left brain, it is all about analytical and logic. Data dictate everything and we play limited roles in the process*."

Our analysis points to the key insight emerging from the above evidence: that those organizations that have an EO are more likely to generate value from big data. An EO represents the way a company is organized in terms of utilizing resources in order to uncover and exploit opportunities. Based on the RBV, how a company is organized, when coupled with its resources, can increase the positive relationship between resources and company performance (Barney, 1995). The findings demonstrate that an EO captures the way a company is organised towards entrepreneurship and can enhance value creation opportunities from big data. Our data reveal that the key elements of an EO—such as innovativeness, risk taking and proactiveness—can partially explain the process of value creation from big data that enables some companies to get ahead of their competitors. Companies with higher levels of EO can be in a better position to effectively utilize big data-related knowledge assets for both the discovery and exploitation of opportunities arising from big data analytics (Covin and Lumpkin, 2011; Davenport and Patil, 2012; Khan and Vorley, 2017). Previously, we proposed a positive relationship between resource coordination between different departments and value creation from big data. Because of the magnitude of the data volume and of the speed at which it should be analysed and acted upon, we further propose that a managerial decision-making process that champions a willingness to capitalize on its big data resources by engaging in entrepreneurial activities at the company level will perform even better in creating value from big data (Wales *et al*., 2013). This leads to the following proposition:

Proposition 2: *An EO moderates the relationship between resource coordination and value creation from big data*.

5. Discussion and Conclusions

The aim of this article was to understand the value creation through big data in dynamic environments such as those observed in emerging economies. Recently, there has been an increasing interest in understanding the role of big data and its resultant implications for performance and knowledge management (Jabbour et al., 2017; Dubey et al., 2018b; Khan and Vorley, 2017). The existing studies have enhanced our understanding on this topic, yet the research on big data is at its infancy and further research has been suggested in developing solid understanding about how firms co-create knowledge and capture value through big data (e.g., Acharya *et al*., 2018; Dubey et al., 2018b; Wamba *et al*., 2017; Khan and Vorley, 2017). In order to understand value creation through big data in emerging economies, we integrated resource orchestration (e.g., Sirmon *et al*., 2007; Sirmon *et al*., 2011) and entrepreneurial orientation (Lumpkin and Dess, 1996; Covin and Lumpkin, 2011).

The findings highlight that resource coordination is vital for firms to create value through big data by firms based in emerging economies. The findings further indicate the important role of entrepreneurial orientation through which resource coordination and asset orchestration lead to the value creation from big data in emerging economies.

5.1 Theoretical contributions

Our study offers several insights for business management in the big data context (e.g., Acharya *et al*., 2018; Akter *et al*., 2016; Wamba *et al*., 2017). The primary contribution of this study is that we explicitly incorporate resource orchestration into the domain of big data and identify EO as one of the key factors through which companies bundle and orchestrate the knowledge assets arising from big data for value creation. While the three frameworks of resource management, asset orchestration, and resource orchestration have been established to describe the use of resources to create value (Helfat *et al*., 2007; Sirmon *et al*., 2007; Sirmon *et al*., 2011), additional empirical research is needed in order to add richness to current theory (Sirmon *et al*., 2011; Chadwick *et al*., 2015). The findings indicate that resource coordination between different departments facilitates the process of value creation from big data. We have thus extended the understanding of resource orchestration in a big data context, whereas previous research has provided key insights by utilizing dynamic capabilities approach (Wamba *et al*., 2017). Our findings are consistent with the hitherto largely underexplored arguments that resources themselves may not create value for companies; it is *how* companies utilize those resources that is important in explaining corporate performance. The findings further indicate that an EO moderates the relationship between resource coordination and value creation from big data. That is, the willingness to be innovative, proactive and taking risks enhances a company's capability to generate value from big data (Covin and Lumpkin, 2011). These findings echoed Chirico *et al.*'s (2011) observations and suggest that an EO can help explain the managerial processes that provide some companies with the ability to utilize their resources to identify and respond to environmental cues earlier than competitors.

Second, while most of the existing literature on resource orchestration is conceptual in nature (e.g., Sirmon *et al*., 2007, 2011), this study provides important empirical insights demonstrating the value of integrating resource orchestration and entrepreneurial orientation in explaining the performance implications of big data. Our findings are therefore consistent with the existing resource orchestration and dynamic capability conceptual apparatus, such as evolutionary and entrepreneurial fitness (Helfat *et al*., 2007). The findings of this study provide an important foundation to explore how resource orchestration and EO may influence the process of generating value from big data. Our research thus could be adopted in further studies as a starting point from which to examine the effectiveness of an EO in shaping resource orchestration to enhance value creation from big data.

In addition, we provide important insights from the important emerging economy of China and show how managers bundle and orchestrate resources and create value from big data. This is one of the first studies to have integrated resource orchestration theory and entrepreneurial orientation in the context of big data, thus demonstrating the value of integrating the RBV with EO in the context of big data. Not much is known about how companies from emerging economies orchestrate and leverage knowledge assets, particularly the valuable knowledge that can be captured through big data for value creation strategies; therefore, the findings of this study have greater value for managers in order to understand the creation of value from big data through the adoption of specific managerial processes and strategies that are conducive to the orchestration and leveraging of resources for the development of competitive advantage in the era of big data (Prescott, 2014).

5.2 Implications for Practice

The findings of this study provides important implications for practice. The findings suggest that resource coordination is important in harnessing value from big data in dynamic environments of emerging markets. Thus, managers need to carefully orchestrate asset base and coordinate internal resources in order to benefit from big data for value creation which will lead to the development of competitive advantage (Barney, 1991; Helfat *et al*., 2007; Sirmon *et al*., 2007; Sirmon *et al*., 2011). The resource coordination for exploitation of big data can be further realized through proactive, innovative and risk-taking entrepreneurial orientation, therefore, managers need to improve and reconfigure internal processes in order to create value through big data.

5.3 Limitations and further research

Our aim was to gain a rich understanding of how companies manage big data resources to create value in the context of emerging economies. With regard to generalizability, it is critical to note that the sample companies operated in a data-intensive area and had very different starting points. However, with companies in other industries generating more data than ever before, the process of value creation from big data that we observed may be generalized to other ventures. We also acknowledge that this research's setting was limited to China. Therefore, future research can expand or test (e.g., by using quantitative methods) across industries and countries the two propositions that we have put forward. Additionally, future studies could examine micro-processes and other strategic orientations—such as learning and marketing orientation—and how these influence the creation of value from big data.

Summarising, one of the key contributions of this study is that it brings the EO into the discourse on resource orchestration and value creation from big data. A key implication of our findings for resource orchestration scholars is that the investigation of the relationship between big data and value creation should also consider its organization. Therefore, further research needs to investigate the effectiveness of an EO in affecting the explorations of ways in which a company is organized for the detection and exploitation of opportunities from big data. In addition, there is a need for more scholarly attention to the development of company control and coordination processes aimed at encouraging and stimulating EO behaviours in individual employees, thus focusing on the central role played by persons and interpersonal interactions in harnessing EO —as pointed out by Salvato and Vassolo (2017)—rather than that of abstract, company-level entities. Lastly, the insights of this study can be applied in the context of sharing economy based firms in order to understand those firms value creation strategies. Furthermore, there is a scope to examine other antecedents such as learning orientation, social networks and absorptive capacity and how these enable firms to create and capture value from big data across emerging and developed markets.

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Tables and Figures

Table 1: Background characteristics and data sources for cases

Company	Founding year	Type (from inception)	Ownership	Number of informants	Data sources
Serong	1999	Online B2C retailer	Private	11	Reports and strategic memos (27) Press articles (36) Semi structured interviews
Targar	1998	Online social network	Private	9	Reports and strategic memos (25) Press articles (38) Semi structured interviews
Yogy	1998	Online group buying site	Private	9	Reports and strategic memos (14) Press articles (19) Semi structured interviews

Gray	1999	Online travel agent	Private	7	Reports and strategic memos (11) Press articles (23) Semi structured interviews

Table 2 Cross case comparison: additional representative quotes

Key themes	Serong	Targar	Yogy	Gray
Resource coordination	"Often we found that people from different disciplines, from different backgrounds often see data from different ways. They also see the pattern in different ways, how it connects to the knowledge they know. When you get people work together in a collaborative way, that's when you really unleash the real potential of the data." "It's not just about plucking numbers, understand the correlations, this is just a very beginning of the journey, it's about understand the business context and scenarios. In order to understand the context, we cannot do this by ourselves, we need to talk people from marketing, product development, or even partners from outside of the companies such as	"Our data team used to be a lone wolf, but now they have people who work on the data, they also have people who are out and about talking to people from different departments, working on different project together. The job we have is not focussing on the data itself, it's about how to make the rest of the people from other departments, make their job much easier". "We can draw many correlations, but the ultimatum question is always coming down to 'so what'. Data without action, data without context is just data, not more. The action and context part requires collaboration far beyond the data team boundary".	"Everyone jumped on the backbone of this data thing and everyone is fighting to get anyone who is good at it. For me, it is more like "ji le (chicken ribs)", tasteless when eaten but a pity to throw away. They do daily report and we look at the data in the morning, but most of the time, it is more like a procedure, do we get much from it, not really". "Sometimes people don't really appreciate the job we have done. We worked really hard on the data, but sometimes, nobody even look at our data. They complained that it is not useful"	"I would say the expectation was very high (from us). It is often alone these lines: "tell me how I can steer my company based on the data, or tell me how I can make money based on the data.' By throwing us in the data sea and expect us to know everything is not data management. We felt pressed and isolated". "We had a bottleneck between the data analyses and data application. How to breakdown the data and feed into different department. They (data analysts) know how to fiddle around data, how to make sense the data, but the hidden layer is that they need to understand the business value of these data. They present the data on the daily basis to us, but most of us, to be

	local communities to understand the contextual condition"			honest, do not really know what we look at, what these data means".
EO				
Proactiveness	The data warehouse that you have generated and stored is a history. The most valuable data is collected, analysed and reacted during the point of customer interaction. The time is not a couple of days, or even a couple of hours, it is less than 60 seconds, even with 60 seconds I am being generous. This means that in order to capture this opportunity, simply responding is not sufficient, we need to take action drive the change and anticipate the change". "With amount of the data we have, we are in a better position to make decisions about the future. We know what to expect and how to approach it."	"Data itself, particularly the real time data is very valuable. You have to be prepared, to anticipate the changes, and you have to act fast. If you are not prepared, by the time you put everything together and act on it, the opportunities are gone. You want our front line staff to work with the data team, we want people can hear the gunfire, know when the gunfire is going to start, and we built a system where these people have all the resources they need to go into the war". "The beauty of big data is the predicative nature. You can use the data to predict, although not 100% correct, most of time you can predict the trends, predict what is going to happen, in what context. We want to make sure people who are in position to execute these	"Somehow we feel that we always play a catch up game. With layers after layers of management, with layers after layers approval, we were never been capture the real value of big data. The real value is not about mining the data we have in the past, this is just too passive and you won't get much from it" "You need to build a different organization structure to enable the agile response to the big data, it is not about takes a month or two to come up with an action plan. This kind of action plan just eats dust of the big data. Being proactive to the big data, to have this kind of mind-set requires a system change, we are too rigid"	N/A

		insights are enough freedom and flexibility to do so”.		
Innovation	“We often neglect the human side of the data business and how people can use data in a different and innovative ways. We tried to strive for a balance between analytical and innovative side of data” “The term ‘big data’ sounds intimidating and very technical. We wanted to change this perception and encourage our staff to have fun with it. That's why I say data cannot overtake all the jobs because there are certain aspects such as curiosity, creativity and imagination, things we are good at but data cannot do. That's exactly what we try to get our people to do when they approach the data, be curious, ask questions, be creative and use their imaginations, use data to create different stories, to create emotional connections with our customers”.	“People got fascinated about data itself and forgot important mechanism to enabling to make these data “alive”, the mechanism I am talking about is culture. You need to have that culture change, the culture that takes an innovative approach when it comes to data” “It is important to create a synergy between data and people. Data is important proving solid evidence, but it can only be to its best potential with the magic touch from people.	“Everything is ‘we need to look at the data’ or ‘let the data do the talk’. We don't have the voice in the process. When it comes to data, we often have a blurred vision, it is like to admire flower in fog weather, and nobody really know the true beauty of the flower”. “The emphasis is always on the analytical side of data. Innovation, well, they (data team) just have to think something different.”	“Crunching big data requires hard-analytical skills. We have great experts in the house”. “We put great investment into our data team, focussing on the data analytical side of business”
Risk taking	“It is great that data can provide many insights about our customers’ behaviour	“Data is a very important resource, but data is a history, we need to discover,	“You don't have to take risk because the insights generated from big data can help you to unravel the	N/A

	but if everything is driven from data, you never get opportunities to take risk and try it out new things. People often afraid to take a risk, but you have to be all in”. “We have the luxury to try it out in a small scale to see how market response. Without taking risks, you will be blinded by many other potential opportunities in the market”	create new opportunities, not just from the data we have, but to create new insights, to shape the data. This requires us to take a plunge, yes, it can be risky, but if are afraid of making mistake”. “If you are afraid of taking risk, then you are definitely in the wrong side of big data business. It is not about play safe with the data you have, it also about explore new ideas and opportunities, to create and drive the future with the help and insight from big data”	misty of the phenomena, so why do we need to try something different”. “The risk is greatly reduced with the power of big data. It provide us with a much safer environment to do our business”	

Figure 1 Framework