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Big data analytics capability and decision making performance in emerging market firms: The role of Contractual and Relational Governance Mechanisms

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Abstract

This study examines the role of big data contractual and relational governance in big data decision-making performance of firms based in China. It investigates the mediation of big data analytics (BDA) capability in the association of contractual and relational governance with decision-making performance. Furthermore, moderating role of data-driven culture in the relationship of BDA capability and decision-making performance is examined. Data are collected from 108 Chinese firms engaged in big data-related activities. Structural equation modelling is employed to test the hypotheses. This study contributes towards the literature on big data management and governance mechanisms, by establishing the relationship of decision-making performance with big data contractual and relational governance directly and through the mediation of BDA capabilities. It also contributes towards knowledge based dynamic capabilities (KBDCs) view of firms, arguing that dynamic capabilities such as BDA capabilities can be influenced through knowledge sources and activities. We add to the discussions on whether contractual and relational governance are alternatives or they complement each other, by establishing the moderating role of big data relational governance in the relationship of contractual governance and decision-making performance. Finally, we argue that social capital can enhance KBDCs through contractual and relational governance in big data context.

Keywords: Big data; contractual governance; relational governance; big data analytics capability; culture; decision-making performance; emerging markets

1. Introduction

The rise of digitization and big data present considerable value creation opportunities to organization (Sheng et al., 2019; Zeng & Khan, 2018), but at the same time there are several challenges, including lack of relevant skills in harnessing value through such transforming technologies (Dubey et al., 2019, Sheng et al., 2019). In the current digital economy, successful companies will be those who have developed the capability of big data driven decision-making (McAfee, Brynjolfsson, & Davenport, 2012). However, big data driven decision-making is not that easy due to the highly unstructured nature of the data, which may require various mechanisms such as contractual and relational governance to capture the value of diverse set of both structured and unstructured data. It also requires efforts and certain capabilities inside the organization in order to ensure the quality of big data driven decisions (Janssen, van der Voort, & Wahyudi, 2017; Shamim, Zeng, Shariq, & Khan, 2019). Thus, it is extremely important to investigate the factors enabling organizations for big data driven decision-making, which in turn leads to better value creation. Extant literature suggests that appropriate management practices are crucial in order to adopt big data driven decision-making in organizations, and decision-making is one of main outcome of big data related management practices (Sheng et al., 2017). For instance, Mcafee et al. (2012) highlight the importance of management practices to make an organization big data driven. In a recent study, Shamim et al. (2019a) identified management practices and big data capability as key factors to ensure better performance of data driven decision-making in organizations.

Deciding based on big data is not just about having access to big data and analyse it for decision-making. Big data driven decision-making follows a chain of activities, including collection of needed data, preparation, analysis, and effective decision-making (Janssen et al., 2017). Each of these activities requires different set of managerial resources and capabilities. Quality of big data collection and preparation heavily depends on data governance mechanisms, particularly contractual and relational governance (Janssen et al., 2017). Analysis and informed decision-making require big data analytics (BDA) capability (Wamba et al., 2017). Janssen et al. (2017) argued that these big data chain activities are interlinked but how contractual and relational governance facilitate BDA capability of organization is underexplored. There are contradictory scholarly views on the interplay of contractual and relational governance. Some scholars view relational governance as substitute of contractual governance (Adler, 2001), and some argue that it complement contractual governance (Poppo & Zenger, 2002). Therefore, it is important to empirically examine the phenomenon. This study analyses this issue in the context of big data contractual and relational governance. Furthermore, we lack a good understanding about whether having a BDA capability is enough for better big data driven decision-making performance or it also requires a relevant organizational culture? This study argues that in some situation BDA capabilities may not be enough for making effective decisions. Experienced decision makers and managers can still make effective decision based on their prior experience, cognition and intuition if there is lack of data driven culture inside the organization. Without data driven culture, organizations cannot exploit BDA capability to its full potential (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019). Mcafee et al. (2012) also reported that big data driven decision-making requires a culture of deciding on the bases of “what we know” instead of “what we think”. Moreover, in many organizations managers use the data to spice up their reports and support the decision they already made (McAfee et al., 2012). These arguments reflect the importance of organizational culture to exploit BDA capabilities. Against the backdrop of this discussion, this study aims to address the following research question: Do contractual and relational governance mechanisms enhance BDA capability leading to big data driven decision-making performance, and what is the role of organizational culture in this context?

BDA refers to a holistic approach managing, processing and analysing big data characterized by high volume, velocity, variety, value, and veracity, for actionable ideas (Akhtar, Frynas, Mellahi, & Ullah, 2019; Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Wamba et al., 2017). Within the big data environment, contractual and relational governance mechanisms take a central stage as through these mechanisms organization can maintain commitment and coordination between big data service providers and transfer of knowledge between internal employees for better value creation. In the big data context, contractual governance refers to the making of agreements and contract with the big data providers to improve the data quality. Relational governance is to build trust among organizational entities and to ensure that the effective knowledge sharing takes place, which is required for big data interpretation (Janssen et al., 2017). The roots of using inter organizational and intra organizational trust, support and information and sharing for value creation can be found in social capital theory (Nahapiet & Ghoshal, 1998).

This study examines the interaction of contractual and relational governance with BDA capability, which leads to data driven decision-making performance. Consistent with Poppo and Zenger (2002) we argue that relational governance can complement contractual governance. To establish this view we test the moderating role of big data relational governance in the relationship of contractual governance with BDA capability and decision-making performance. Furthermore, this study also examines the moderating role of data driven culture in the relationship of BDA capability and big data driven decision-making, which is not reported in the existing literature.

This study takes inspirations from the social capital theory, and knowledge based dynamic capabilities (KBDCs) view of the firm to link big data contractual and relational governance with BDA capabilities and decision-making performance. Social capital refers to interpersonal relationship network which provides resources such as information, trust, and support for value creation (Bizzi, 2015). Dynamic capabilities (DCs) refer to organizational ability to create and reconfigure competencies (Teece, Pisano, & Shuen, 1997; Teece, 2007) , and KBDCs view argues that DCs mainly depend on the knowledge (Zheng, Zhang, & Du, 2011). Existing literature acknowledges big data as important strategic resource and BDA as DC (Côrte-Real, Oliveira, & Ruivo, 2017; Shamim et al., 2019). Big data contractual and relational governance ensures the provision, and quality of big data along with the related knowledge to facilitate BDA (Janssen et al., 2017). Therefore, it makes social capital theory and KBDCs view as an important lens to explore the above issues.

2. Theoretical background and hypotheses

According to the resource-based view (RBV) of the firm, organizations should exploit their strategic assets and resources, which are valuable, rare, inimitable, and organisable (Barney, 1991). Knowledge based view (KBV) of firm suggest that knowledge is one of the main strategic resource of organization, and basic purpose of the firm is to convert the knowledge into commercial outcomes (Grant, 1996; Shamim, Cang, & Yu, 2017). DCs view is an extension of RBV and suggests that possession of strategic resources is not enough and to achieve sustainable competitive advantage, organization should also have the ability to create and reconfigure the competencies to create value out of these resources (Teece et al., 1997; Teece, 2007). KBDCs view argues that DCs mainly depends on the knowledge. Learning mechanisms and knowledge management drives the development of DCs in organization (Eisenhardt & Martin, 2000). The fusion of these varied streams of literature put forward the idea of KBDCs view. KBDCs view refers to organizational ability to acquire, combine, and generate knowledge to explore, analyse, and address the environmental dynamics (Zheng et al., 2011). It suggests that DCs depends on the ability of firm to acquire, generate, and combine knowledge resources (Shamim et al., 2019; Zheng et al., 2011).

One of the systematic ways of looking at trust, support, and knowledge resources from other individuals or firms such as partners, vendors, data providers, is by the lens of social capital theory (Schuller & Theisens, 2010). Social capital is part of intellectual capital and places value on social interactions. It makes individuals in the organization more valuable and difficult to replace who have created social capital through the communities and groups (Young, 2012). Social capital refers to the collective capabilities resulting from the social networks (Huysman & Wulf, 2006). Literature acknowledges social capital as relational resource (Nahapiet & Ghoshal, 1998). Social capital enables the trust, support, and provision of knowledge for value creation (Bizzi, 2015), which is the foundation of relational governance (Janssen et al., 2017; Poppo & Zenger, 2002) .

In the context of this study social capital theory and KBDC view provide suitable theoretical foundations. In the existing literature, KBDCs and DCs view in general are used as overarching theoretical framework to discuss big data related capabilities (Shamim et al., 2019; Shamim et al., 2019; Wamba et al., 2017). Provision of big data related knowledge through social capital enables the firm to improve the quality of decision-making. Social capital theory is also visible in existing literature to discuss the issues with big data value creation (Hazen, Skipper, Ezell, & Boone, 2016; Malgonde & Bhattacherjee, 2014). Big data contractual and relational governance ensures the provision, and quality of big data along with the related knowledge to facilitate BDA (Janssen et al., 2017). Along with enabling the firms to manage access to big data, social capital also enables the provision of big data related knowledge to the teams responsible for data processing, analysis, and decision-making, such as data source, and challenges associated with data (Janssen et al., 2017). Existing literature acknowledges BDA as DC (Côrte-Real et al., 2017; Shamim et al., 2019). Furthermore by facilitating the availability of big data and information, contractual and relational governance facilitate the analysis of data and information, and analysis of information leads to knowledge creation (Shamim, Gang, & Yu, 2016; Uriarte, 2008), which is essential for DCs development i.e. BDA capability in the context of this study. On the basis of these arguments we assume that social capital can enhance KBDCs through contractual and relational governance mechanism in the context of big data.

2.1. Contractual and relational governance in big data context

In governance structure discussions, the concept of contractual and relational governance is rooted in the alliance governance literature (Lee & Cavusgil, 2006). Contractual governance refers to the use of formal and legally binding contracts or agreements to govern the inter-firm exchange. It facilitates the knowledge transfer and strengthens the alliance between firms (Lee & Cavusgil, 2006; Macneil, 1977). Relational governance emphasizes more on mutual trust, and commitment (e.g., Poppo et al., 2016; Zhou & Xu, 2012). This view is further supported by social capital theory (e.g., Adler & Kwon, 2002; Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998), which highlights the importance of relational capital such as mutual trust that facilitates the knowledge transfer and learning. It encourages intensive interaction between concerned individuals which helps to locate key information e.g. source of knowledge and key processor of knowledge (Kale, Singh, & Perlmutter, 2000). Scholarship suggests that aspects of social capital such as shared vision integrated in strong personal relationship can serve as effective governance mechanism (Uzzi, 1996). Both contractual and relational governance can influence the decision-making process in organizations (Mustakallio, Autio, & Zahra, 2002). However, their efficacy depends on the environment and exchange related factors (e.g., Poppo et al., 2016). Since emerging markets suffer due to institutional voids, thus trust based governance mechanisms role become important in generating value through economic exchange (e.g., Zhou & Xu, 2012).

In big data context, contractual and relational governance emphasis on the supply of big data and ensuring the quality of data and value creation through it. It also involves the sharing of knowledge to interpret, analyse, and contextualize big data (Janssen et al., 2017). The making of agreements and contracts with the providers of big data, to increase the data quality is main focus of contractual governance. It also ensures mutual understanding of big data for clear responsibilities and procedures. Sometime contractual governance is not enough and firms need good level of relational governance to build trust among organizational entities in order to curb opportunism and to ensure relevant knowledge sharing to facilitate big data interpretation. It emphasizes on communication and knowledge sharing, which is crucial for understanding and processing the big data for value creation (Janssen et al., 2017). In this context, contractual and relational governance mechanisms role become important to mitigate potential opportunism and facilitate exchange between the parties (Cao & Lumineau, 2015; Poppo & Zenger, 2002; Williamson, 1996).

Big data driven decision-making involves a chain of big data activities, which involves the collection and preparation of big data i.e. cleansing, combining, and aggregating data for analysis and it influences decision-making performance (Shamim et al., 2019). Collection and preparation of big data is strongly linked with big data contractual and relational governance, which make them more crucial to enhance BDA and decision-making. Companies use governance mechanism to improve the quality of big data and to create right conditions for data processing (Janssen et al., 2017).

2.2. Decision-making performance

In the existing literature, decision-making performance is described in terms of accuracy of decision and time taken in decision making (Speier, Vessey, & Valacich, 2003). Some scholars used a broader lens to look into decision-making performance and discussed it in terms of decision effectiveness and efficiency (Visinescu, Jones, & Sidorova, 2017), hence it includes accuracy and use of resources. Shamim et al. (2019a) also followed the conceptualization of Visinesce et al. (2017) and explained decision-making performance in terms of effectiveness and efficiency, in the context of big data driven decision-making.

Big data driven decision-making categorizes as informational value creation through big data (Elia, Polimeno, Solazzo, & Passiante, 2019). Data driven decision-making means the decisions are based purely on the data, instead of depending on the hunches (Provost & Fawcett, 2013). Big data enables the firm to take data driven decisions and enhances decision-making performance (Janssen et al., 2017). Scholars suggest that data driven decision-making positively influences the firm performance, and data driven companies are more productive (Brynjolfsson, Hitt, & Kim, 2011). Data driven decision-making requires the support of data sciences. In fact many decisions are now being supported by artificial intelligence and other related technologies. Several industrial sectors are adapting the automatic data driven decision-making, and companies from the financial and telecommunication sectors are the early adapters (Provost & Fawcett, 2013). It highlights the importance of firm’s capabilities to manage and analyse the data.

Literature suggests that, in the modern economy one of critical success factor is to decide on the bases of big data (McAfee et al., 2012). However, big data driven decision-making requires certain big data capabilities (Shamim et al., 2019a; Shamim et al., 2019b). Most of the studies emphasis on BDA capability (Akter et al., 2016; Dubey et al., 2019; Wamba et al., 2017). Big data affects the way organizations make their decision, and who make decisions. When data is expensive, limited, and not digitally available, in this situation it is justified to let the well placed people make the decisions on the basis of their experience. This phenomenon is labelled as intuitive decision-making. For the important decisions, such people are normally high up in the organization, or they can be outsiders who are being consulted for their expertise in the subject matter. Such outsiders are normally very expensive. McAfee et al. (2012) coined the terms HIPPO for the highest paid person's opinion. Many companies, even in the big data community, often rely on HIPPOs for the decision-making. The genuine data driven senior executives ignore their own intuitions if it does not agree with what data says. In order to reap the maximum benefit of big data for better decision-making performance, organizations need to mute the HIPPOs (McAfee et al., 2012).

The above mentioned phenomenon of unavailability of big data can be linked with contractual governance. To avoid the HIPPO and to decide on the bases of big data, firms need to have access to good quality big data, which can be ensured by strong contractual governance in terms of big data. However, in the context of emerging economies where the environmental uncertainty is high, contractual and relational governance mechanisms might act as complements to each other rather than substitutes (e.g., Abdi & Aulakh, 2017; Zhou & Xu, 2012). Relational governance creates the trust on data provider in terms of quality and processing, which leads to better decision-making performance (Janssen et al., 2017), and might also facilitate the relationship of big data contractual governance and decision-making performance. Mustakallio et al. (2002) also argued that contractual and relational governance in general are associated with decision-making process. Exploratory findings of Janssen et al. (2017) also proposed that big data contractual and relational governance are linked with big data driven decision-making performance. KBDCs view also suggests that DCs e.g. big data decision-making (Shamim et al., 2019a), depends on the knowledge sources (Shamim et al., 2019; Zheng et al., 2011) such as contractual and relational governance. Visinesce et al. (2017) also argued that decision-making performance is dependent on the quality of information, which can be ensured through contractual governance. Problem complexity also influences the decision-making performance (Visinescu et al., 2017), and in terms of big data related complexity, relational governance play crucial role to reduce it. These arguments are also consistent with the social capital theory; therefore, it can be assumed that trust, support and knowledge resources from the relationship network through contractual and relational governance mechanism can enhance KBDCs such as big data decision-making performance. Furthermore, consistent with the stance of Poppo and Zenger (2002) that relational governance and contractual governance complement each other; we assume that big data relational governance moderates the relationship of big data contractual governance and big data decision-making performance. Based on these arguments and logical beliefs it is rational to assume that companies stronger in big data contractual and relational governance are in a better position to enhance big data decision-making performance, and relational governance moderates the relationship of contractual governance and decision-making performance The preceding discussion leads us to suggest the following set of hypotheses:

H1: Big data contractual governance is positively associated with decision-making performance

H2: Big data relational governance is positively associated with decision-making performance

H3: Big data relational governance positively moderates the relationship of big data contractual governance and decision-making performance; that is organizations that have superior big data relational governance are in a better position to strengthen the relationship of big data contractual governance and decision-making performance.

2.3. Big data analytics capability

BDA refers to a holistic approach of analysing and processing big data for value creation (Wamba et al., 2017). It is now considered as a key factor to improve efficiency and effectiveness having strategic and operational potential. Wamba et al. (2017) argued that BDA capability mainly depends on three components i.e. BDA infrastructure flexibility, BDA management capability, and BDA personal expertise capabilities. BDA infrastructure flexibility involves BDA connectivity, compatibility, and modularity. BDA management capabilities involve BDA planning, BDA control, BDA investments, and BDA coordination. BDA personal expertise capability refers to BDA technical knowledge, BDA technology management capability, BDA business knowledge, and BDA relational knowledge (Akhtar, Khan, Tarba, & Jayawickrama, 2018; Wamba et al., 2017). BDA capability construct designed by Wamba et al. (2017) is one of the most comprehensively designed constructs. However literature also reports leadership, talent management, and culture as important factors leading to BDA management capability, particularly for decision-making (Shamim et al., 2019). Shamim et al. (2019b), and Zeng and Glaister (2018) added big data experimentation, contextualization, democratization, and execution as part of big data management capability construct. All these components enable organizations to decide on the bases of data i.e. data driven decision-making. BDA is now an established influencer of firm performance (Germann, Lilien, Fiedler, & Kraus, 2014). BDA helps firms to evaluate the strategies through the lens of data (Amankwah-Amoah, 2016). Particularly in the context of this study BDA is becoming extremely crucial component of decision-making process and enabling firms for data driven decision-making (Hagel, 2015; Janssen et al., 2017). Literature acknowledges BDA as DC (Shamim et al., 2019a), and KBDC view argues that DCs are actually based on knowledge-based resources (Zheng et al., 2011). Therefore, BDA as KBDC is essential for decision-making performance (Janssen et al., 2017). Janssen et al. (2017) also suggested that BDA capabilities could lead to better decision-making performance. Shamim et al. (2019a) also found that big data could facilitate the process of big data driven decision-making leading to more effective and efficient decisions. Based on the above arguments, we suggest that:

H4: BDA capability is positively associated with decision-making performance

2.3. *Big data analytics capability and governance mechanisms*

Component in BDA construct reflects association with contractual and relational governance. Big data contractual governance provides facilitating contracts and agreements with the data provider and ensuring the quality of data. Contractual governance ensures the exploitation of resources for better value creation (van den Broek & van Veenstra, 2018) Strong contractual governance can enhance the connectivity, compatibility, modularity control and coordination, which are important component of BDA capability of organization (Wamba et al., 2017). It hints that big data contractual governance influences BDA capability which leads to data driven and better decision-making through the use of big data. On the other hand, relational governance ensures the provision and sharing of relevant knowledge based on trust-oriented relationships that facilitate in the processing and analysis of big data for better value. Wamba et al. (2017) argued that technical, business and relational knowledge in terms of BDA are important for BDA personnel expertise, which is important component of BDA capability. In this scenario, big data contractual and relational governance basically facilitating DCs i.e. BDA capabilities ensure the acquisition and application of knowledge, which is also consistent with KBDCs view. Therefore, it is rational to argue that relational governance can enhance BDA capability leading to better data driven decision-making in organizations. Big data contractual and relational governance can influence big data driven decision-making performance however, BDA capability can further facilitate this relationship. Extant literature also supports the view that big data management practices are linked with big data decision-making and value creation activities, however big data related capabilities mediate these relationships (Shamim et al., 2019; Shamim et al., 2019). Furthermore, following Poppo and Zenger (2002) and drawing insights from the social capital theory we argue for the moderation of relational governance in the relationship of contractual governance and BDA capability. Quality data through contractual governance when mixed with knowledge, support, and trust through relational governance can bring better results. Based on this discussion, we propose that:

H5: Big data contractual governance is positively associated with BDA capability

H6: Big data relational governance is positively associated with BDA capability

H7: BDA capability mediates the relationship of contractual governance and decision-making performance

H8: BDA capability mediates the relationship of relational governance and decision-making performance.

H9: Big data relational governance positively moderates the relationship of big data contractual governance and BDA capability; that is organizations that have superior big data relational governance are in a better position to strengthen the relationship of big data contractual governance and BDA capability.

2.4. The moderating role of data driven culture

In the organizational context, culture refers to set of norms, values, attitudes and behavioural trends formulating the core identity of organization (Denison, 1984). Organizations need to develop a data driven culture to reduce the dependency of instincts and hunches (McAfee et al., 2012). It is one of the main management challenges that data driven organizations are facing (McAfee et al., 2012; Shamim et al., 2019). Data driven culture is a key facilitator of data driven decision-making (Gupta & George, 2016). Existing studies also acknowledge the role of organizational culture in the development of DCs e.g. big data related capabilities (Dubey et al., 2019; Gnizy, E. Baker, & Grinstein, 2014; Shamim et al., 2019).

There are evidences in the literature that culture is an influencer of DCs, and culture facilitates the acquisition, and transformation of internal and external resources (Chirico & Nordqvist, 2010), which fuels DCs, and literature acknowledges big data related capabilities as DCs (Shamim et al., 2019; Shamim et al., 2019). Mcafee et al. (2012) argued that in order to harness full potential of big data, data driven organizations need to create a data driven culture. Without a data driven culture, managers and decision makers in data driven organizations can still use hunches and intuitions for decision-making but using data just to justify their decision, which is already taken (McAfee et al., 2012; Shamim et al., 2019). It indicates that BDA capabilities will not lead to better decision-making performance, if organizational culture does not encourage data-driven decision-making. Organizational culture is a more prominent reason for failure of big data initiatives than data characteristics and technological reasons (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). Gupta and George (2016) also argued that data driven culture enhances the organizational ability to create value from big data. Dubey et al. (2019) also support the view that culture can moderate the value creation through big data in terms of prediction and decision-making. On the basis of these arguments it is logical to assume that data driven culture can moderate the relationship of BDA capabilities and decision-making performance, and organization with data driven culture are in better position to use their BDA capabilities for better decision-making. Thus, we propose that:

H10: Data driven culture moderates the relationship between BDA capability and decision-making performance; that is, those organizations that have a superior data driven culture strengthen the relationship between BDA capability and decision-making performance compared to those organizations that have a lower level of data driven culture.

Figure 1 shows the above-proposed relationships

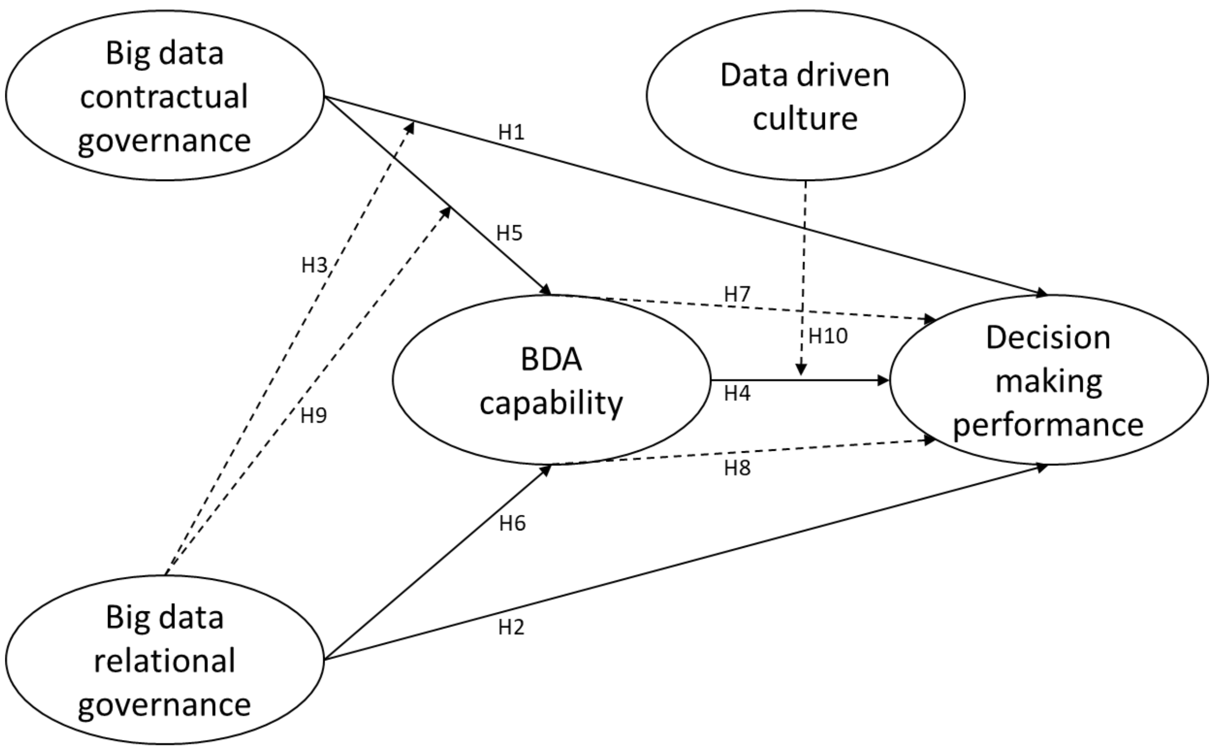

Figure 1. Conceptual model

3. Methodology

This study follows the deductive approach and employed quantitative techniques to test the hypotheses. Primary data collected from China provides a context of emerging economy. Recent literature highlights the involvement of firms in emerging economies in big data activities, particularly China is appeared as one of the most digital economy creating value from big data (Shamim et al., 2019; Shamim et al., 2019; Zeng & Khan, 2018). Data is collected through a survey using structured questionnaire.

3.1. Context, sample and data collection procedures

Following a survey based data collection, this study collected data from Chinese firms actively engaged in big data activities, and these firms make the population of this study. This study leverages the empirical context of one of the important emerging economy, China, because it is one of the most rapidly growing digital economy where most of the firms are actively engaged in utilizing big data for value creation activities (Zeng & Glaister, 2017; Zeng & Khan, 2018). Furthermore, emerging economies provide important context since they are rapidly growing and attracting huge investment across the manufacturing and service sectors. It is in this context that it becomes important to investigate the factors related to technology management and strategy in emerging and developing economies, because existing research on this topic has predominately focused on industrialized economies with stable institutional environment, and context that influences and supports the outcome of technology strategy (Amankwah- Amoah, 2019; Amankwah-Amoah & Hinson, 2019). Particularly in terms of value creation through big data, context is very important because value creation and management of big data is considerably different across countries. Big data is a source of external knowledge, which becomes more crucial in emerging countries context, because of the issue of institutional voids (Khan et al., 2018). Institutional voids refer to the lack of support from institutions such as Government, for knowledge creation and innovations (Khan et al., 2018; Wu, 2013). In this situation firms need to follow external sources of knowledge, such as big data (Shamim et al., 2019). Contractual and relation governance in terms of big data becomes even more important in this context because it ensures the provision and quality of big data, and knowledge related to processing and analysis of big data (Janssen et al., 2017). KBDCs view also suggests that in order to develop DCs e.g. BDA capabilities organizations need to pay more attention to the knowledge sources. It is important to examine the interplay of contractual and relational governance in Chinese context, where the institutional environment is considerably different than the western economies.

Firms were selected from the list of China big data enterprise ranking “which was released at 4th world data expo in China. Questionnaires were distributed to more than 400 firms. CEOs or other top managers responded to the questionnaire. A local consultancy firm in China helped us to gain access to these companies. Through this round of data collection, we received 86 usable questionnaires.

Another round of data collection took place during a business networking event on the day of Chinese New year. Questionnaires were distributed to the owners or senior managers of the relevant companies who attended the event. They were requested to fill the questionnaire in their convenient time. This round of data collection resulted in 22 usable responses. Two round of data collection yielded 108 usable responses in total and each of response iis from different company. For the sake of methodological parsimony we tend to maintain the homogeneity among respondent firms, in terms of firm characteristics. Some commonalities among firms are in terms of age, origin, status, number of employees. All the firms are at least 10 year old, and are original Chinese firms. All the firms are privately owned with number of employees from 100 to 250. The selected companies are from the sectors of online retailing, travel, IT solutions, telecommunication, block chain technologies and financial services’ providers. All the firms are active user of big data generated by their global customers.

Common method bias is usually a problem with cross sectional research design. To reduce the chances of common method bias we took several steps. Firstly we ensured the anonymity of the responses. Secondly, the items in the questionnaire were randomized to make it difficult to identify dependent and independent variables. Thirdly, we collected data in two waves.

3.2. Questionnaire items

Questionnaire is a combination of adapted and self-developed items. Decision-making performance is measured by adapting four items from Shamim et al. (2019a). Five items from Shamim et al. (2019b) are adopted to measure data driven culture. Big data contractual governance is measured by developing four items, and big data relational governance is measured by adapting the scale from Poppo and Zenger (2002). To measure BDA capabilities six items are adapted from Akhtar et al. (2018). Dimensions used in Akhtar et al. (2018) are consistent with Wamba et al. (2017) and Akter et al. (2016). All three studies argued that items in BDA capabilities construct should cover availability of experts, tools, and techniques. All the items are measured using seven point likert scale ranging from strongly disagree (1) to strongly agree (7)

3.3. Data analysis

This study follows quantitative approaches to analyse the data. Smartpls software package is used for data analysis, particularly to apply structural equation modelling following partial least square method. Partial least square is a variance based approach imposing less limitation on sample size and distribution and it provides effective solution for multicolinearity issues (Chin, Marcolin, & Newsted, 2003). Reliability is tested using Cronbach alpha. Convergent and discriminant validity is examined following the approach of Fornell and Lacker (1981).

4. Results

4.1. Reliability and validity

Reliability of constructs is measured through Cronbach's alpha. To establish reliability, value of Cronbach alpha should be greater than 0.7 (George, 2011). Results in table 1 show that Cronbach alpha for all the constructs is more than the required value of 0.7. Convergent validity can be established if factor loadings are greater than 0.65, average variance extracted (AVE) is more than 0.5 and composite reliability (CR) is higher than AVE of the construct (Fornell & Larcker, 1981). Table 1 shows that result meet the criteria of Fornell and Larcker (1981) and convergent validity is established. Factor loadings for all the items are greater than 0.65. AVE of each the factors is greater than 0.5 and CR is higher than AVE.

Table 1. Reliability and convergent validity

Variable	Items	Factor loadings	AVE	CR	Cronbach alpha
Big data contractual governance	CG1	.91	.77	.93	.90
	CG2	.84			
	CG3	.91			
	CG4	.84			
Big data relational governance	RG1	.87	.70	.87	.78
	RG2	.84			
	RG3	.79			

BDA capability	BDAC1 BDAC2 BDAC3 BDAC5 BDAC6 BDAC7	.84 .82 .76 .80 .86 .69	.64	.91	.89
Data driven culture	OC1 OC2 OC3 OC4 OC5	.80 .86 .77 .71 .80	.63	.89	.85
Decision-making performance	DDDM1 DDDM2 DDDM3 DDDM4	.85 85 .87 .83	.73	.91	.87

Fornell and Larcker (1981) criteria for discriminant validity suggests that squared correlation among construct should be less the AVE of construct. Results in table 2 indicate that discriminant validity is also established. Squared correlation of all the constructs is less than AVE of constructs. AVE is shown in bold at diagonals.

Table 2. Discriminant validity

	Factors	**1**	**2**	**3**	**4**	**5**
1	BDA capabilities	**.64**				
2	Big data contractual governance	.53	**.77**			
3	Data driven culture	.54	.64	**.63**		
4	Decision-making performance	.62	.62	.62	**.73**	
5	Big data relational governance	.50	.50	.60	.59	**.70**

4.2. Hypotheses testing

Structure equation modelling is employed for path analysis and hypotheses testing. Initially we tested the direct association of big data contractual and relational governance with decision-making performance. Results in table 3 indicate that big data contractual governance is significantly and positively associated with decision-making performance ($\beta = .39$, $p < .001$). Big data relational governance is also positively and significantly associated with decision-making performance ($\beta = .35$, $p < .01$). These findings support H1 and H2.

Following Baron and Kenny (1986) approach, we then entered BDA capabilities as mediator into the model. BDA capability is significantly related to decision-making performance ($\beta = .28$, $p < .01$). BDA capability is also positively associated with big data contractual ($\beta = .48$, $p < .001$) and relational governance ($\beta = .38$, $p < .001$). Results also indicate that there is indirect association of decision-making performance with big data contractual ($\beta = .13$, $p < .05$) and relational governance ($\beta = .10$, $p < .05$), through the mediation of BDA capabilities. After entering BDA capabilities as mediator into the model the direct relationship of decision-making performance with big data contractual and relational governance is reduced from $\beta = .39$ to $\beta = .26$, and $\beta = .35$ to $\beta = .25$. However the relationships are still significant as $p <.05$, which shows that the mediation is partial. These findings support H4, H5, H6, H7 and H8.Results show that relational governance moderates the relationship of big data contractual governance and decision-making performance ($\beta = .19$, $p < .01$). It supports H3. However results do not support H9, because the moderation of relational governance in the relationship of contractual governance and BDA capabilities is not significant ($\beta = .06$, $p > .05$). Furthermore, H10 is also rejected because the moderation of data driven culture in the relationship of BDA capabilities and decision-making performance is not supported $\beta = -.09$, $p > .05$)

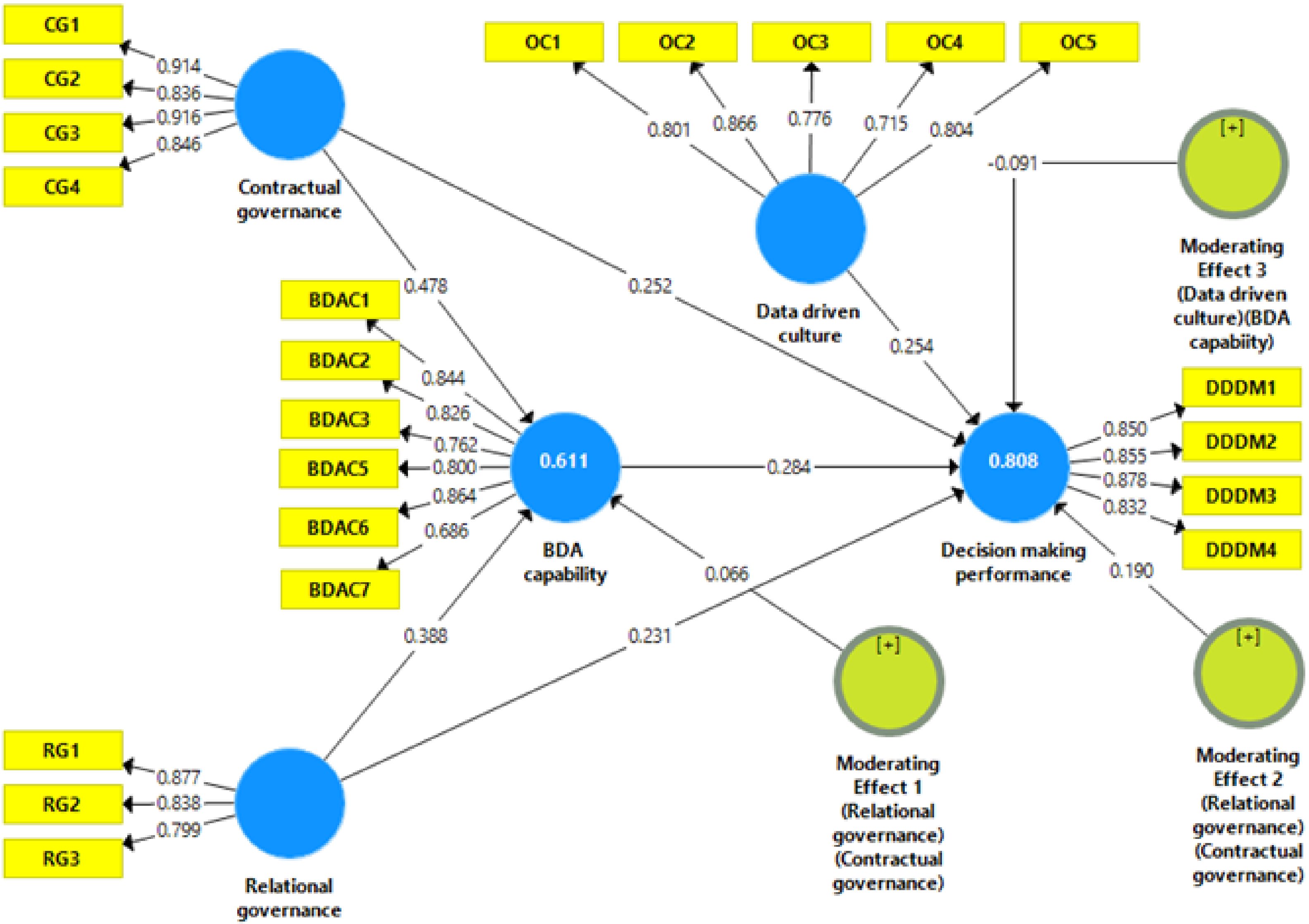

Figure 2. Path analysis

Table 3. Path analysis and hypotheses testing

Path	Direct effects β/t-value	indirect effects β/t-value	Total effects β/t-value	Moderating effects	Hypotheses	Result
Decision-making performance ← Big data contractual governance	.39***/4.12				H1	Accepted
Decision-making performance ← Big relational governance	.35**/3.24				H2	Accepted
Decision-making performance ← (Contractual governance)(Relational governance)				.19**/2.68	H3	Accepted
Decision-making performance ← BDA capabilities	.28**/2.80				H4	Accepted
BDA capabilities ← Big data contractual governance	.48***/4.48				H5	Accepted
BDA capabilities ← Big data relational governance	.38***/4.09				H6	Accepted
Decision-making performance ← BDA capabilities ← Big data contractual governance	.26**/2.84	.13*/2.23	.39***/3.90		H7	Accepted
Decision-making performance ← BDA capabilities ← Big data relational governance	.25**/2.67	.10*/2.22	.35***/4.09		H8	Accepted
BDA capability ← (Contractual governance)(Relational governance)				.06/.68	H9	Rejected
Decision-making performance ← (BDA capabilities)(Data driven culture)				-.09/1.33	H10	Rejected

5. Discussions and conclusion

This study examines the association of big data contractual and relational governance with decision-making performance through the mechanisms of BDA capabilities in Chinese firms actively utilizing big data for superior value creation. It also adds to the discussion on whether contractual and relational governance are alternatives or they complement each other. Consistent with Poppo and Zenger (2002), we support the scholars with a view point that they complement each other, particularly in the context of emerging market firms. Our results provide evidence of moderating role of relational governance in the relationship of contractual governance and big data analytics capabilities, which lead to better and decision-making performance in Chinese firms. China is a suitable context to investigate the issues of value creation through big data, because China is now considered one of the AI superpower, and one of the most data driven economy (Chakravorti, Bhalla, & Chatuvedi, 2019). The findings indicate that big data contractual and relational governance are positively associated with decision-making performance and the indirect relationship through BDA capabilities is also significant. It means that companies with high level of contractual and relational governance are in a better position to make accurate and timely decisions. Furthermore, contractual and relational governance also enhance the firm's BDA capabilities, which is also helpful to enhance decision-making performance in the context of big data driven decision-making. These findings are consistent with the initial exploration of Janssen et al. (2017). However, the results do not support the idea that culture moderates the relationship between BDA capabilities and decision-making performance. Though data driven culture is positively associated with decision-making performance, however it is not moderating the relationship of BDA capabilities and decision-making performance. Based on this finding, it can be argued that a better idea is to test the moderation of culture in the relationship of BDA capabilities and tendency of data driven decision-making instead of decision-making performance. Tendency of doing something can be more closely associated with culture instead of showing performance. Mcafee el al. (2012) also supports the idea that culture is associated with data driven decision-making.

This study offers implication for business managers and researchers by highlighting the importance contractual and relational governance in terms of big data. Our investigation shows how social capital can contribute towards KBDCs, such as BDA capability and decision-making. The findings suggest that in order to ensure data driven decision-making performance, firms should pay attention to the organization or activities involved in the acquisition of big data. Big data contractual and relational governance are central in this context. Through strong contractual and relational governance, firms can ensure the supply of good quality data and related knowledge, which has the potential of enhancing decision-making performance and also BDA capabilities. Janssen et al. (2017) and Shamim et al. (2019a) also suggested that sole focus on big data analysis itself is not sufficient because value creation through big data follows a chain of big data related activities and the role of data provider and capability to acquire relevant data is also crucial for positive outcomes. Firms should emphasize on the value chain of big data to strengthen the inputs for data analysis, capabilities and value creation activities e.g. knowledge creation, innovation, and decision-making. Results show that contractual governance has slightly higher influence on BDA capabilities and decision-making performance than relational governance, which indicates the greater importance of it. Firms should make suitable agreements with data providers to ensure the data quality, communication and understanding of big data. Exchange of views should be promoted to enhance the understanding of data within the firm. Firms can achieve these through contractual and relational governance (Janssen et al., 2017). In the context of China, firms should also consider that the institutional environment in China is different than many western countries e.g.

involvement of government in business, and dominance of state owned firms. It can influence the quality, nature and outcomes of contractual and relational governance.

Another theoretical implication is that, contractual and relational governance should not be treated as alternatives. Our findings reveal that they complement each other. Furthermore, in the context of big data value creation, contractual and relational governance mechanisms can be treated as big data management capabilities leading to BDA capability. Furthermore, in the context of big data decision-making, culture should be treated as moderator in the relationship of BDA capability and tendency of big data driven decision-making, instead of decision-making performance.

This study contributes towards the literature on big data management. Particularly by establishing the relationship of decision-making performance with big data contractual and relational governance. Existing literature mainly discusses the BDA capabilities and this is one of the rare studies addressing the governance issues in terms of big data, and linking it with data driven decision-making. Another important contribution is the investigation of mediating role of BDA capabilities in the relationship of decision-making performance with big data contractual and relational governance. It also contributes towards KBDCs view of firms, arguing that DCs such as BDA capabilities can be influence through knowledge sources and activities. Furthermore, it also contributes towards the literature on contractual and relational governance by investigating in the context of big data. We also contribute to the discussions on whether contractual and relational governance are alternatives or they complement each other, by establishing the moderating role of big data relational governance in the relationship of contractual governance and decision-making performance. In conclusion this study establishes the association of contractual and relational governance in terms of big data with decision-making performance, directly and also through the mediation of BDA capabilities. In this way we contribute by linking social capital theory and KBDCs view. Discussing the issues related to big data management in Chinese context provides an understanding of big data management and value creation in emerging economy context, which is an important contribution.

This study also has some limitations particularly the cross sectional research design and issue of common method bias associated with it. Common method bias is usually a problem with cross sectional research design. However we took several measures to reduce the common method bias. Firstly we ensured the anonymity of the responses. Secondly, the items in the questionnaire were randomized to make it difficult to identify dependent and independent variables. Thirdly, we collected data in two waves. This study is limited to China, where institutional environment is very different than western economies, so finding could be different in other economies especially in western economies. Future research should investigate these issues in other countries. Another limitation is that, for methodological parsimony, we tried to maintain the homogeneity among the respondent firms. However this approach is consistent with existing literature (Shamim et al., 2019). Future research can cover variety of firms with different demographics and other characteristics. Furthermore it needs more in depth exploration that what kind of value firms can create through big data contractual and relational governance? A qualitative research design would be suitable to explore the kinds of value firms can create with the help of big data contractual and relational governance. Particularly in a context where firms do not have BDA capabilities, it would be interesting to explore the role of big data contractual and relational governance in value creation through big data. Future research might look at this issue with the lens of resource dependency theory, where data providers and platform firms hold the access and control of big data, which is a strategic resource. Future research can also investigate the role of relational governance in internal big data team such as social capital among people who collect data, process data, analysis data and decision maker, and how it affects the decision-making performance.

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Appendix 1

Questionnaire

C G	We make agreements with big data providers	1	2	3	4	5	6	7
	Agreements with big data providers increase the data quality	1	2	3	4	5	6	7
	We make agreement with other firms to ensure mutual understanding of big data	1	2	3	4	5	6	7
	Agreements with other firms improve the communication	1	2	3	4	5	6	7
R G	We have extremely collaborative relationship with our big data vendor	1	2	3	4	5	6	7
	We and our big data vendor share long and short-term plans with each other	1	2	3	4	5	6	7
	We can rely on the big data vendor to keep promises	1	2	3	4	5	6	7
B D C	We have excellent expertise to process structural data	1	2	3	4	5	6	7
	Our analytics personnel (i.e., team) actively get insights from unstructured data	1	2	3	4	5	6	7
	We effectively process complicated data & information							
	The programming skills of our personnel greatly helps us to get analytical insights from the large datasets produced from smart-devices we use regularly*	1	2	3	4	5	6	7
	Our personnel effectively get insights from web-based data	1	2	3	4	5	6	7
	We effectively use real-time information for day-to-day operations							
	Our IT infrastructure strongly focuses on information integration by using advanced technology							
	We frequently disseminate useful information across our departments*							
O C U L	Our decisions are based on data	1	2	3	4	5	6	7
	Dependence on hunches for decision making is strongly discouraged in our organization	1	2	3	4	5	6	7
	Depending on data is a part of our organizational routine	1	2	3	4	5	6	7
	We have a culture of data driven working	1	2	3	4	5	6	7
	Our executives use lots of data to justify the decision already taken through traditional approach*	1	2	3	4	5	6	7
D M P	I believe that we make accurate decisions	1	2	3	4	5	6	7
	The decision we made resulted in desired outcomes	1	2	3	4	5	6	7
	We have to spend lot of time to make the decisions*	1	2	3	4	5	6	7
	We make timely decisions	1	2	3	4	5	6	7