Innovation Performance Fosters Strategy Development: Evidenced in the Case of New Product Development and Big Data Capability

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Abstract

Research has consistently sought empirical evidence showing the benefits of developing big data related dynamic capabilities as a way to strategize big data operations, but done little exploration of what contributes to the development of such capabilities. To fill this gap, this study proposes that firm innovation performance measured in new product development drives the development of big data strategy reified in big data capability. It then draws on multiple theoretical traditions to build a research model that conceptualizes new product development as a key motivator behind firms' development of big data capability and two supply chain capabilities as its enhancement. Survey data was collected and analyzed to test the hypotheses that constitute the research model. The paper concludes with a discussion of contributions to theory and research as well as practical implications of the findings.

Keywords: Dynamic capabilities, new product development, big data capability, supply chain relationship building, and supply chain knowledge cocreation

Introduction

A result of increasing digitalization in both work and life in recent years is rapid accumulation of electronic data. Because of its unprecedented nature in volume, variety, and velocity, this type of data is called big data (McAfee & Brynjolfsson, 2012). To extract value from it, firms must develop big data analytics (Grover, Chiang, Liang, & Zhang, 2018; Mikalef, Boura, Lekakos, & Krogstie, 2019; Wamba et al., 2017), deploy supporting technologies and infrastructure (Wamba et al., 2017), and invest in a combination of human, financial, and intangible resources as foundations sustaining their analytics (Mikalef et al., 2019). Through diagnostic analysis of big data cases and theoretical inference, researchers (e.g., Chen, Preston, & Swink, 2015; Grover et al., 2018; Gupta & George, 2016; Wamba et al., 2017) argued that it is important for firms to develop big data related dynamic capabilities in order to enhance their performance. More and more empirical evidence has been presented to support this argument. For example, big data capabilities are found to strengthen supply chain operations (Chen et al., 2015), enhance both market, financial, and operational performance (Gupta & George, 2016; Wamba et al., 2017), and increase decision making quality and efficiency (Shamim, Zeng, Shariq, & Khan, 2019).

Dynamic capabilities are strategic in nature (Winter, 2003). Thus, these past research studies assumed that firm performance is an outcome of strategy development, in the case of big data operations, especially when they align with the firm's overall business strategy (Akter et al., 2016). Moreover, they suggested that these big data related dynamic capabilities are developed in alignment with the managerially planned or formulated organizational strategy. However, strategy formulation is a process of both planned and emergent actions (Henfridsson & Lind, 2014). Organizational actions are aligning in mutual directions, within each of the categories of sensing, seizing, and reconfiguring dynamic capacities, iteratively redeploying organizational resources and competencies to realize, refine, and even develop strategy (Yeow, Soh, & Hansen, 2018). This suggests that in the development of dynamic capabilities there are both cases of following predetermined strategy and new strategy emerging. Therefore, in the context of big data operations, performance may also contribute to strategy development.

Although the big data related dynamic capabilities serve multiple purposes, they can be generically labeled as big data capability (BDC), just as those of IT as IT capability (Bharadwaj, 2000) and those of IS as IS capability (Peppard & Ward, 2004). Similarly, on the performance side, as the literature indicates, among multiple areas, firm innovation results from BDC (Mikalef et al., 2019). Further, innovation is typically revealed in new product development (NPD) (Szymanski, Kroff, & Troy, 2007). Two classic examples showing new product development or innovation in general as an outcome of BDC are Netflix's creation of the new TV series, *House of Cards* (Carr, 2013) and the establishment of Uber as an innovative business model (Pigni et al., 2016). Thus, based on the previously referenced dialectical view towards the relationship between performance and strategy, we raise two research questions here:

1. *How is BDC developed?*
2. *Can NPD play a role in its development?*

Addressing these two research questions, this current study aims to examine whether NPD contributes to developing BDC. As firms operate and perform in supply chains, both NPD and BDC are shaped by the supply chain context. Thus, two supply chain concepts, relationship building (RB) and knowledge cocreation (KC), will be covered in this study's scope of examination. With this research design, this study seeks to make three contributions. First, it attempts to point to a new direction in big data research by switching our attention from primarily on seeking to understand what contributions big data can make to the firm to simultaneously investigating what will be helpful to developing BDC. This study will substantiate such efforts by showing whether NPD will contribute to the development of BDC. Second, this study will also reveal whether contextual factors facilitate that process. More specifically, this study will show whether supply chain RB and KC, besides NPD, will contribute to the development of BDC, and more importantly, whether they moderate the impact of NPD on BDC. As RB and KC are treated as two organizational capabilities, following previous studies (for example, Grewal and Tansuhaj (2001) in marketing research), this study will help to reinforce an argument articulated in the literature that multiple capabilities can be developed and they combine to show a synergistic effect of dynamic capabilities.

Third, and most importantly, the findings of this study will help to renew our understanding of the dialectical relationship between strategy and performance in the context of big data operations. Practically, this study will inform big data practitioners of what could help them to effectively develop BDC. Further, it could help them in their decision making on whether they should invest in big data projects.

The rest of the paper will be organized as follows. First, we will give an overview of the theories that we will draw on in proposing our research model. Then we will introduce in detail our model by presenting definitions of the concepts involved and reviewing the relevant literatures so as to advance our hypotheses. Next, we will describe our processes of data collection, construct measurements and validation, and hypothesis testing. Finally, we will discuss the findings with respect to how they contribute to both theory and practice. Meanwhile, we will critically assess quality of this research by discussing possible limitations and offer future research directions in this area.

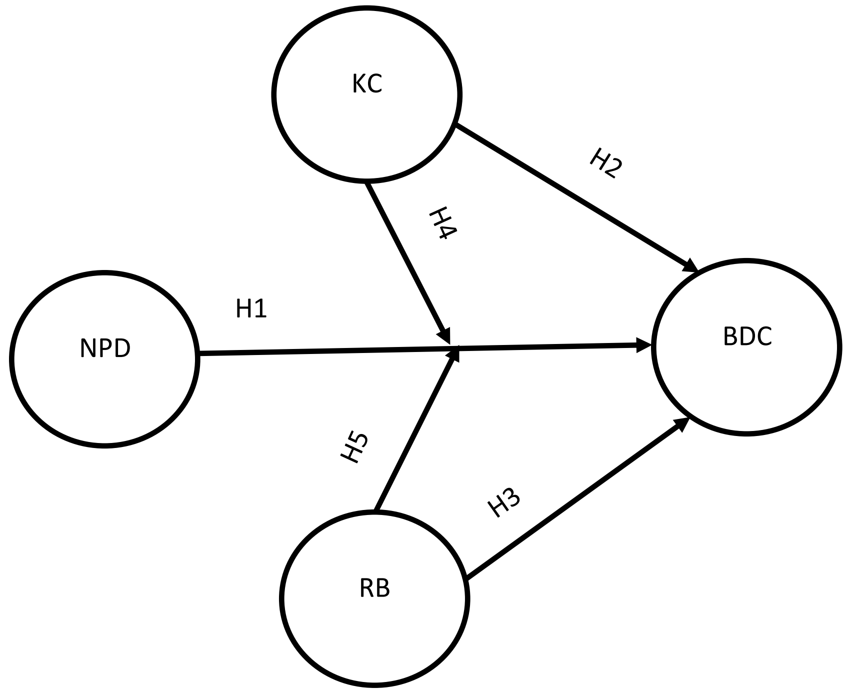
Theory and Hypotheses

We draw on multiple theories to build the theoretical foundation for our research model. First, according to the resource-based view (RBV), to survive and thrive in the changing business environment, firms must create and capitalize on their strategic resources to develop their competitive advantage (Barney, 1991). As an extension of the RBV, the dynamic capabilities perspective emphasizes that firms must transform their resources into dynamic capabilities (Teece, 2007; Teece et al., 1997). This theoretical tradition explains and highlights the importance of developing BDC in firms, especially in today's business environment that is undergoing a digital transformation. Next, the theory of strategic orientations strongly suggests a link between entrepreneurship orientation to BDC (Lin & Kunnathur, 2019). Thus, it should also theoretically support the argument that NPD contributes to development of BDC, as the former, a strong indicator of exploratory innovation, best exemplifies entrepreneurship orientation. Finally, the resource dependence theory (Pfeffer & Salancik, 1978) holds that firms rely on their external environment, especially other businesses and firms for resources that are critical to their survival, suggesting the need of firms for building relationships with other firms and collaboratively creating knowledge, an important resource. Moreover, the theoretical literature of dynamic capabilities indicates that dynamic capabilities show a synergistic effect, mainly in that well-established capabilities help to promote new ones (Bingham, Heimeriks, Schijven, & Gates, 2015). This justifies the view that supply chain KC and RB, two dynamic capabilities, help to build BDC and enhance NPD's contribution to it. These theories constitute the theoretical foundation for the research model shown in Figure 1.

Big data capability

According to the dynamic capabilities perspective, changes in the business environment usually stimulate firms to develop dynamic capabilities that would enable them to take advantage of the changes and create their competitive advantage. In our thriving "Age of Data" (Mikalef et al., 2019), extensive use of electronic devices in the workplace as well as private life creates huge amounts of data, now commonly known as big data. This represents a major change in the business world that fully qualifies as a turbulent environment that calls for development of dynamic capabilities (Girod & Whittington, 2017; Karna, Richter, & Riesenkampff, 2015; Teece et al., 1997). Moreover, adding to the motivating effect on firms, abundant evidence shows that big data

Figure 1: Research Model



is of increasing business value (Barton & Court, 2012; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Pigni et al., 2016). These two trends combined constitute an external motivation for firms to deal with big data.

In practice, some firms are far from being successful in their big data initiatives (Liu, 2014; Ransbotham & Kiron, 2017). This is because these firms mainly just treat big data as resources only but have not aligned its use with firm strategy (Grover et al., 2018), and more important, have not moved a step further to develop a dynamic capability around it (Mikalef et al., 2019). A predominant view emerged in the literature is that big data undertakings must be conceptualized as a dynamic capability (Braganza et al., 2017; Chen et al., 2015; Grover et al., 2018; Gupta & George, 2016; Mikalef et al., 2019; Wamba et al., 2017). Further, just as the trajectory of dynamic capabilities development shows, this big data related capability, once developed, should exhibit the three functions of sensing, seizing, and reconfiguring that Teece (2007) originally described.

After analyzing interview data collected from seven large US firms and other cases, Lin, Kunnathur, and Li (2020) reported three major findings regarding big data practices in organizations. First, besides showing those distinctive features already outlined in prior literature, big data is understood and practiced as a collection of dataset (the raw data), toolset (infrastructure, hardware, and software, etc.), skillset (analytics, skills, and knowledge necessary for handling big data), and mindset (understanding the value and motivation of investing in big data) (Pigni et al., 2016). Second, organizational strategy is highly embedded in big data practices. Instances of both big data practices serving and enacting existing organizational strategy and new strategy emerging in big data practices are present in organizations. Third, organizational big data practices exhibit the functions of sensing, seizing, and reconfiguring of dynamic capabilities. More specifically, for the sensing function, big data is used to help to identify both opportunities and risks. The seizing function is practiced in the synergistical utilization of the dataset, toolset, skillset, and mindset for realizing those identified opportunities and addressing the risks. For the reconfiguring function, organizational strategy motivates and guides integration of the resources used in big data practices for keeping the search for new opportunities and sensing new risks and addressing them. These findings suggest that big data practices should be conceptualized as a big data capability, which is further defined as "*a firm's dynamic capability of identifying sources where large volumes of various kinds of data flow out in high speed and collecting, storing, and analyzing such big data for the purpose of accomplishing the firm's strategic as well as operational goals*" (Lin et al., 2020, p. 216).

Supporting the view that big data practices should be conceptualized as a dynamic capability, the research literature has supplied increasing amount of empirical evidence showing that big data capability positively contributes to firm performance. These contributions include, among others, improving decision making quality (Shamim et al., 2019; Ylijoki & Porras, 2016), enhancing both logistics and supply chain management performance (Wamba & Akter, 2019; Wang, Gunasekaran, Ngai, & Apadopoulos, 2016), and enhancing employee ambidexterity via big data value creation (Shamim, Zeng, Choksy, & Shariq, 2019). But most strikingly, BDC promotes innovation (Mikalef et al., 2019; Ylijoki & Porras, 2016), which is densely concentrated in NPD.

New product development contributing to big data capability development

BDC is highly strategic in two ways: it ensures that big data undertakings are guided by the firm's strategy; and it fosters emergence of new strategies from those undertakings for the firm (Lin et al., 2020). This is a good hint that, as an internal strength, firm's strategy formulation and application helps to differentiate firms in developing BDC. As the literatures of strategic management, entrepreneurship, and marketing strongly suggest, over time, a firm develops a mindset or mentality that guides its strategy formulation and application, and decision making on creation and deployment of critical resources (Bettis & Prahalad, 1995; Prahalad & Bettis, 1986). This mindset or mentality is generically named as strategic orientation (Day & Wensley, 1983; Day, 1994).

One specific strategic orientation is called entrepreneurship orientation, which refers to *a firm's mindset characterized by innovativeness, proactiveness, and risk-taking* (Covin & Slevin, 1989). Lin and Kunnathur (2019) already found that entrepreneurship orientation positively contributes to BDC. Entrepreneurship orientation can be specifically shown in firm performance such as NPD. As a performance concept, NPD is defined as *an organizational process of initiating ideas for a product, assessing their success likelihood in the market, specifying their technical requirements and standards, creating and testing prototypes, and finally putting them on sale in the market* (Doll, Hong, & Nahm, 2010; Kourfteros, Cheng, & Lai, 2007; Pavlou & Al Sawy, 2006; Perols, Zimmermann, & Kortmann, 2013; Schoenherr, Griffith, & Chandra, 2014).

Based on its definition, NPD can best represent entrepreneurship orientation. First, NPD involves product innovation in the fullest sense (Song, Montoya-Weiss, & Schmidt, 1997; Szymanski, Kroff, & Troy, 2007). Next, launching a new product in a market means that the firm anticipates customer needs and acceptance. In this sense, it is proactive. Further, NPD can be a failure (Heidenreich, Kraemer, & Handrich, 2016; Ogawa & Piller, 2006). This is especially so when the product belongs to a new or emerging product category and thus customers do not understand it enough (Feiereisen, Wong, & Broderick, 2008). Apparently, NPD involves a lot of risk of failure. Riskiness increases with strategic emphasis and product complexity inherent in NPD (Sharma, Saboo, & Kumar, 2018). Indeed, entrepreneurship orientation is positively related to NPD (Chen, Lin, & Tsai, 2020; Davis, Morris, & Allen, 1991). Given its affinity to entrepreneurship orientation, we have ample reason to argue that NPD will be positively related to BDC.

Additionally, the literature on customer knowledge management in the process of NPD tends to enhance our argument. It has been well recognized that NPD is also a process of gaining and managing knowledge about customers (Cooper, 2014; Zhang, Zhou, Lu, & Chang, 2017). More specifically, it is critical to NPD that a firm uses effective approaches, mechanisms, and devices to collect, store, access, and analyze data about customers (Fidel, Schlesinger, & Cervera, 2015; Olson, 2018). Firms must extract information about customer preferences and requirements for products from their raw data (Joshi & Sharma, 2014; Shimomura, Nemoto, Ishii, & Nakamura, 2018), and then further refine them as firm knowledge about customer consumption. To do that, firms can rely on techniques such as data mining, which, according to Zhan, Tan, and Huo's (2019) review, is extensively used in NPD. As the customer knowledge management part of NPD is so heavily data-driven, firms that engage themselves in NPD should have a high proclivity toward BDC. This short discussion of the strategic orientation and more specifically of the entrepreneurship orientation literature and the literature on customer knowledge management in NPD leads us to propose the following hypothesis:

H1: New product development is positively associated with big data capability.

Synergizing effect of knowledge cocreation and relationship building capabilities on big data capability

BDC, once developed, can create knowledge for firms, such as knowledge about customers and markets. However, its own development relies on knowledge as well. Our earlier description and definition of BDC imply that this capability is characterized by the ability to produce and transfer knowledge, which is reified in the ability to identify sources of data, process them into information, transform processed information into knowledge, and then communicate knowledge at the right time and to the right party. Thus, another capability that a firm should demonstrate while developing BDC is one of creating knowledge.

Although definitions of knowledge creation vary in the literature, the process view of knowledge creation is rooted in Nonaka's work (Nonaka, 1994; Nonaka & Konno, 1998; Nonaka & Takeuchi, 1995) that has elaborated on the theory of knowledge creation. Drawing on Polanyi (1967), Nonaka (1994) argued that knowledge can be classified into two types: explicit and tacit knowledge. Explicit knowledge is well codified knowledge that is relatively easy to transmit, whereas tacit knowledge is knowledge that is inseparable from the context and deeply rooted in action and commitment. Explicit and tacit knowledge then interact with each other to generate new knowledge through four patterns: socialization (tacit to tacit), externalization (tacit to explicit), internalization (explicit to tacit), and combination (explicit to explicit).

This knowledge creation process does not happen just internally in a firm. A firm can rarely produce all kinds of needed knowledge. The theory of resource dependency (Pfeffer & Salancik, 1978) captures this idea. In line with this theory, firms, because of their internal constraints, seek to collaborate with other firms such as their supply chain partners to coproduce knowledge that is highly needed but cannot be produced entirely by themselves alone. Thus, besides knowledge creation, knowledge cocreation is also needed in the process of BDC development. In this study, knowledge cocreation is defined as *a capability of engaging supply chain partners in multiple processes of collaboration to produce knowledge about their business environments*.

While NPD, an internal strength, represents a firm's entrepreneurship orientation that cultivates the development of BDC, other factors can help the firm to acquire external resources needed in its development. According to the theory of resources dependency, firms find themselves in need of resources for their development and operations, and therefore must interact with other firms for the purpose of complementing each other in resources (Barringer & Harrison, 2000; Scott, 1987). More specifically, firms must develop interorganizational relationships with other firms so as to reduce resource dependence (Mitchell & Singh, 1996). Therefore, in the case of developing BDC, firms must demonstrate a capability of reaching out to other firms such as suppliers and customers. This is termed as relationship building capability that is defined as *the ability of creating an environment conducive to building mutual trust and long-term collaboration with supply chain partners* (Griffith, Harvey, & Lusch, 2006; Johnston, McCutcheon, Stuart, & Kerwood, 2004; Monczka, Petersen, Handfield, & Ragatz, 1998; Tangpong, Michalisin, & Melcher, 2008).

While the theory of resource dependency suggests the need of KC and RB capabilities in developing BDC, the dynamic capabilities literature provides theoretical support to the argument that these two capabilities have a synergistic effect on BDC. In exploring the question of how capabilities emerge and where they come from, Ethiraj, Kale, Krishnan, and Singh (2005) found that capabilities are developed as a result of: a) tacit accumulation of experience embedded in routines and learning by doing (Nelson & Winter, 1982; Winter, 1990), and b) deliberate investments in organizational structure to make constant improvements in those routines and processes (Zollo & Winter, 2002). These well-established ideas suggest that firms can develop multiple capabilities through concurrent learning that is made possible by codification of experience facilitated by organizational structure (Bingham et al., 2015). In line of this theoretical discourse on capabilities, we argue that KC and RB capabilities, once well established, can facilitate the development of BDC, as firms can apply their learning experiences accumulated from those two cases to that of BDC.

Recent research has already shown that BDC impact performance through other capabilities. For example, Mikalef et al. (2019) found that big data analytics capability positively contributes to firms' innovation performance through other dynamic capabilities. Similarly, Wamba et al. (2017) shows that big data analytics capabilities positively influence both financial and market performance via other dynamic capabilities. We argue that this can happen the other way around, namely, other dynamic capabilities can impact performance through BDC. Based on the suggestions from the theoretical underpinnings, we propose the following hypotheses:

H2: Knowledge cocreation will be positively associated with BDC.
H3: Relationship building will be positively associated with BDC.

NPD and BDC: The moderating effect of knowledge cocreation and relationship building capabilities

The resource dependency theory can also be applied to NPD. While developing new products, firms require acquisition of external resources. Knowledge is an important resource to NPD in many ways. For example, market knowledge, which includes knowledge about prospective customers and competitors, as well as other market aspects to a given product type (De Luca & Atuahene-Gima, 2007), is crucial at each stage of NPD (Dabrowski, 2019). Thus, a market knowledge competence will facilitate NPD (Atuahene-Gima & Wei, 2011; Claudy, Peterson, & Pagell, 2016; Li & Calantone, 1998). Knowledge about consumer tastes, likes, and needs is a prerequisite to NPD. Similarly, consumer knowledge about the new product is critical to adoption of the new product (Ackermann, Teichert, & Truong, 2018). These research findings regarding knowledge's importance to NPD suggest that the KC capability would enhance NPD's effect on BDC. Besides, NPD requires exploiting external knowledge sources (Ferreras-Mendez, Newell, Fernandez-Mesa, & Alegre, 2015). This is where the RB capability comes into play. As both capabilities are enhancements of NPD, we can expect that they will positively moderate the relationship between NPD and BDC. Thus, the following hypotheses can be posited:

H4: Knowledge cocreation positively moderates NPD's effect on BDC.

H5: Relationship building positively moderates NPD's effect on BDC.

Methods

Research design and measures

This study used a questionnaire-based survey method to collect data. This research design fits the goal of this study well in several ways. First, it enables good generalizability of the research findings, easy replication, and simultaneous investigation of multiple concepts (Pinsonneault & Kraemer, 1993), all of which are objectives inherent in this study. Survey research is particularly beneficial to explanatory and predictive research as it ensures confidence in the generalizability of the findings (Straub, Boudreau, & Gefen, 2004). This study belongs to such an explanatory and predictive research design. These noted strengths would benefit this study as it seeks to explore the relationships between the constructs and make general statements about big data practices.

The survey questionnaire used in this study consists of both self-developed and adapted multi-item scales. Following Churchill's (1979) approach, we used a three-phase procedure to develop the BDC and RB scales: item generation, pre-pilot study, and pilot study. In the item generation phase, we thoroughly reviewed the relevant literatures and determined the content domain of the constructs. The pre-pilot study was then conducted with 10 scholars with expertise in the topic and eight big data experts from industry. The drafted measurement items for the two constructs were shared with the scholars and their feedback and comments were solicited. This was to check face validity of the scales. Using an adapted version of the Q-sort approach (Churchill, 1979), we asked the industry experts to first read the constructs, their definitions, and the measurement items, and then place the measurement items under the constructs that they think the items measure well. The items were reworded based on feedback and comments from both the scholars and industry experts. This process involved several iterations. This step was used to ensure substantive validity of the scales. Only items with a 0.5 substantive validity value or higher were retained.

The scales determined in the first two phases were then further tested using a small-scale pilot study. A list of potential participants was generated using the LexisNexis database, with the following types of information: position title, specialty, mail address, phone number, email address, firm size, SIC code, business description, and sales/revenue amount. While creating the list, we performed several rounds of search using key words such as "Chief Operations Officer", "VP

Manufacturing", "Manufacturing Manager", "Plant Manager", "Manufacturing Director", "Production Manager", "Plant Operations Manager", "Chief Information Officer", "Chief Technology Officer", and "IT Manager", etc. A total of 45 responses were obtained in this pilot study, 42 of which were complete and usable. The 42 complete responses were then analyzed using SPSS. The scales were then further refined based on the pilot study results. The measurement items retained after this third phase constitute the scales used in the large-scale survey questionnaire.

The BDC scale has a total of 16 items measuring big data operations, supporting infrastructure, analytics, and strategy implication with a Cronbach value of 0.92. The RB scale has 8 items measuring the qualities of trust, commitment, collaboration, and long-term orientation in the relationships with buyers and suppliers. These qualities were identified and examined in the RB literature. Most prior studies focused on one or two of these qualities and developed corresponding measurement scales, for example, Griffith et al. (2006) for long-term orientation, Johnston et al. (2004) for trust, Monczka et al. (1998) for collaboration and commitment. We developed the eight-item scale for RB based on those individual quality scales developed in those prior studies. This scale has a Cronbach value of 0.93. The NPD scale was adapted from prior studies by combining items measuring product competitive advantage (Swink & Song, 2007), product innovativeness (Song et al., 1997), and NPD competence (Schoenherr et al., 2014). Its Cronbach value is 0.80. The eight-item KC scale was adapted from Anand et al. (2010), and Ho and Ganesan (2013), measuring production of explicit and implicit knowledge through socialization, externalization, combination, and internalization. It has a Cronbach value of 0.84. The measurement items for all the four constructs are listed in the Appendix.

Besides these four constructs, there are two control variables in this study: industry and firm size. Industry is a nominal variable. The responses from survey participants could roughly be classified into two groups: manufacturing and service. The former includes automotive, aerospace, chemical, and consumer products, while the latter refers to IT service, finance, telecommunications, construction, logistics, retail, media, healthcare, utilities, and consulting. Firm size is measured by the number of employees.

Sample and data collection

As the unit of analysis for this study is the individual firm, the sample for this survey research should be key employees with enough knowledge about the topic, big data practices in in their firms. For this reason, Phillips and Bagozzi's (1986) key informant approach was employed in the process of data collection. We learned from the industry experts who participated in the pre-pilot study and pilot study that key informants for this study should be employees in high level managerial positions in operations, IT, supply chain, and business analytics.

Given the difficulties of accessing and contacting enough key informants, we outsourced data collection to Qualtrics.com, a commercial research firm, which has a large list of business panel members representing different firms in a variety of industries. Qualtrics.com sent email invitations to its panel members in the following positions: 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. Although it is increasingly popular for academicians to collect data for research studies via this means, serious concerns and challenges associated with this approach must be addressed. To do that, we followed the recommendations from Schoenherr, Ellram, and Tate (2015). To ensure data quality, a series of measures and mechanisms were instituted, such as blurring the research statement, using screening questions and attention filers, and recording ip addresses and time amount used by each respondent, etc.

Initially a total of 2700 panel members were identified as qualified potential participants for this study. With the removal of certain members with unclear contact information, a new total of 2200 remained in the list. An email was sent to invite them to participate in the survey. A total of 273 responses was obtained within two days shortly after the email was sent out. As this number already exceeded the number of responses we wished to get (due to our financial constraints), the survey was immediately closed. After removing 22 incomplete or less reliable responses, we determined that the 251 complete responses constitute the final sample for this study.

Addressing common method bias, non-response bias, and multicollinearity concerns

We used two methods commonly used in the literature to detect common method bias: Hartman's single-factor test, and the common latent method factor test (Liang, Saraf, Hu, and Xue, 2007). First, according to Podsakoff, MacKenzie, and Lee (2003), the Hartman's single-factor test is to perform a factor analysis to see whether a single factor loads on all the measurement items. For this purpose, we performed both an exploratory factor analysis and a confirmatory factor analysis. Our exploratory factor analysis results showed that no such a single factor emerged. Further, the largest percentage of variance is 34.34%, less than the 50% red line. Similarly, the confirmatory factor analysis results showed that the total percentage of variance is 38%, again less than the 50% red line. Thus, one general factor did not account for the majority of the covariance among the variables.

Next, based on the recommendation of Liang et al. (2007), we conducted a common method latent factor test, in which a common method factor was added to the model with links to all the observed measurement items in addition to the four factors (constructs) of BDC, NPD, KC, and RB. The results showed that the loadings of the items measuring each of the four constructs are significant, whereas they are not when the items were all linked to the common method latent factor. Additionally, the measurement items' variances for each of the four constructs are substantially greater than their variances for the common method latent factor. All these results conclusively show that common methods bias is unlikely to be a serious concern in the dataset.

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 0.05 level in all the five *t*-tests, suggesting no evidence of non-response bias in the data.

In addition, regression diagnostics tests were conducted to assess linearity, normality, and multicollinearity. Linearity was confirmed through plotting standardized residuals against the standardized predicted values. Normality was established for all the variables through the Shapiro-Wilk test. Multicollinearity was tested using SPSS, treating one variable as a dependent variable and all others as independent variables iteratively. The variance inflation factor (VIF) values are all below 3.3 (Petter, Straub, & Rai, 2007), suggesting that multicollinearity is not a concern in this dataset.

Results

Table 1: Measurement Quality Indicators

Latent Construct	Item	Mean	Standard Deviation	Loading	Composite Reliability	Cronbach's Alpha
Big Data Capability	BDC1	5.38	0.66	0.55	0.91	0.92
	BDC2	5.23	0.78	0.60		
	BDC3	4.32	0.81	0.50		
	BDC4	5.21	0.87	0.57		
	BDC5	4.20	0.83	0.65		
	BDC6	5.16	0.87	0.66		
	BDC7	5.13	0.95	0.65		
	BDC8	5.12	0.90	0.69		
	BDC9	5.12	0.92	0.65		
	BDC10	4.99	1.01	0.63		
	BDC11	5.06	0.99	0.71		
	BDC12	4.94	1.09	0.58		
	BDC13	5.14	0.97	0.64		
	BDC14	5.09	1.02	0.71		
	BDC15	5.19	0.94	0.64		
	BDC16	5.05	0.90	0.64		
New Product Development	NPD1	5.09	0.89	0.63	0.81	0.80
	NPD2	5.18	0.93	0.58		
	NPD3	6.05	0.91	0.68		
	NPD4	4.89	0.83	0.72		
	NPD5	5.19	0.90	0.76		
Knowledge Cocreation	KC1	5.39	0.83	0.64	0.84	0.84
	KC2	5.14	0.85	0.59		
	KC3	5.20	0.91	0.70		
	KC4	5.16	0.87	0.66		
	KC5	5.14	1.02	0.61		
	KC6	4.98	0.91	0.57		
	KC7	5.11	0.96	0.67		
	KC8	5.14	1.01	0.55		
Relationship Building	RB1	5.34	1.01	0.84	0.93	0.93
	RB2	4.28	1.02	0.81		
	RB3	4.21	1.03	0.78		
	RB4	5.14	0.92	0.78		
	RB5	4.37	0.92	0.77		
	RB6	5.31	0.96	0.81		
	RB7	5.21	1.02	0.77		
	RB8	5.22	0.92	0.75		

Descriptive statistics, reliability, and validity

To test validity and reliability, we performed a confirmatory factor analysis using AMOS. A preliminary test shows that the control variables are not significantly related to the other constructs. Thus, the measurement model covers the four constructs of BDC, NPD, KC, and RB. All these constructs were modeled with reflective measurement items. The confirmatory factor analysis results indicate that the model overall has good fit. The CMIN/DF ratio (1.52) shows superior model fit. The CFI (0.94) and TLI (0.93) values indicate good fit, as they are close to the 0.95 cutoff line. Lastly, the RMSEA value (< 0.05) shows superior model fit. The confirmatory factor analysis results provide a rich set of indicators about reliability and validity of the measurement model, which are presented in Table 1.

Construct reliability was tested using Cronbach's alpha and composite reliability score (Fornell & Larcker, 1981). Cronbach's alpha measures internal consistency among all items used for one construct. The Cronbach's alpha values for all the four constructs in this dataset exceed 0.8, much higher than the threshold of 0.70 (Nunnally & Bernstein, 1994). Similarly, composite reliability serves a similar purpose but is considered a more rigorous reliability measure in structural equation modeling (Raykov, 1998). The composite reliability value for each construct in this dataset is higher than 0.80, significantly exceeding the cutoff value of 0.70 (Bagozzi & Yi, 1988; Gefen, Straub, & Boudreau, 2000; Nunnally, 1978). Thus, construct reliability for each construct in this study was confirmed by both the Cronbach's alpha and composite reliability scores.

To assess convergent validity, we examined the loading score of each measurement item for each construct. The higher item factor loading scores are, the higher convergent validity (Anderson & Gerbin, 1988). All the item loadings are presented in Table 1. The loading scores for BDC ranges from 0.50 to 0.71, 0.58 to 0.76 for NPD, 0.55 to 0.70 for KC, and 0.75 to 0.84 for RB. These loading scores help to establish convergent validity for all the constructs, as they are equal to or higher than the cutoff point of 0.5 (Byrne, 2010).

Table 2: HTMT Values

Constructs	**1**	**2**	**3**	**4**
1. Big data capability				
2. New product development	0.80			
3. Knowledge cocreation	0.73	0.66		
4. Relationship building	0.46	0.32	0.54	

Traditionally, discriminant validity was tested by examining the average variance extracted (AVE) for each construct (Fornell & Larcker, 1981). Recently, Hensler, Ringle, and Sarstedt (2015) identified flaws of the Fornell and Larcker's (1981) approach and argued that a new criterion called the heterotrait-monotrait ratio (HTMT) is a better assessment indicator of discriminant validity. The HTMT ratio is based on the average of the correlations of indicators across constructs measuring different concepts relative to the average of the correlations of indicators within the same construct. Based on this method, HTMT values below 0.85 indicate sufficient discriminant validity. In our test (see Table 2), all the HTMT values are below 0.85, indicating that the constructs all have sufficient discriminant validity.

Hypothesis testing

To test the hypotheses, multiple regression analyses were conducted. The three independent variables, then, the two two-way interaction terms were entered into the model. The correlations between the constructs are presented in Table 3. Results of the multiple regression tests are listed in Table 4.

Table 3: Correlations

Constructs	1	2	3	4	5	6
1. BDC	1	0.75**	0.64**	0.43**	0.79**	0.70**
2. NPD	0.75**	1	0.54**	0.27**	0.88**	0.74**
3. KC	0.64**	0.54**	1	0.47**	0.87**	0.62**
4. RB	0.43**	0.27**	0.47**	1	0.43**	0.85**
5. NPD*KC	0.79**	0.88**	0.87**	0.43**	1	0.78**
6. NPD*RB	0.70**	0.74**	0.62**	0.85**	0.78**	1

** $p < .01$.

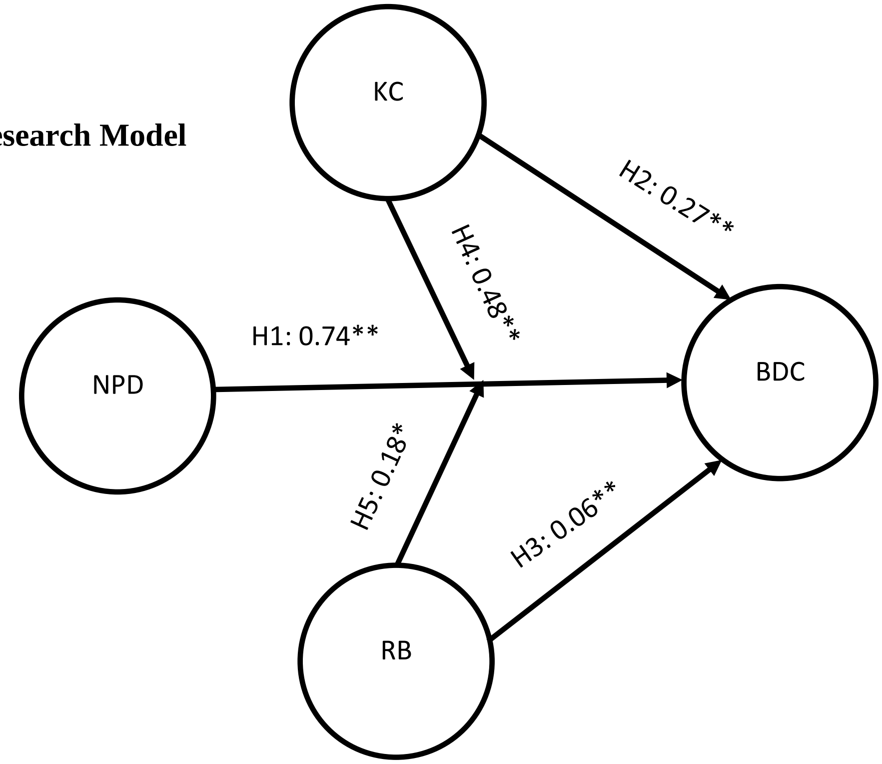
Table 4: Regression results

Hypothesis	Independent variable/Interaction terms	Standardized coefficient	Standard error	*P* value	Lower bound	Upper bound
H1	NPD	0.74	0.13	0.001	1.92	2.44
H2	KC	0.27	0.15	0.001	0.10	0.35
H3	RB	0.06	0.10	0.001	0.34	0.72
H4	NPD*KC	0.48	0.003	0.001	0.01	0.02
H5	NPD*RB	0.18	0.002	0.01	0.002	0.01

Hypothesis 1 stated that NPD is positively related to BDC development. As shown in Table 4, NPD is positively associated with BDC ($\beta = 0.74$, $p < 0.001$). Thus, hypothesis 1 is supported. Hypothesis 2 indicated that KC positively contributes to BDC. The multiple regression analysis results show that KC is positively associated with BDC ($\beta = 0.27$, $p < 0.001$). H2, is, therefore, supported. Hypothesis 3 suggested that RB is positively associated with BDC. The regression analysis results ($\beta = 0.06$, $p < 0.001$) supports hypothesis 3, indicating that RB positively contributes to BDC.

Hypothesis 4 stated that KC positively moderates the effect of NPD on BDC development. This hypothesis is supported by the multiple regression analysis results ($\beta = 0.48$, $p < 0.001$), showing that the more capable a firm is of KC the stronger effect NPD has on BDC development. Lastly, hypothesis 5 posited that RB positively moderates the impact of NPD on BDC such that the more capable a firm is of RB, the stronger impact NPD has on BDC development. As shown in Table 4, RB positively reinforces the relationship between NPD and BDC ($\beta = 0.18$, $p < 0.01$). Thus, hypothesis 5 is supported. Based on these results, the adjusted conceptual model is now presented in Figure 2.

Figure 2: Confirmed Research Model



** ***p* < 0.001**
* *p* **< 0.01**

Discussion

Numerous reports of big data creating business value in the popular press have motivated scholarly exploration of this issue. In this newly opened research frontier, more and more participating researchers (e.g., Braganza et al., 2017; Chen et al. 2015; Grover et al., 2018; Gupta & George, 2016; Mikalef et al., 2019; Wamba et al., 2017) articulated a view that firms should develop big data related dynamic capabilities if they want to be successful in their big data initiatives. This view must be supported with empirical evidence. Thus, prior and current big data research has primarily focused on investigating performance benefits associated with BDC. This study, however, makes a shift in research direction by exploring plausible factors that may contribute to the development of BDC.

This exploration has resulted in significant findings that help to extend our understanding of big data, and more important, BDC. One major finding is that NPD is positively associated with BDC. Further, this study also finds that two supply chain concepts representing organizational dynamic capabilities, knowledge cocreation and relationship building, positively contribute to the development of BDC. Moreover, the analysis results of this study show that both KC and RB positively moderate the impact of NPD on BDC. With these findings, this study contributes to the research literature in three ways.

First, this study starts to address a research gap: no knowledge of what plausible factors could contribute to the development of BDC in our understanding of the overall big data issue. In doing this, this study opens another line of inquiry in the field of big data research parallel to the one that seeks to reveal how BDC benefits firm performance. Starting this line of research helps not only to fill the research gap, but also to guide firms on how they could develop BDC. More specifically, in this line of research, this study shows that NPD facilitates the development of BDC. Previously, we learned from the other line of research that BDC constitutes a contributor to innovation (Mikalef et al., 2019). We can reasonably treat NPD as an outcome of the operations of BDC. This study helps to illuminate that the relationship between NPD and BDC is complex by showing that the former contributes to the latter. Thus, this study extends our understanding of the big data issue such that we now realize that NPD, and maybe more broadly, firm innovation, and BDC mutually enhance each other.

Adding to the first contribution is the finding that KC and RB promote the development of BDC, just as NPD does. Yet, the significance of this finding is beyond the understanding that they are simply another two contributors to the development of BDC. Rather, it constitutes the second theoretical contribution of this study: it demonstrates how firms can create an external environment conducive to the development of BDC. While NPD represents an internal firm innovation performance, KC and RB are two organizational dynamic capabilities that help to build a stable supply chain and then capitalize on it to enhance internal firm performance. In this sense, this finding suggests that KC and RB help to create an external environment that supplies to the firm resources needed in the development of BDC such as knowledge. Strategic management research shows that the business environment mandates deployment of certain dynamic capabilities over others in enhancing firm economic performance (Girod & Whittington, 2017; Karna et al., 2016). This study reaffirms the view articulated in the strategic management literature, more specifically, the dynamic capabilities literature that it is important for firms to consider and assess the environment while deploying dynamic capabilities. Further, this study extends the view to the context of developing BDC by showing that the environment is equally important in the process of dynamic capabilities development.

Third, this study contributes to the dynamic capabilities literature in that it provides empirical evidence supporting the view that multiple dynamic capabilities can develop in one firm and existing ones pave the way for developing new ones through the process of structure enabled concurrent learning (Bingham et al., 2015). This study treats KC and RB as two organizational capabilities, in alignment with the dynamic capabilities perspective. Thus, with the finding that these two capabilities positively moderate the effect of NPD on BDC, this study empirically supports the view about the synergistic effect of dynamic capabilities. Moreover, it contributes to the big data research in that it shows with empirical evidence that two supply chain capabilities, KC and RB, can reinforce firm innovation capability's contribution to BDC, besides their direct influence.

The fourth contribution of this study is that the findings offer further insight into the relationship between strategy and performance. The operations and supply chain management literature was dominated by a static view about this relationship, as identified in the field of information systems, that strategy is predetermined and planned ahead, and guides business performance when it is applied (Henfridsson & Lind, 2014). Prior studies helped to affirm this static view, as they keep showing that well-developed BDC facilitates performance. With the finding that NPD contributes to BDC, this study shows that in organizational big data operations strategy is both applied and developed. Put it in another way, when engaged in NPD, firms enact, adjust, and even create strategy, in this case, BDC, in their own actions. Thus, this study contributes to the literature in that it helps to articulate a dynamic view toward the relationship between strategy and performance.

Apart from the theoretical contributions, this study generates practical implications for organizations. One takeaway from this study for organizations is that innovation-oriented organizations, especially those that favor exploratory innovation (March, 1991), as NPD represents such exploratory innovation, are in a favorable position to develop BDC. To develop such capabilities, when organizations are continuously engaged in NPD, they should strive to build and maintain good relationships with their supply chain partners. Doing that will help them to cocreate knowledge with their partners, which is needed in their process of developing BDC.

Despite these contributions and managerial implications, this study has some limitations inherent in its design. Even though common method bias is not a serious concern, the use of the survey research method limits the generalizability of its findings. Further, data collected through this method is less objective, as it may represent personal views of the participants. However, given the fair sample size, such personal bias conceded to a secondary place, and more important, patterned views about the issue and topics emerged and effectively captured in the data. Nevertheless, data collected from other means such as organizational documents and records may yield different results. Therefore, future research should consider collecting data from other means. Further, future research could consider examining other factors as possible contributors to the development of BDC.

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Appendix: Survey Instrument

Codes	*Questionnaire Items*
	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.
	New Product Development (NPD)
NPD1	Working with our supply chain partners, we have developed new products that offer some unique features to the customer.
NPD2	Working with our supply chain partners, we have developed new products that superbly meet customers' needs.
NPD3	Working with our supply chain partners, we have developed new products that are of high quality.
NPD4	Working with our supply chain partners, we have developed new products that have superior technical performance.
NPD5	Working with our supply chain partners, we have developed highly innovative new products.

	Knowledge Cocreation (KC)
KC1	My firm and our supply chain partners have created new skills and knowledge by working together.
KC2	My firm and our supply chain partners formally codify objective project results into standard operating procedures.
KC3	My firm and our supply chain partners systematically recording objective findings and results for future reference.
KC4	My firm and our supply chain partners use codified reports to initiate discussions about project performance.
KC5	My firm and our supply chain partners implement documented changes using on-the-job training.
KC6	My firm and our supply chain partners extensively discuss our projects.
KC7	My firm and our supply chain partners formally and systematically list implied customer requirements.
KC8	My firm and our supply chain partners convert subjective customer requirements to objective requirements.
	Relationship Building (RB)
RB1	Trust level in the relationship with your buyers.
RB2	Commitment level in the relationship with your buyers.
RB3	Collaboration level in the relationship with your buyers.
RB4	Long-term orientation level in the relationship with your buyers.
RB5	Trust level in the relationship with your suppliers.
RB6	Commitment level in the relationship with your suppliers.
RB7	Collaboration level in the relationship with your suppliers.
RB8	Long-term orientation level in the relationship with your suppliers.