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Strategic orientations, developmental culture, and big data capability

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ABSTRACT

Prior research articulated the importance of developing a big data analytics capability but did not show how to cultivate this development. Drawing on the literature on this topic, this study develops the concept of Big Data capability, which enhances our understanding of Big Data practice beyond that captured in previous literature on the concept of big data analytics capability. This study further highlights the strategic implications of the concept by testing its relationship to three strategic orientations and one aspect of organizational culture. Findings show that customer, entrepreneurial, and technology orientations, and developmental culture are important contributors to the development of Big Data capability.

1. Introduction

The role of Big Data in creating business value has been well documented in the practitioner and research press (e.g., see Barton & Court, 2012; Carr, 2013; Pigni, Piccoli, & Watson, 2016; Sanders, 2016). For example, multiple case studies have recorded how major well-known firms such as Walmart, eBay, Progressive Insurance, Target (Sanders, 2016), and Uber used Big Data to enhance their business performance (Pigni et al., 2016). Meanwhile, the scholarly literature also began to provide empirical evidence supporting the view that Big Data benefits firm performance (see, e.g., Gupta & George, 2016; Wamba et al., 2017). Yet there is evidence, which shows that many firms have not yet successfully leveraged Big Data to transform their business functions such as supply chain operations (Chen, Preston, & Swink, 2015; Sanders, 2016).

Parallel to the reports of success and failure stories of Big Data is a revelation of its multiple facets in the literature. To date, the literature from both scholarly and non-scholarly sources has revealed various aspects of Big Data: for example, data in diverse formats and unprecedented scale (McAfee & Brynjolfsson, 2012), real-time digital data flows (Pigni et al., 2016), analytics (Barton & Court, 2012; Chen et al., 2015), high tech (Esteves & Curto, 2013), an emerging profession (Davenport & Patil, 2012), and data culture (Ross, Beath, & Quaadgras, 2013), among others. In an attempt to explain these above-mentioned success and failure cases, recent studies (e.g., Chen et al., 2015; Gupta & George, 2016; Wamba et al., 2017) drew on the dynamic capabilities perspective to argue that Big Data's contribution to firm performance rests on a related organizational dynamic capability, big data analytics capability. This argument is theoretically sound, as the dynamic capabilities literature (see, e.g., Eisenhardt & Martin, 2000; Helfat & Peteraf, 2003; Winter, 2000; Zollo & Winter, 2002) both conceptually and empirically validated the view that such capabilities enhance firms' competitive advantage (Teece, 2007; Teece, Pisano, & Shuen, 1997). Moreover, recent studies (Braganza, Brooks, Nepelski, Ali, & Moro, 2017; Chen et al., 2015; Gupta & George, 2016; Wamba et al., 2017) supported this argument with empirical evidence.

However, analytics is just one area of the bountiful domain that the all-encompassing term, Big Data, refers to. The concept of *Big Data **Analytics** Capability* can only cover the analytics part, but fails to capture many other non-analytics aspects of Big Data previously identified. A broad and comprehensive dynamic capability concept regarding Big Data is still missing in the literature. Additionally, prior and current research has not yet revealed what factors help to facilitate the development of this Big Data related dynamic capability.

This study aims to fill these two knowledge gaps identified in the current Big Data literature. First, this study develops and tests a concept of this Big Data related dynamic capability, which is broader in meaning than the *Big Data Analytics Capability* concept. To date, this study represents the first attempt to develop and test such a broad concept. On the basis of this, this study will further explore possible factors contributing to this Big Data related dynamic capability, which include three antecedents and one moderator: market, entrepreneurial, and technology orientations, and developmental culture. Examination of these three antecedents and one moderator is theoretically based. Dynamic capabilities are strategically grounded (Helfat & Peteraf, 2015; Teece, Peteraf, & Leih, 2016; Winter, 2003). This suggests that a

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starting point in pursuing an understanding of the driving force behind the development of the Big Data related dynamic capability can be to explore a firm's strategic willingness or preparedness. Past research indicates that strategic orientation conceptually represents such strategic willingness and preparedness (Day & Wensley, 1983). More specifically, this strategic orientation is reflected in a firm's overall attitudes or mentality toward the market (customers), entrepreneurship, and technology, and therefore is subdivided into customer, entrepreneurial, and technology orientations (Hakala, 2011). As strategic orientation is deeply rooted in a firm's values and beliefs (Gatignon & Xuereb, 1997), it is shaped by the firm's organizational culture.

Thus, this study will contribute to the literature in two ways. First, by developing the concept of Big Data capability, this study will offer a more comprehensive conceptual understanding of Big Data practice that involves an interplay of multiple factors than the concept of big data analytics capability currently used in the literature. With practical implications, the concept of Big Data capability will be helpful in explaining the performance differential in Big Data practice among organizations, including deployment and usage. Next, this study will test the validity of the concept by further exploring its 'strategicness', a substance of dynamic capabilities. Examining the three antecedents and one moderator, and their relationships with Big Data capability (BDC) will advance our knowledge of what factors facilitate the development of this capability.

2. Conceptual background and hypotheses

Inquiring about drivers of organizational success and sustainability, strategy research has pointed to resources (Barney, 1991), knowledge (Grant, 1996), and organizational capabilities (Eisenhardt & Martin, 2000; Helfat & Peteraf, 2003; Winter, 2000; Zollo & Winter, 2002) as being influential. The dynamic capabilities perspective holds that capabilities are developed based on the combined and strategic use of resources, knowledge, and competencies (Teece, 2007; Teece et al., 1997). As our early review showed, Big Data is undoubtedly a collection of various resources, from which, analytics, representing competencies, is applied to generate knowledge. However, knowledge generation relies on organizational capabilities (Gold, Malhotra, & Segars, 2001). Further, organizational capabilities assume usage and deployment of resources and knowledge (Teece et al., 1997). Thus, organizational capabilities are stronger and sustainable drivers of organizational success than resources and knowledge (Teece, 2007).

2.1. An overview of dynamic capabilities

While operational capabilities help to keep the organization running properly (Fortune & Mitchell, 2012), it is dynamic capabilities, among organizational capabilities, that help organizations to gain and maintain a competitive advantage (Teece, 2007; Teece et al., 1997), as they are path-dependent and firm-specific (Collins, 1994). Dynamic capabilities have three components: sensing, seizing, and reconfiguring, all of which serve strategic purposes (Teece, 2007). Sensing is to identify opportunities as well as threats, seizing to deploy and utilize resources and competences to capture those opportunities and address the threats, and reconfiguring represents organizational efforts to redevelop and redeploy resources and competencies for continuous renewal (Teece, 2007). Overall, dynamic capabilities are congruent with organizational strategic direction (Teece et al., 2016).

2.2. Dynamic capabilities emerging in Big Data practice

These revealed basic characteristics of dynamic capabilities have emerged in Big Data practice. To begin with, the organizational sensing and seizing functions are very noticeable in Big Data practice. While sensing requires high alertness to environmental information (Zaheer & Zaheer, 1997), seizing takes the next step to convert what has been sensed to be beneficial to the firm as concrete resources, assets, or competencies for the firm. In today's business environment, technology, competitors, regulatory events, significant changes in economic and political conditions, and other factors point to the inevitability of changes in the business environment (Tushman & O'Reilly III, 1996). To keep their competitive advantage sustainable, firms have to develop an ability to respond, manage and even benefit from revolutionary changes (Tushman & O'Reilly III, 1996). Such changes usually foretell new market trends that call for new product development. More specifically, Big Data facilitates the sensing role in identifying market requirements and opportunities so that firms can enjoy first-mover advantages. Then it enacts seizing by transforming the requirements, potentials, and opportunities into concrete products.

Recent examples of Big Data-enabled entrepreneurial accomplishments are live evidence of how Big Data practice reifies organizational sensing and seizing. Benefited from big data analysis that powerfully revealed viewers' tastes such as favorite actors and actresses, Netflix created and marketed a new TV series, *House of Cards*, that brought them millions in new revenue (Carr, 2013). Similarly, the sensing power of Big Data is illustrated in the Uber case, where real-time flow of digital data streams stemming from Big Data was perceived to be mountains where golden nuggets can be extracted (Pigni et al., 2016). Turbulent environments call for the execution of organizational capabilities (Girod & Whittington, 2017; Karna, Richter, & Riesenkamp, 2015), especially dynamic capabilities (Teece et al., 1997). Helping firms to develop new products as a response to the turbulent environment, Big Data practice contributes significantly to such dynamic capabilities. Besides new product development, sensing and seizing can also be shown in strategic alliance development (Schilke & Goerzen, 2010). Forming strategic alliances is also an effective way of obtaining required resources that are beyond the boundaries and limitations of the firm (Das & Teng, 2000). Big Data practice can seek and provide information about other firms that may facilitate forging strategic partnerships with these other firms.

Further, coping with the turbulent business environment mandates the exercise of the reconfiguring or transformation function of dynamic capabilities. Reconfiguring means that firms take action to renew and reorganize its resources and competences to address unique needs mandated by the changing environment (Teece et al., 1997). Just as it enacts organizational sensing and seizing, Big Data practice serves the reconfiguring function as well. Understanding environment changes is, to a large extent, to gain dynamic knowledge of competition and its causes. Big Data practice involves use of Big Data management technologies and mastery of skills to collect and analyze information (resident in Big Data) about competitors. Then knowledge of competition generated in Big Data practice serves to guide the firm for how to reorganize and reconfigure its resources, assets, and competencies so as to maintain its competitive advantage over its competitors.

2.3. Big Data capability

Big Data practice may guide its own progression and metamorphosis. As any capability has a lifecycle, a progression of growth, maturity, and decline (Helfat & Peteraf, 2003), Big Data as a capability is no exception. However, Big Data practice is both operational and dynamic. As an operational capability, Big Data practice refers to operational routines of identifying, collecting, storing, and analyzing Big Data, which consist of an interplay of resources, assets, skills, and competencies. Because it is a special capability of generating knowledge, Big Data practice generates knowledge about self- transformation, i.e., providing knowledge for how to create, update, and reconfigure resources, assets, and competencies needed for its operational routines of identifying, collecting, storing, and analyzing Big Data. This feature of generating knowledge for self-transformation makes Big Data a dynamic capability. This Big Data related dynamic capability has four basic features, which can be represented by a full package of resources, skills, competencies, and cultural values; namely, dataset, toolset, skillset, and mindset (Pigni et al., 2016).

First, and foremost, Big Data is simply a dataset. More specifically, Big Data refers to large volumes of various types of data (McAfee & Brynjolfsson, 2012) that are scattered in different organizational information systems, unconnected in structure (Davenport & Patil, 2012). Similarly, Big Data also constitutes sources of digital real-time data streams (Pigni et al., 2016). In addition to data, another main type of resource used in Big Data practice is the combination of hardware, software, and complex IT infrastructure that enables collection, storage, transformation, and analysis of big data. This constitutes the toolset. Further, Big Data practice requires the attainment of data analytics skills, an organizational knowledge-shaping competency (Chen et al., 2015). This is the skillset. Even though this is not an exclusive list, these features of Big Data are enough to show that Big Data practice is not a standalone technology but a multifaceted toolkit of interactive elements. Most importantly, there is a mindset that helps to hold these interactive elements together (Pigni et al., 2016) that can be likened to being a significant part of the soul of the organization or its spirit. This mindset or spirit underlying the Big Data multiplicity eventually leads to the development and shaping of organizational strategy. If Big Data analytics alone can be viewed as a dynamic organizational capability (Chen et al., 2015), given these characteristics, it is more compelling for us to argue that the Big Data multiplicity should be treated as a dynamic organizational capability. This detailed discussion of Big Data practice in light of the dynamic capabilities theory leads us to define *Big Data Capability as a firm's capability of identifying sources, where large volumes of various kinds of data flow out at high speed, and collecting, storing, and analyzing such Big Data for the purpose of accomplishing the firm's strategic as well as operational goals*.

3. Strategic orientations and developmental culture

As our previous discussion pointed to a strategic foundation of Big Data capability, it is compelling for us to explore what constitutes this strategic foundation, which may be a great contributor of Big Data capability. Two threads of theoretical discourse in strategic management strongly suggest the existence of such strategic facilitators. First, according to Prahalad and Bettis (1986), business strategy determines business performance. The concept of dominant logic suggests that a firm, just like a person, over time develops its mentality or mindset that conceptualizes its business, develops its business strategy, and guides decision making on allocation of critical resources (Bettis & Prahalad, 1995; Prahalad & Bettis, 1986). Such a mindset consists of mental maps that guide strategy formulation and application. This mindset is referenced as the firm's strategic orientation that guides the firm on what resources to be used, how to transcend individual capabilities, and integrate the resources and capabilities into a cohesive whole (Day, 1994).

Second, researchers from the fields of strategic management, entrepreneurship, and marketing have been inquiring about what specific factors constitute this overall strategic orientation, which enables firms to achieve competitive advantage (Hakala, 2011). They find that successful firms display some perceivable traits or tendencies in their strategy formulation and application, which are collectively known as strategic orientations (Day & Wensley, 1983). One such strategic orientation is *market orientation*, which refers to *a disposition of a firm that motivates and encourages generation and dissemination of market information including both the expressed and latent needs of customers and response to that information* (Narver & Slater, 1990). Another one is *entrepreneurial orientation*, which is defined as *a firm's tendency to value innovativeness, proactiveness, and risk-taking for the purpose of new market entry* (Covin & Slevin, 1989). The third one is *technology orientation*, which is *a firm's disposition of prioritizing technology in their strategy formulation as well as business operations, and seeking to maintain a technological superiority over its competitors* (Gatignon & Xuereb, 1997; Hurley & Hult, 1998).

Research in the last several decades consistently shows that these strategic orientations contribute to firm performance (Hakala, 2011), which is also the key concern of BDC as well. Further, Big Data is critical to understanding the market. Thus, a firm that is very market oriented would be interested in Big Data. Similarly, an entrepreneurial firm would also have a keen interest in Big Data as it can assist the firm in discovering and analyzing possibilities. The case of Uber is an illustration of this. Likewise, Big Data is highly technological in nature. Thus, an argument can be built that market, entrepreneurial, and technology orientations are important prerequisites to the development of BDC.

Moreover, these strategic orientations are deeply rooted in values, beliefs, and higher level grand human assumptions (Day, 1994), which constitute organizational culture (Schein, 1986). Recent research suggests a strong link existing between organizational culture and strategic orientations. For example, Zhou, Gao, Yang, and Zhou (2005) found that participative culture is beneficial to an innovation orientation, which is part of entrepreneurial orientation. Similarly, Brettel, Chomik, and Flatten (2015) found that organizational culture strongly impacts entrepreneurial orientation. Moreover, cultural values are a powerful motivator (Lathm & Pinder, 2005). Among the four competing cultures, developmental culture, because of its combination of flexibility and external focus (Denison & Spreitzer, 1991), emphasizes such values as innovation, growth, openness, resource acquisition, risk-taking, creativity, and adaptability or sensitivity to the external environment (Hartnell, Ou, & Kinichi, 2011), which are close to those inherent in most of the strategic orientations and BDC. Developmental cultural values drive firms to take risks and develop creativity to identify and respond to customer needs (Cameron, Quinn, DeGraff, & Thakor, 2006).

Additionally, the flexibility focus of developmental culture emphasizes adaptability and promotes employees' creativity, both facilitating innovation (Aiken & Hage, 1971). Similarly, its external focus enables firms to monitor more closely the market change and investigate unfulfilled customer needs through environmental scanning (Miller & Friesen, 1982). Because of their fit into the strategic orientations, developmental cultural values would intrinsically push a firm to be market and entrepreneurially oriented as well as to develop BDC. In this sense, developmental culture serves as an intrinsic motivator to both the strategic orientations and BDC. Thus, we argue that developmental culture moderates the relationship between the three strategic orientations and BDC. (Insert Fig. 1 Here)

4. Hypotheses

The previous section established a theoretical framework (see Fig. 1) for this study as well as an overall rationale for developing the concept of BDC and further investigating the role of three strategic orientations and developmental culture in facilitating the development of BDC. This section further reviews the literature on the constructs and more importantly, discusses how the three strategic orientations and developmental culture may relate to BDC. These relationships are specifically framed as research hypotheses.

4.1. Strategic orientations and Big Data capability

A firm's strategic orientations show what strategy it will use to guide its decision making, resource allocation, and marketplace interaction (Gatignon & Xuereb, 1997; Zhou, Yim, & Tse, 2005). Past research examining strategic orientations mostly focused on their effect on firm performance. Yet the research findings stemming from that thread of literature can still inform the determination of the relationship between strategic orientations and BDC. Although past research (e.g., Narver & Slater, 1990; Slater & Narver, 1995) pointed to the link between strategic orientations and firm performance, more research is needed to provide reasons for why strategic orientations contribute to firm

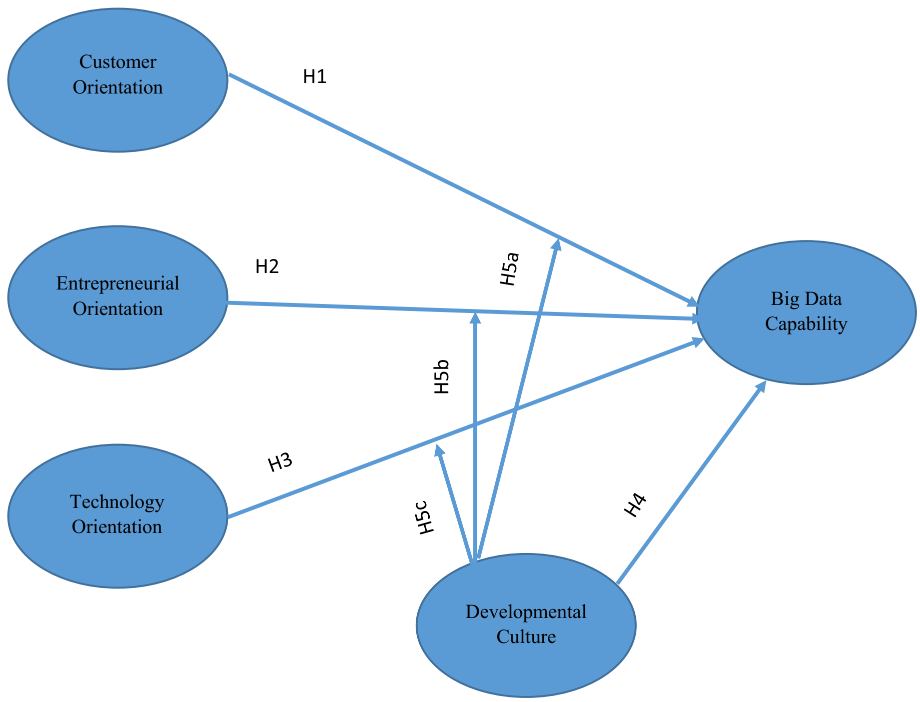

Fig. 1. Conceptual model.

performance (Gatignon & Xuereb, 1997). This study attempts to offer one such reason, namely BDC.

Past research approached the relationship between strategic orientations and firm performance from the perspective of organizational learning. Firms with strategic orientations are usually learning-oriented as well (Liu, Luo, & Shi, 2002). Further, strategic orientations help to enhance firm performance because of their learning capability (Wang, 2008). In other words, the strategic orientations of a firm greatly strengthen its learning capability, which then contributes to its performance (Hortinha, Lages, & Lages, 2011). If a firm prioritizes learning, it must be actively engaged in gathering and processing information, and transforming it into knowledge, which are core abilities of BDC. This thread of research literature leads us to link strategic orientations to BDC.

Similarly, the marketing literature suggests that the path from strategic orientations to firm performance is via innovation, i.e., product innovation (Gatignon & Xuereb, 1997; Han, Kim, & Srivastava, 1998; Thoumrungroje & Racela, 2013), or innovation capability (Hortinha et al., 2011). A firm's innovation capability heavily relies on its ability to use and act on information, and generate knowledge, which is a core element of BDC. Thus, strategic orientations may relate to BDC, as they both contribute to innovation. Moreover, past research also shows that strategic orientations positively contribute to relative advantage, achieved mainly by designing innovative products (Gatignon & Xuereb, 1997). Designing innovative products is a reflection of a firm's differentiation capability that helps it to obtain relative advantage (Chen, Chen, & Zhou, 2014). To take advantage of their differentiation capability, firms design innovative products to meet customer needs (Gatignon & Xuereb, 1997). Understanding customer needs and other changes in the market can effectively be accomplished by collecting and analyzing relevant data about customers and the market. Similarly, designing innovative products requires both new technical knowledge and new knowledge about customers and the market. These two competencies that firms must demonstrate in obtaining relative advantage are inherent in BDC. Indeed, these strategic orientations combine to constitute dynamic capabilities (Thoumrungroje & Racela, 2013), one of which is BDC. Thus, it can be argued that firms with these strategic orientations are likely to develop BDC, compared to those that lack such strategic orientations.

Consistent with the above outlined research finding regarding the orientation-innovation-performance path, market orientation is found to be an enricher of innovation (Grinstein, 2008; Han et al., 1998; Kirca, Jayachandran, & Bearden, 2005; Mavondo, Chimhanzi, & Stewart, 2005; Verhees & Meulenberg, 2004). Likewise, as shown above, BDC can also motivate and enable innovation by discovering what can and will be new products in the market on the basis of analyzing big data about the market and customer needs. Thus, there must be some coherence between market orientation and BDC. Further, market orientation provides firms a cultural motivator for organizational learning that stimulates knowledge creation and sharing about the market (Slater & Narver, 1995). More specifically, market orientation is positively related to introducing new-to-the-world products and reducing the number of me-too products launched by a firm (Lukas & Ferrell, 2000). This link between market orientation and product differentiation success is most likely due to the market intelligence that the firm has generated and responded to, which will be enhanced by BDC. The literature generally supports the association between a long-term market orientation and a firm's ability of garnering information and knowledge about customers' expressed as well as latent needs (Kumar, Jones, Venkatesan, & Leone, 2011). Based on these findings of past research, we hypothesize:

H1. *Market orientation is positively related to Big Data capability.*

Besides market orientation, entrepreneurial orientation is another strategic orientation that has been linked to firm performance (Lumpkin & Dess, 1996; Wiklund, 1999; Zahra & Covin, 1995). Two dimensions of entrepreneurial orientation quickly point to a link between this orientation and BDC. One is innovativeness, which has already been shown earlier to be related to BDC. The other is proactiveness, a tendency of a firm to respond to market opportunities by seizing initiatives in the market (Lumpkin & Dess, 2001). Earlier analysis of market orientation research has already linked responsiveness to market intelligence to BDC. Entrepreneurial orientation contributes to the development of BDC in a similar way as market orientation does, because many studies (e.g., Renko, Carsrud, & Brannback, 2009; Thoumrungroje & Racela, 2013) found that both orientations follow the same path in contributing to performance. For example, just as market orientation, entrepreneurial orientation has been found to be a contributor to new product introduction (Davis, Morris, & Allen, 1991). Likewise, past research also suggests that entrepreneurial orientation facilitates knowledge creation (Li, Huang, & Tsai, 2009). Further, firms with entrepreneurial orientation are more likely to be responsive to emerging trends in the market (Covin & Slevin, 1991). Additionally, besides directly contributing to firm performance, entrepreneurial orientation facilitates market orientation, which then contributes to firm performance (Matsuno, Mentzer, & Ozsomer, 2002). Thus, it can be reasoned that entrepreneurial orientation facilitates the development of BDC just as market orientation is hypothesized to do so. The preceding analysis leads to our second hypothesis.

H2. *Entrepreneurial orientation is positively related to Big Data capability.*

As BDC involves the ability to adopt, and use technology, and generate technical knowledge, it presupposes a technological orientation. Additionally, past research (e.g., Chen et al., 2014; Hortinha et al., 2011; Renko et al., 2009; Salavou, 2005) indicates that technological orientation works in a similar way as the other two strategic orientations do to contribute to performance. Thus, we propose our third hypothesis as follows:

H3. *Technology orientation is positively related to Big Data capability.*

4.2. Developmental culture and Big Data capability

The technology adoption and culture literature suggests a positive link between developmental culture and BDC. For example, in discussing their findings, Harper and Utley (2001) emphasized that flexibility is critical to firm success benefited from technology implementation. Likewise, Zammuto and O'Connor (1992) suggest that the cultural orientation of flexibility is positively associated with success in manufacturing technology implementation. As flexibility is a key orientation of developmental culture, those studies strongly suggest that developmental culture constitutes a favorable organizational context for technology adoption. As shown above, and inherent in our previous definition, BDC is heavily technological. BDC assumes technology adoption and implementation, as Big Data involves utilizing technological tools to collect, store, and analyze big data (Pigni et al., 2016). Thus, developmental culture must be conducive to development of BDC. Additionally, in a recent meta-analysis of the studies on organizational culture and organizational effectiveness, Hartnell et al. (2011) found that developmental culture is highly positively associated with innovation. As developmental culture emphasizes external focus, it is fair to conclude that external focus contributes to innovation. As shown early, BDC motivates and facilitates innovation. A common ground may exist between developmental culture and BDC. Thus, the following hypothesis can be established:

H4. *Developmental culture is positively related to Big Data Capability.*

It has been suggested that culture should be examined for its effect on the relationship between strategic orientations and firm performance (Hakala, 2011). It can be further argued that organizational culture may support or disapprove a strategic orientation. If organizational culture supports a strategic orientation, which has a positive relationship to performance, that relationship will be enhanced. On the other hand, in a disapproving organizational culture, even a positive relationship between a strategic orientation and performance will be weakened. Organizational culture's role in the relationship between strategic orientations and performance can be extended to the relationship between strategic orientations and development of BDC, as BDC is mainly expected to enhance performance. Developmental culture, based on our earlier discussion, consists of values that are close to those implied in the strategic orientations and BDC. More specifically, as our early discussion indicates, developmental culture promotes innovation, creativity, and growth. An innovative culture is more likely to promote and maintain market orientation than a bureaucratic culture (McClure, 2010). Further, developmental culture is externally oriented. Market orientation is external in nature, as it is concerned with customer needs and preferences, and competitor's status. Similarly, developmental culture may promote entrepreneurial orientation, as it facilitates innovativeness, proactiveness, and risk-taking (Brettel et al., 2015).

However, in the case of technology orientation, the interaction between developmental culture and technology orientation would not produce similar effects on development of BDC as those between developmental culture and market and entrepreneurial orientations. This is because developmental culture and technology orientation are related to organizational structure in different directions. As shown earlier, developmental culture favors flexibility and decentralization. But prior research pointed to a link between technology orientation and centralization. More specifically, a centralized organization facilitates advancement of a firm's foundational technology more than a decentralized structure (Argyres & Silverman, 2004). Further, mass production, a site of technology use for operations, is positively related to centralization (Reimann, 1980). Mass production or manufacturing in general requires high efficiency, automation, and standardization, which can only be accomplished with a high level of organizational control. A centralized structure facilitates such organizational control. This is in line with Ouchi's (1977) argument that technology affects structure through the organizational control system. Perrow (1970), Hrebiniak (1974), and Van de Ven (1977), all made a similar argument that technology requires a structure that fits the goal of making production task requirements predictable and programmable. In the production process, the much needed automation is enabled by technology. In this case, technology dictates a structure that manages or controls information flow and uncertainty (Reimann, 1980). Automation routinizes the production process or task performance. Decades of technology-structure research also suggest a strong association between routineness enabled by technology and centralization (Miller et al., 1991). Technology orientation, based on its definition, is more task-focused. Firms with a technology orientation tended to adopt and use state of the art technology to improve their work processes and task performance. Thus, past technology-structure research suggests that technology orientation is more associated with a centralized structure. Given that developmental culture and technology orientation relate to structure in different directions, their interaction would produce a negative effect on BDC. In regard of the above analysis, the following hypotheses can be proposed:

H5a. *Developmental culture positively moderates the relationship between market orientation and Big Data capability such that the effect of market orientation on Big Data capability is greater for firms with a stronger developmental culture compared to its effect on Big Data capability for firms with a less strong developmental culture.*

H5b. *Developmental culture positively moderates the relationship between entrepreneurial orientation and Big Data capability such that the effect of entrepreneurial orientation on Big Data capability is greater for firms with a stronger developmental culture compared to its effect on Big Data capability for firms with a less strong developmental culture.*

H5c. *Developmental culture negatively moderates the relationship between technology orientation and Big Data capability such that the effect of technology orientation on Big Data capability is smaller for firms with a stronger developmental culture compared to its effect on Big Data capability for firms with a less strong developmental culture.*

5. Methodology and data collection

5.1. Questionnaire development and measures

Development of the Big Data capability measure involved three phases: 1) item generation, 2) pre-pilot study, and 3) pilot study. Churchill Jr.'s (1979) approach for developing and testing new scales was followed in the development of this scale. The items measuring the construct of Big Data capability (Big Data operations, updating IT infrastructure, advanced analytics, and Big Data for strategy) were generated based on the results of a thematic analysis of qualitative interviews which constitute another paper, recent discussions of Big Data in the popular press, business journals for practitioners, and academic business literature, especially the works of Chen, Chiang, and Storey (2012), McAfee and Brynjolfsson (2012), Chang, Kauffman, and Kwon (2014), Peppard and Ward (2004), and Teece et al. (1997).

The pre-pilot study was conducted with ten academicians who published work on the topic and eight industry experts with experience in Big Data. Feedback and comments from the academicians were used to check face validity of the newly drafted measurement items and improve the items. Using an adapted version of the Q-sort approach (Churchill Jr., 1979), we asked the eight industry experts to read the construct and its dimensions, their definitions, and the items measuring them, and then match the scale items with the construct dimensions that they think the items measure well. This is to assess substantive validity of the scale items. Items with a 0.5 or higher value of substantive validity were retained. Some items were reworded based on comments and feedback from both the academicians and industry experts.

After the pre-pilot study, a small-scale pilot study was conducted to further improve the newly developed measurement scales. The pilot study questionnaire was posted on a research website (www.qualtrics.com). A list of potential participants was created using the LexisNexis database, with the following information: position title, specialty, mail address, telephone number, email address, firm size, SIC code, business description, and sales/revenue information. In the process of creating the list, a variety of job titles were used as key words such as: “Chief Operations Officer”, “VP Manufacturing”, “Manufacturing Manager”, “Plant Manager”, “Manufacturing Director”, “Production Manager”, and “Plant Operations Manager”. A total of 45 responses were obtained in this pilot study, of which only 42 were complete and usable. The 42 complete responses were analyzed using SPSS. Further deleting items was based on the results of this pilot study (Cronbach's alpha, Corrected Item-Total Correlation (CITC), and factor loading values).

The final version of the Big Data capability scale has a total of 16 items measuring Big Data operations, updating IT infrastructure, advanced analytics, and strategic uses of Big Data. However, the confirmatory factor analysis of the large-scale survey data used in this study yielded a single dimension structure for the Big Data capability construct. But the results also supported retaining all the 16 items in the scale.

The construct of market orientation has two dimensions: customer orientation and competitor orientation, based on Narver and Slater's (1990) conceptualization. We choose their conceptualization because this study emphasizes generation of knowledge about customers and knowledge sharing between supply chain partners. The market orientation scale has a total of 10 items with 6 items measuring customer orientation and 4 items measuring competitor orientation. These 10 items have been adapted mostly from Narver and Slater (1990). Since we have emphasized that generating knowledge about customers includes probing into and meeting customers' latent needs, we have incorporated some items from Narver, Slater, and MacLachlan's (2004) scale that specifically are used to measure those latent customer needs into our scale measuring market orientation.

Multiple instruments measuring entrepreneurial orientation are now available in the literature. Since our definition of this construct has emphasized the three dimensions of innovativeness, proactiveness, and risk-taking, we basically adopt Covin and Slevin's (1989) instrument as it has items specifically measuring the three dimensions. Their instrument also includes items measuring competitiveness and technological innovation. Since competitiveness is not included in our definition, and since we have a separate technology orientation, the items from their scale measuring competitiveness and technological innovation are not adopted in our instrument. Item 4 in our instrument is adopted from Lumpkin and Dess (2001) to replace the item from Covin and Slevin's (1989) (In dealing with its competitors, my firm is very often the first business to introduce new products/services, administrative techniques, operating technologies, etc.). We contend that that item from Covin and Slevin (1989) was poorly designed as it contains multiple meanings.

Our technology orientation scale has five items. Items 1 and 2 are adapted from Salavou (2005), and items 3 and 4 are adapted from Zhou, Yim, and Tse (2005). In both articles, they used items that deal with new product performance. As we have a separate scale measuring NPD, those items appear to be redundant in this technology orientation scale. For this scale, the items should entirely be on technology. In Gatignon and Xuereb (1997), three of the four items deal with NPD. And Salavou (2005) and Zhou et al. (2005) both adapted their scales from Gatignon and Xuereb (1997). Item 5 is adapted from Gatignon and Xuereb (1997).

Finally, our scale measuring the construct of developmental culture is adapted from Quinn and Spreitzer (1991), which has four items. After data was collected from the large-scale survey study, for each construct, reliability and validity were further assessed based on dimension-level corrected item-total correlation (CITC) scores and Cronbach's alpha values, dimension-level exploratory factor analysis and construct-level factor analysis results. The constructs and their measurement items adopted in the analysis of the large-scale survey data are presented in the Appendix A.

Two control variables are included in this study: industry and firm size. Industry is a nominal variable. Based on the responses from survey participants, the following industries were identified: manufacturing, IT, finance, automotive, telecommunications, construction, logistics, retail, media, healthcare, aerospace, utilities, chemical, consulting, and consumer products. Organization size, which is measured by the number of employees, ranges from 10 to 100,000, with a mean of 4603.

5.2. Respondents and data collection procedure

Before the large-scale data collection process began, attention and efforts were directed on determining respondents for this study. It was decided that respondents for this study must be employees with enough knowledge about the phenomenon under study, i.e., Big Data practices in their organizations. Thus, the key informant approach was followed in the data-collection process (Phillips & Bagozzi, 1986). Based on interviews with industry experts in the instrument development and initial validation stage of this study, we learned that employees with high-level managerial positions in information technology, operations, and business analytics were potential key informants for this study. Thus, employees with the following positions were contacted for an invitation of participating in this study as survey respondents: CEO, COO, CIO, CTO, VP of Manufacturing, Operations Manager, IT Manager, Supply Chain Manager, Manufacturing Manager, Manufacturing Director, Plant Manager, Production Manager, and Analytics Manager.

Given the difficulties of locating and gaining access to enough key informants, we outsourced data collection to Qualtrics.com, a commercial research firm, which has a large list of business panel members who represent different firms in different industries. Email invitations were sent to its panel members by Qualitrics.com with the statement of the purpose of the study. They were directed to an online survey posted on Qualtrics.com's website.

It becomes increasingly popular among academicians to outsource data collection to commercial research companies. Yet serious concerns and challenges associated with such a practice emerged. All such concerns and challenges point to data quality. To ensure data quality, we followed recommendations from Schoenherr, Ellram, and Tate (2015). More specifically, we took the following measures to ensure data quality. First, we informed Qualtrics.com representatives of the purpose of this research project, and the detailed requirements for potential respondents. These requirements helped Qualtrics.com to locate a sample of potential respondents. Second, following Schoenherr et al.'s (2015) practice, we did not provide an initial statement at the beginning of the survey showing the purpose of the project so as to avoid the possibility that respondents form a pattern in their responses that reflect what they think we want as shown in the purpose statement. Third, we used screening questions at the beginning of the survey to ensure that only the respondents with the required characteristics take the survey and all other potential respondents would be disqualified. One such screening question, for example, was whether their organization utilizes Big Data. Fourth, Qualtrics.com implemented some attention filters throughout the survey questionnaire to help to ensure that respondents focus their attention on the questions. Also, Qualtrics.com set a mechanism that automatically removes responses that were done in less than 9 min. This technical add-in helped to avoid those "speeders" (Schoenherr et al., 2015). Fifth, locations of all respondents and the ip addresses were recorded so as to check whether there were repeat respondents. Sixth, a "Not Applicable" response option was provided to each questionnaire item except for the open-ended and screening questions.

A total of 2700 panel members that were identified as managers in the manufacturing, operations, and IT industry, were targeted as potential respondents for this survey. Out of this list, 2200 were randomly selected and an email was sent to them to solicit their participation in this study. The site where the survey questionnaire items were posted was closed when complete responses reached the number we initially requested. A total of 273 responses was obtained. After a careful examination, 22 problematic responses were deleted. Thus, the final sample for this study was 251 responses. The response rate for this study was 12%. However, this response rate should be interpreted carefully. The process was such that once the total number of complete responses required by the researcher was obtained, the survey was immediately closed. This excluded other potential respondents the opportunity for doing the survey. If it was conducted in the traditional way, more completed responses would have been expected, as it would not close the door to late respondents.

6. Validity and reliability assessment

Validity and reliability of the constructs involved in this study were tested through confirmatory factor analysis (CFA). The CFA results indicate a good model fit for the measurement model ($x^2 = 605.27$, $df = 364$, $CMIN/DF = 1.66$, $p < .001$, $CFI = 0.92$, $RMSEA = 0.05$). The test statistics including mean, standard deviation, loading, and composite reliability values are all reported in Table 1.

Construct reliability was tested using the composite reliability score (Fornell & Larcker, 1981). The composite reliability values of all the constructs are greater than 0.70, the threshold (Nunnally, 1978). These results indicate that items measuring the same construct are highly intercorrelated and that the constructs have good construct reliability.

Construct convergent validity was assessed using item factor loading scores. High item factor loadings provide evidence of convergent validity (Anderson & Gerbing, 1988). The CFA test results indicate that the items measuring all the constructs are greater than the cutoff point of 0.5 except for one item measuring entrepreneurial orientation (0.47). Even though it is relatively low, that item was still retained in the study, because it was consistently used in previous studies that used the entrepreneurial orientation construct, which provided evidence of high convergent validity.

Table 1
Descriptive statistics, factor loadings, composite reliability, and Cronbach alpha values.

Construct	Mean	Standard deviation	Loading	Composite reliability	α
Customer Orientation	12.62	1.32		0.72	0.68
CUSO2			0.55		
CUSO6			0.77		
Entrepreneurial Orientation	17.90	2.26		0.74	0.76
EO3			0.59		
EO4			0.68		
EO5			0.47		
Technology Orientation	30.87	3.24		0.81	0.79
TO1			0.72		
TO2			0.64		
TO3			0.54		
TO4			0.62		
TO5			0.64		
Big Data Capability	98.32	9.72		0.93	0.92
BDC1			0.58		
BDC2			0.59		
BDC3			0.52		
BDC4			0.56		
BDC5			0.62		
BDC6			0.67		
BDC7			0.64		
BDC8			0.71		
BDC9			0.68		
BDC10			0.62		
BDC11			0.74		
BDC12			0.57		
BDC13			0.60		
BDC14			0.70		
BDC15			0.64		
BDC16			0.66		
Developmental Culture	25.39	2.52		0.82	0.76
DC1			0.68		
DC2			0.65		
DC3			0.68		
DC4			0.67		

Following prior studies (e.g., Swafford, Ghosh, & Murthy, 2006), we evaluated non-response bias, using a *t*-test. *t*-tests were performed comparing the responses of the first 30 and last 30 respondents with five items measured with an interval scale as dependent variables, which were randomly selected from the questionnaire. No significant difference was found between the two groups at the *p* value of 0.05 level in all the five *t*-tests, suggesting no evidence of non-response bias in the data.

Common method bias was assessed by performing Hartman's single-factor test, in which a single factor loads on all of the measurement items (Podsakoff, MacKenzie, & Lee, 2003). In doing this test, two models were created using IBM Amos 2: a single factor model and a conventional confirmatory factor analysis model, in which each factor loads on its own items. The results indicate that the single factor model resulted in a chi-square value higher than that of the confirmatory factor analysis model (1040.24 vs. 605. 27), suggesting that common method bias was not a serious concern in this data set.

Additionally, we performed regression diagnostics tests in terms of linearity, normality, and multicollinearity. We confirmed linearity through plotting standardized residuals against the standardized predicted values. Besides, normality was also confirmed for all the variables through the Shapiro-Wilk test. Further, multicollinearity was tested for all the independent variables iteratively using SPSS. The variance inflation factor (VIF) values are all below 2, suggesting that multicollinearity is not a concern in this dataset.

Table 2
Correlations.

	1	2	3	4	5	6	7	8
1. BDC	1	0.48***	0.64***	0.68***	0.52***	−0.22***	−0.39***	−0.43***
2. CO	0.48***	1	0.43***	0.56***	0.29***	−0.15**	−0.17**	−0.09
3. EO	0.64***	0.43***	1	0.65***	0.43***	−0.19**	−0.31***	−0.32***
4. TO	0.68***	0.56***	0.65***	1	0.46***	−0.12*	−0.36***	−0.42***
5. DC	0.52***	0.29***	0.43***	0.46***	1	−0.43***	−0.53***	−0.41***
6. CO*DC	−0.22***	−0.15**	−0.19**	−0.12*	−0.43***	1	0.54***	0.55***
7. EO*DC	−0.39***	−0.17**	−0.31***	−0.36***	−0.53***	0.54***	1	0.84***
8. TO*DC	−0.43***	−0.09	−0.32***	−0.42***	−0.41***	0.55***	0.84***	1

*** $p < .001$.
** $p < .01$.
* $p < .05$.

7. Analysis and results

The sample used in this study includes five variables. Descriptive statistics of the variables are presented in Table 1. Their correlations (including those for the composite variables created to test interaction effects), together with the p values, are shown in Table 2. To test the hypotheses, multiple regression analyses were performed. The three independent variables, then, the moderator variable, and then the three two-way interaction terms were entered into the model. Results of multiple regression tests are listed in Table 3.

Hypothesis 1 stated that market (now narrowed to customer) orientation positively contributes to the development of BDC. As shown in Table 2, customer orientation is positively related to BDC ($\beta = 0.16$, $p < .01$). Thus, Hypothesis 1 is supported. Hypothesis 2 suggested that entrepreneurial orientation positively contributes to the development of BDC. The multiple regression analysis results indicate that entrepreneurial orientation is positively related to BDC ($\beta = 0.28$, $p < .001$). Hypothesis 2, is, therefore, supported. Further, Hypothesis 3 posited that technology orientation positively contributes to the development of BDC. The results show that technology orientation is positively related to BDC ($\beta = 0.24$, $p < .001$), thus lending support to Hypothesis 3. Hypothesis 4 stated that developmental culture positively contributes to development of BDC. This hypothesis is also supported by the results ($\beta = 0.23$, $p < .001$).

Hypotheses 5a, b, and c suggested that the interaction between developmental culture and market orientation and that between developmental culture and entrepreneurial orientation are positively related to development of BDC, but that between developmental culture and technology orientation would lead to a negative impact on BDC. The results of this study only support Hypothesis 5c, which stated that developmental culture negatively impacts the relationship between technology orientation and BDC such that the stronger a firm's developmental cultural values the lower effect its technology orientation has on the development of BDC ($\beta = -0.28$, $p < .001$). The interaction between customer orientation and developmental culture is positively related to BDC, but the relationship is not significant. The interaction between entrepreneurial orientation and developmental culture is positively related to BDC, but the relationship is not significant.

8. Discussion

In this study, we developed the Big Data capability concept to capture Big Data understandings and practices in companies. We then tested the validity of this concept in a large-scale survey and investigated its relationship to three strategic orientations and an organizational culture. With the research design and the findings, this study has made two major contributions to Big Data research.

First, the development of the concept of Big Data capability represents an enhanced understanding of Big Data practices in organizations. The findings of this study provide strong support to the view that Big Data transcends from a technical artifact to a concept of dynamic organizational capabilities (Chen et al., 2015). Further, these findings help to show that only when the various elements are integrated under organizational strategic directions and thereby develop into a dynamic organizational capability, Big Data initiatives would likely help firms to reap in benefits such as entrepreneurial promises (Pigni et al., 2016) and new product development (Carr, 2013).

More importantly, the conceptualization of Big Data as a dynamic capability helps to capture what is all involved in Big Data practice and integrate all these elements in a theoretical manner. While previous research mostly focused on Big Data as raw data (McAfee & Brynjolfsson, 2012), analytics (Barton & Court, 2012; Chen et al., 2015), or disaggregated dataset, toolset, and skillset (Pigni et al., 2016), only the resources part of Big Data was captured and theorized. Such a theoretical approach is blind to other possible elements of Big Data, especially the strategic part. From a strategic management point of view, if Big Data is conceptualized as resources, then organizational attention would be directed to the technical aspects but not the strategic part. Only when Big Data is viewed as a dynamic capability rather than resources, companies can hope to gain and maintain a competitive advantage (Teece et al., 1997).

This finding is illustrated by the case study of John Hopkins University's model of Data Management Services through their Data Archive (JHU DMS/DA) (Shen & Varvel, 2013). According to Shen and

Table 3
Regression results.

Hypothesis	Independent variable/interaction terms	Standardized coefficient	Standard error	P value	Lower bound	Upper bound
H1	Customer orientation	0.16	0.39	0.00	0.42	1.95
H2	Entrepreneurial orientation	0.28	0.24	0.00	0.75	1.69
H3	Technology orientation	0.24	0.20	0.00	0.31	1.12
H4	Developmental culture	0.23	0.21	0.00	0.48	1.32
H5a	Customer orientation * Developmental culture	0.07	0.47	0.23	−0.36	1.49
H5b	Entrepreneurial orientation * Developmental culture	0.14	0.63	0.09	−0.17	2.32
H5c	Technology orientation * Developmental culture	−0.28	0.58	0.00	−2.99	−0.72

Note: Dependent variable = Big Data Capability.
Standard errors clustered by BDC.

Varvel (2013), this is a big data project that involves integration of technological resources (big data management infrastructure, hardware, and software) and human resources (deployment and implementation of employee skills, knowledge, and competencies in handling and analyzing big data, and reporting analysis results), and strategic application of these integrated resources (providing data management and archival services for internal faculty researchers from across disciplines and external National Science Foundation grant proposal writers). Shen and Varvel (2013) also discussed metrics of success for this case. Thus, these features detailed in the case study strongly suggest that a dynamic Big Data capability with characteristics defined and discussed above is developed in this case, helping to gain a competitive advantage as shown in the success metrics.

Further, when Big Data is conceptualized as a strategic issue, then practicing Big Data would involve the whole organization especially top management, as strategic decision making is mostly rested in top management (Fortune & Mitchell, 2012; Kor & Mesko, 2013). Moreover, conceptualizing it as a dynamic capability motivates companies to integrate their business processes and routines so as to achieve their competitive advantage. In that regard, this study has made an important contribution to the literature in that the concept of Big Data capability adds to our knowledge of a technology-based organizational dynamic capability. This conceptualization benefits future research as it provides a conceptual basis for future research to further explore Big Data related organizational outcomes as well as processes. For managers, these results suggest that companies should develop an overall Big Data capability in order for them to gain a competitive advantage. To develop such an overall capability in Big Data, companies should enhance their technological resources, use them to facilitate internal operations, encourage their employees to develop Big Data analytical skills, and align their Big Data competences with their strategic goals.

Our second contribution is that this study demonstrated a connection between Big Data capability and three existing concepts of strategic orientations. This helps to enhance the vitality and vigor of the existing concepts and their applicability. The relationship between Big Data capability and three strategic orientations affirmed in this study reinforced the strategic dimension of the concept of Big Data capability. More specifically, based on an extensive review of the literature on strategic orientations, we articulated a grand hypothesis that three such strategic orientations (customer, entrepreneurial, and technology) would contribute to the development of BDC. The results of this study supported this grand hypothesis. This is encouraging news to the research community, as it has affirmed the link between strategic orientations and development of Big Data capability. These findings provide a theoretically vigorous explanation for how Big Data capability can be developed.

These findings are further supported with evidence from published case studies. First, the case of Netflix's *House of Cards* provides evidence supporting the relationship between market (customer) orientation and BDC. Market orientation in this case is revealed in Netflix's attention to customers' (viewers) tastes (what stories or plots they like best, and what actors and actresses they favor most, etc.) (Carr, 2013). Second, Uber's case (Pigni et al., 2016) best showcases the link between entrepreneurial orientation and BDC. It is the entrepreneurial insight of the Uber creators that helped them identify the business value of the real-time flows of digital data streams. Finally, technology orientation's contribution to development of BDC is exemplified in the five case studies examined in Bärenfänger, Otto, and Österle (2014). Bärenfänger et al. (2014) examined five European industrial and service sector companies with regard to investment in and implementation of the in-memory computing (IMC) technology. Three of these companies, with their insight into its potential business value, invested in and implemented the IMC technology in their big data projects (HR data management, margin simulation management, and inventory and personnel management), and most importantly, this technology was well integrated with their internal business resources and processes, and employee resources. The other two companies, based on their assessment, did not see the business value of this technology in their projects, and thus did not pursue it further. These case studies show whether BDC (integration of resources and strategy application) will emerge depends on their insight into the business value of a new technology (a demonstration of technology orientation).

For practitioners, these findings suggest that firms should be strategically minded when they start Big Data initiatives and practice. Being strategically minded means that their Big Data initiatives and practice must be market, or more specifically customer directed, and call for their entrepreneurial spirit. Additionally, these findings imply that technology orientation is integral to the development of a technology-related organizational dynamic capability. Thus they have to strive to be technologically superior in order to develop and maintain their competitive advantage.

Moreover, consistent with our hypothesis, developmental culture does have significant effect on the relationship between technology orientation and Big Data capability. This result may suggest that technology orientation and developmental culture are possibly supplementary to or even substitutive of each other. When a firm has a high technology orientation, the firm is culturally less motivated to seek further external resources to support the development of Big Data capability. But when technology orientation is low, a firm with a high developmental culture would actively seek other external resources to help them to develop that capability. This finding receives further empirical support from the literature. For example, after examining 49 published Big Data case studies, Ylijoki and Porras (2016) found that when companies lack technological competency, as revealed in “the required analytical and technical capabilities” (p. 302), they turn to external sources for help. This view is further echoed by Dave Zodikoff, CIO of the Amrose Employer Group, who, in sharing his company experiences in big data business, concluded that reaching out must be an important attribute of their organizational culture (Henry, Zodikoff, & Lang, 2012). This is testimony of the role of developmental culture that emphasizes external orientation in Big Data capability.

Nevertheless, the validity of this finding can be further tested through future research. Thus, future research should direct some attention on this perplexing relationship. Furthermore, this finding has two major practical implications. One is that companies have to achieve a technological superiority if they want to develop a Big Data capability. Such a technological superiority is shown in a firm understanding that this capability is technology-based and thereafter, follow-up actions of enhancing their technological infrastructure, hardware, and software. If, technology happens not to be their core competency, then they should strive to seek external resources in order to develop this capability. Outsourcing, and strategic alliances are possible means for seeking such external resources. This is another major practical implication stemming from this finding.

Despite these contributions, the findings of this study have limited generalizability because of an issue inherent in the research design of this study. Although the elements of Big Data capability successfully went through an empirical test in the survey, the small sample size in the interview study may have made it possible that other important elements of Big Data capability are missing. In this regard, the concept of Big Data capability still has room for improvement. Furthermore, the survey data is cross-sectional. Thus, our knowledge of Big Data capability is static not dynamic. To overcome these weaknesses, future research needs to consider other samples or adopt other research methods.

Appendix A. Survey instrument

Codes	*Questionnaire Items*
	Customer Orientation (CUSO)
CUSO2	Our firm constantly monitors our level of commitment to serving customer needs.
CUSO6	Our firm measures customer satisfaction systematically and frequently.
	Entrepreneurial Orientation (CUSO)
EO3	In dealing with competitors, my firm typically initiates actions which competitors then respond to.
EO4	Our firm has a strong tendency to be ahead of other competitors in introducing novel products.
EO5	In general, the top managers of my firm have a strong proclivity for high-risk projects (with chances of very high returns).
	Technological Orientation (TO)
TO1	The policy of this firm has been to always consider the most up-to-date production technology available.
TO2	We have a long tradition and reputation in our industry of attempting to be first to try out new technologies.
TO3	Technological innovation is readily accepted in our program/project management.
TO4	Technological innovation based on research results is readily accepted in our firm.
TO5	Our new products are always at the state of the art of the technology.
	Developmental Culture (DC)
DC1	Innovation and change
DC2	Creativity
DC3	Flexibility, decentralization
DC4	Expansion, growth, and development
	Big Data Capability (BDC)
BDC1	We are able to identify sources of big data that meet our needs.
BDC2	We are able to collect big data that meet our needs.
BDC3	We are able to store large volumes of data.
BDC4	We are able to process big data with a fast speed.
BDC5	We adopt state of the art technologies to process big data.
BDC6	We constantly update our computing equipment to process big data.
BDC7	We constantly update our IT architecture to process big data.
BDC8	We constantly update our IT infrastructure to process big data.
BDC9	We are good at data analytics which is mainly data mining and statistical analysis.
BDC10	We are good at text analytics that deals with unstructured textual format data.
BDC11	We are good at web analytics that deals with web sites.
BDC12	We are good at mobile analytics that deals with mobile computing.
BDC13	We rely on Big Data to identify new business opportunities.
BDC14	We rely on Big Data to develop new products.
BDC15	We rely on Big Data to enhance our innovativeness.
BDC16	We rely on Big Data to formulate our business strategy.

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