Role of cloud ERP and big data on firm performance: a dynamic capability view theory perspective

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Received 7 June 2018
Revised 7 September 2018
Accepted 8 September 2018

Abstract

Purpose – Technological developments have made it possible for organizations to use enterprise resource planning (ERP) services without indulging in heavy investments like IT infrastructure, trained manpower for implementation and maintenance and updating the systems regularly to maintain business competitiveness. Plug and play model offered by cloud ERP has led to a constant creation of large data sets which are structured, semi-structured and unstructured by nature. Thus, there has been a need to analyze such complex data sets and the purpose of this paper is to focus on how cloud ERP and big data predictive analytics (BDPA) will impact the performance of a firm.

Design/methodology/approach – A dynamic capability view (DCV) theory-based model was developed and the authors have collected data by using an online questionnaire from India. Thereafter, the authors have analyzed it by employing structural equation modeling.

Findings – SEM analysis of 231 respondents showcases that the use of DCV theory to define the relationships of cloud ERP and BDPA has been the right move. Out of the 13 hypotheses empirically tested, only 7 hypotheses were supported by the data.

Research limitations/implications – The study showcases cross-sectional data from India. It would be interesting for this study to see if the country-level differences would influence these relationships between cloud ERP and financial performance, BDPA and financial performance and cloud ERP and BDPA.

Originality/value – This study empirically tests the relationship of cloud ERP and BDPA through a model based on DCV theory.

Keywords Big data, Organizational culture, Structural equation modelling, Firm performance, Cloud ERP, Dynamic capability view

Paper type Research paper

1. Introduction

Enterprise resource planning (ERP) systems provide firms extensive facilities and capabilities to share and transfer data and processes of organizations inside and outside the enterprise into a single system and single database (Peng and Nunes, 2013). Sharing data

This work is partially supported by Natural Science Foundation of China 6171101169, National Key R&D Plan – Key Special Plan on Public Security Risk Mitigation/Response 2017YFC0804003, Technologies and Equipment Guangdong Education Bureau Fund 2017KTSCX166, the Science and Technology Innovation Committee Foundation of Shenzhen JCYJ20170817112037041.

Management Decision

0025-1747
DOI 10.1108/MD-06-2018-0633

between firm's departments or firms across the supply chain helps in many aspects (*inter alia* in the form of decision support) and aims to achieve the objectives of better firm performance (FP). Elmonem *et al.* (2016) commented ERP as a category of business management software system that aims to integrate all functional units, typically a suite of integrated applications in a cooperative way. It facilitates organizations to collect, record, manage and interpret data from these business activities. The fact is that, ERP has so far been widely implemented by different organizations with different sizes in many sectors and in many countries to seek competitive advantages in the market.

With time going by, ERP has revolutionized, and continuous up gradation has taken place to strengthen its functionality of resources sharing and integration capabilities of functional units. Scholars increasingly tout internet-enabled ERP systems as an important perspective for the performance of a firm or even firms across the supply chain. With the advent of cloud computing technologies in the late 2000s, Peng and Gala (2014) highlight that there exists an increasing trend for firms to move their ERP-based applications and database into the cloud. According to Salleh *et al.* (2012), cloud ERP as a concept has been a boon to the FP, *inter alia* for small and medium enterprises over large companies since they could conform to the infrastructure requirements of the on-premise ERP solution as well as the high cost. Cloud computing brings firms the very model that enables ubiquitous access to share data and resources to achieve coherence, get the application up and run faster, often over the internet.

Exploring the cloud enterprise resource planning (CERP) system enabled with predictivity ability may help to resolve high uncertainties and gain more competitive advantages than other competitors in the dynamically changing market. According to Duan *et al.* (2013), CERP systems give the enterprise a chance to access the advanced computing resources that are available over the cloud, and even support the firms to manage their business functions to achieve higher productivity. Beheshti (2006) also argued that CERP systems are capable to manage and handle the large volume of operations and information that is created daily within the firm. Besides the potential benefits for operational performance (OP), one of the main drivers from a CERP would be the technical and operational integrations of functional processes to harmonize the data and information stream based on product lifecycle (PLC) (material flow of goods or services) (Qian *et al.*, 2016). In view of Beatty and Williams (2006), this would happen through integrating the values across PLC within a seamless business process streamlining, which could potentially precede the firm's market competitiveness and responsiveness in the rapidly changing environment. Therefore, implementing ERP systems on the cloud platform is showcased for resolving the limitations of ERP systems and provides better scalability, reliability, availability and cost efficiency that are all the very components for a higher FP.

On the other hand, big data predictive analytics (BDPA) would be the next big frontier of innovation, efficiency, productivity and competitiveness of an organization (Srivastava, 2014; Waller and Fawcett, 2013). Reaping the benefits of big data, CERP systems enhanced with e-commerce capabilities and its ability of integration and sharing resources and capabilities, collaboration with corporate alliance (suppliers, partners and even customer portals), and tracking of incoming resources and outgoing final products extends the visibility and control from inside and outside with big data analytics (McAfee *et al.*, 2012). In doing so, upstream and downstream firms in the supply chain could provide reporting capabilities to management via sharing information (i.e. data) needed to support strategic decision-making that is of huge importance for long-term benefits of firms in the supply chain. Organizations in various sizes from various areas are jumping on the bandwagon of big data and predictive analytics (BDPA) due to the data sharing and interactive nature of CERP systems for firm competitive advantages.

By definition, BDPA is a decision-making field which consists of big data; use various statistical tools and techniques and machine learning, deep learning artificial intelligence and

even data mining to derive potential insights from huge data sets, improving the market performance (MP) and OP of a firm (Gupta *et al.*, 2018a). Analyzing big data using predictive techniques would be a necessity for decision support, although big data alone is ubiquitous (Prescott, 2014; Duan and Xiong, 2015). Extracting potential insights from large data sets via analytics techniques are an all-encompassing term among the senior executives to make decisions for their enterprises. McAfee *et al.* (2012) highlight that firms of various sizes need to take the data-driven decision-making into strategy practices via which the top management decision-makers execute any plans based on data instead of gut feeling. Apart from data, Waller and Fawcett (2013) argue that the appropriate managerial skills (MS) and technical skills (TS) play a non-substitutable role in the success of predictive analytics initiatives. Matthias *et al.* (2017) include that the application and exploitation of BDPA would create first-mover competitive benefits for sustainable improvement for a firm. Consistent with the rich research around (surrounding) the extraction of valuable data and potential insights from a large database, we argue that BDPA may be a well-accepted technology for decision-making on the performance of a firm. For instance, organizations may react differently to the same CERP systems on the FP due to the differences in the ability of BDPA capability.

The existing research and studies on CERP and BDPA, respectively are very rich, but the vast majority of them focus merely on its own capabilities and effects. In contrast, knowledge on the joint role of CERP and BDPA capabilities for the performance of a firm is scant. Very few scholars investigated on the specific relationships of CERP and BDPA, CERP and FP, BDPA and FP. Such a void leaves a significant gap between firm's resources and capabilities and its performance. To address this gap, we propose a theory-driven and empirically proven model that aligns CERP and BDPA and could explain the impacts of CERP and BDPA on FP drawing on dynamic capability view (DCV) model (Teece *et al.*, 1997). More specifically, our current research objectives of this paper are to address two main issues as follows:

(1) develop a theoretical framework based on DCV theory to understand the role of cloud-based ERP services and BDPA on the performance of a firm; and

(2) empirically validate this theoretical framework by employing structural equation modeling (SEM).

This paper is organized as follows. In Section 2, we begin with a brief review of the relevant literature pertaining to CERP and BDPA. In Section 3, we describe our theoretical model based on DCV and hypotheses development. In Section 4, we would outline the research methodology and data analytics for the empirical validation of this theoretical framework by employing SEM. Section 5 consists of our discussion related to our analysis results, including theoretical contribution, managerial implications and limitations and further directions. In Section 6, we conclude with our discussion results.

2. Theoretical background

2.1 Dynamic capability view

In the strategic management area, the distinct mechanism of capability-building resource-based view (RBV) is for understanding how we could create our economic competitiveness for a firm. According to Teece *et al.* (1997), in order to locate a firm's position in the market via its resources, the RBV theory was the first concept among the management strategy literature. Wernerfelt (1984) supplemented the conception that resources could be studied and examined as the source of a firm with competitive advantages. RBV tends to support firms to create more economic advantages than their competitors by being more effective at defining internal and outside resources and deploying strategic resources, and subsequently building capabilities (Makadok, 2001; Kim *et al.*, 2015). However, Kraaijenbrink *et al.* (2010) asserted that RBV was not able to

address how firms utilize resources and capabilities in a dynamic market as RBV is primarily a static theory that helps the firms to maintain a competitive advantage by employing resources at their disposal. Therefore, the DCV as an extension of RBV (Wang *et al.*, 2016) was proposed which promotes innovation (Lawson and Samson, 2001).

Going back to the origins of capabilities, it began with the request that static nature of RBV could not fully showcase how the resources of a firm developed and integrated in a rapidly changing market (Teece *et al.*, 1997; Winter *et al.*, 2003; Smith *et al.*, 2014). Teece *et al.* (1997) defined the dynamic capabilities as the abilities to deploy, integrate, build and reconfigure the competencies inside and outside a firm to resolve the dynamically changing market. Lawson and Samson (2001) highlighted dynamic capabilities support enterprises to improve the profits by managing firm's capabilities (efficiency, quality, velocity, flexibility, etc.) in a dynamic and uncertain environment. Given the need of rapid responsiveness of a firm's resources stock to increasingly dynamically changing environments, Vogel and Güttel (2013) indicated that dynamic capabilities would be of inherent strategic relevance to a firm, to keep pace with competitive dynamics. As such, DCV theory would be regarded as the distinct process that allows resources and focuses on learning and change capabilities to relate them to FP.

Given that one of the main objectives of this study is to identify various resources that will enable firms to create CERP and BPDA capabilities, which in turn may lead to superior MP and OP, the choice of DCV as a theoretical framework for this study seems appropriate.

In this paper, DCV is used to conceptualize BDPA and CERP as capabilities that have an impact on FP. Resources like data (D), MS) and TS support BDPA (capability), which impacts on MP and OP. In a similar manner, dynamic capabilities grouped into organizational factors (OF), people factors (PF) and technological factors (TF) constitute CERP (capability) that has an impact on MP and OP of an organization (Figure 1).

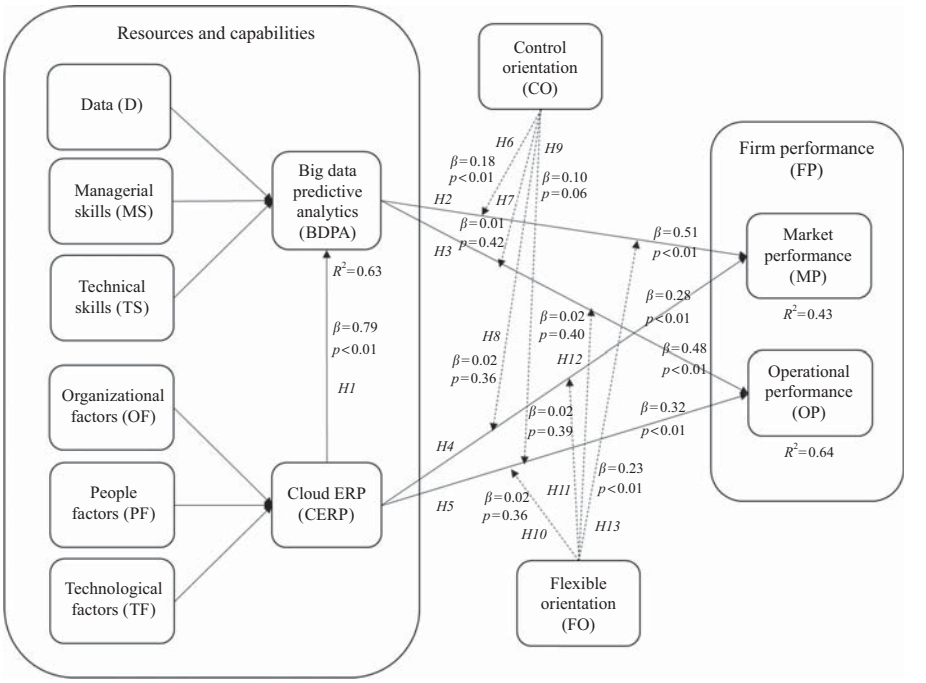

Figure 1.
Theoretical framework

2.2 Cloud-based ERP (CERP)

Most recently, one of the most popular trends is cloud computing that has a huge potential to reshape the way ERP systems operate. Armbrust *et al.* (2010) defined cloud computing as both the applications and systems software in the information centers. Cloud computing would be a key computing paradigm for the next ten years, anticipated by Smith *et al.* (2014). Literature has highlighted the role of ERP in the cloud computing enables many applications of web services via the internet (Chen *et al.*, 2015).

It is not surprising that toward developing a fully functional CERP system has been a center of focus by both firms and researchers, given that CERP is built to provide firms with huge benefits of flexibility, improved accessibility, scalability, lower upfront and operating costs, rapid implementation, cost transparency, sales automation, higher security standards and free trials (Gupta and Misra, 2016). The power of CERP usually refers to the performance of an organization, including MP and OP. These benefits derived from CERP system not only saves the cost of operation when improving the effective productivity but also supports the changed business size into the dynamically changing market when satisfying the firm's needs of new markets shares more quickly than competitors.

2.3 Toward the conceptualization of CERP capability

The key competitive edge for a firm now is its capability to define, standardize and adapt its processes and information with supplier, partner, customers based on PLC in a dynamically changing environment (Chen *et al.*, 2015). Cloud computing allows firms convenient and on-demand access to share a pool of configurable resources. Therefore, cloud computing supports to improve the operational efficiency and help firms to achieve dynamic capabilities (Battleson *et al.*, 2016).

In this paper, we argue that CERP could be conceptualized as a capability with the aid of cloud computing. This paper would identify the dynamic capabilities that explain how firms could effectively respond to market dynamism by developing CERP capability. CERP capability is created by the intrinsic factors combination of OF, PF and TF (Gupta and Misra, 2016) for they are under the control of cloud user. In terms of the determinants of CERP capability, OF, PF and TF are briefly discussed below.

2.3.1 Organizational factors (OF). The research proposed that the success of CERP capability building was affected by OF (Law and Ngai, 2007) and suggests that OF act as the major determinants of FP (Hansen and Wernerfelt, 1989). Determining the appropriate organizational factor or the construct of performance involves communicating the top management strategy to front-line subordinates and organizational structures and systems to people simultaneously. The OF are considered here to capture the multi-dimensional phenomena – strategic goals and objective, implementation strategy, business process re-engineering, organizational resistance, project management and budget and even communication.

The important organizational factor in CERP is the alignment between CERP and organizational objectives. The fit between strategic goals and objectives and CERP systems is brutal critical to achieving FP (Law and Ngai, 2007). In terms of the implementation strategy, it would be set before the implementation of CERP for it guides the future function and capability for our CERP capability. The project budget has a positive impact on better outcome for the enterprise as it is in sync with the implementation strategy (Hasibuan and Dantes, 2012; Somers and Nelson, 2004). Business process re-engineering is the extent to which organizations have to change and re-engineer the existing business process to fit the coming new system in line with the requirements of customization or new markets development (Saleh *et al.*, 2013). What is asserted by prior research is that more the abilities an organization holds for business process re-engineering to change, more powerful could

be its ERP systems (Grover *et al.*, 1995). Consequent with re-engineering business process in CERP solutions, organizational resistance may be also be a hindrance factor to operate smoothly (Utzig *et al.*, 2013). Project management is indispensable role for the CERP capability, which refers to set the vision and directions for business process and harness the cooperation and potentials of employees to exploit the technological capabilities of CERP (Al-Mashari *et al.*, 2003; Esteves and Pastor-Collado, 2001), as well as efficient execution of implementation strategy (Gupta and Misra, 2016). Communication has to be in sync with the project management for better understanding the roles between superior–subordinate and among employees with good working relationships across the project. Most projects failed due to its communication, either a lack of thereof or miscommunication. The need for effective communication is permanent and would affect all the factors listed above. All these measurement constructs would be in the collaboration as OF in executing CERP system.

2.3.2 People factors. People are the biggest potential power of a firm. According to Lalsing *et al.* (2012), PF have been proven to be the most critical success factors for development systems. From the employee's perspective, there would be many measure constructs identified to cover the PF. The key components which are being created as PF are user involvement, vendor selection, project team, top management support, training of user and trust on vendor (Gupta and Misra, 2016).

During building CERP capability, there would be a non-substitutable consideration that actively involves user (Françoise *et al.*, 2009; Hasibuan and Dantes, 2012). User involvement and participation could help to ensure user's requirements with our better quality and user-friendly CERP systems since user involvement in the decision-making process result in greater attachment to the CERP capability and functionality (Lalsing *et al.*, 2012; Françoise *et al.*, 2009). In addition, training of user is also perceived. Needless to say, our CERP system would not create any values and profits if the employees do not know how to operate it. The need for user training and support is crucial in building CERP capability.

Vendor selection is an important decision regarding building CERP capability since most organizations purchase ERP packages from vendors. Based on the end-users requirements and owners' consultants, organizations could take guidance to map the needs of the organizations with the respective vendor (Saleh *et al.*, 2013; Françoise *et al.*, 2009). In addition, trust on the vendor is a necessity to keep the good working relationship between firms and cloud vendor. Vendor support provides extended technical assistance for emergency aid and maintenance, updates, service responsiveness and user training (Somers and Nelson, 2001) during the period of CERP existence.

Project teamwork refers to the amount of knowledge and skills that are responsible for CERP capability building and business operation process. Umble and Umble (2002) suggested ERP teams should be composed of cross-functional members who possess skills, good reputations on past accomplishments and decision-making responsibility. In addition, the team would be supported by the leadership of the company.

Literature underlines the role of top management in orchestrating resources and creating capabilities and subsequently helping to achieve the competitive advantages of a firm (Hitt *et al.*, 2016; Chadwick *et al.*, 2015). Top management not only defines new objectives that could provide employees a clear vision of the orientation the organization is taking with careful consideration to the objectives but also supports all the decisions that need to be made to handle any conflicts that may happen. Thus, top management is required to commit and support for CERP system with enthusiasm, full consideration and even continuously monitoring among all the process (Prajogo and Olhager, 2012).

2.3.3 Technological factors (TF). Factors related to technologies that shall be affecting building CERP capability would be considered for the selection of ERP packages, IT infrastructure, data integrity and system testing, and its functionality of

cloud ERP modules. Selecting ERP packages based on different cloud layers from a vendor should be strategic in nature in such a way that it matches the required business process (Gupta and Misra, 2016) and enhances the organization's competitiveness and efficiency. IT infrastructure refers to the important components required for the CERP's existence, operation and management in the form of hardware and software (Alaskari *et al.*, 2012; Somers and Nelson, 2001), which is more significant to CERP vendor rather than the user. Data integrity is a critical aspect to the design, implementation and usage of CERP systems that are required to store, process and even retrieve data, as well as for the maintenance and the assurance of the accuracy and consistency of data over its entire lifecycle (Boritz, 2005). To make sure that CERP system would operate quickly and smoothly after the go-live, it is often tenable that system testing would continue as long as errors remain. Functionality is supposed to be in the sync with the selection of ERP vendor since it makes sure the consistency between ERP modules and organization business requirements. The decision for all these TF needs to be done before building the implementation of CERP (Gupta and Misra, 2016).

2.4 Big data and predictive analytics

Given business processes with CERP capability and data sharing with the up and down partners are moving online, large-scale data would be created from these applications. As what most researchers asserted, BDPA would be the next big thing for firms to gain competitiveness in the dynamically changing market (Akter *et al.*, 2016; Wamba *et al.*, 2015). BDPA is actually an interdisciplinary field due to leveraging not only the statistical technologies such as regression, time-series analysis, etc., but also the computer and data science tools including data mining, machine learning, etc. (Dubey and Gunasekaran, 2015). It would be defined as a systematic process of descriptive analytics for explaining the data rules, predictive analytics for picture future insights and the final prescriptive analytics for optimizing or simulating the outcomes of organizational decisions.

In addition, recent scholars have acknowledged that BDPA is an organizational capability that they would process and exploit to know how organizations could achieve and sustain competitiveness regarding MP and OP of a firm (Gupta and George, 2016; Wamba *et al.*, 2017). So how organizations could exploit resources and capabilities to build a BDPA capability would be examined next, which is defined as a firm's edge to assemble, integrate and deploy its big data-specific resources to gain market share or improve profitability. Drawing upon DCV logic, we suggest that firms need a unique combination of data, MS and TS as the resources of building a firm-specific BDPA capability for making operational decisions or predictions.

2.5 Toward the conceptualization of BDPA capability

2.5.1 Data (D). The world is witnessing an unprecedented huge interest in big data that is heralded as the next big hit for firms to gain the competitive edge (Frisk and Bannister, 2017; Rajput and Singh, 2018). The term "big data" is often used to describe a resource that features big in volume, big in forms (structured data, unstructured data and often semi-structured data) and big in velocity (fast-changing and real-time streaming), which most firms could approach (Lamba *et al.*, 2018). Gupta and George (2016) highlighted that data are also the premise of deriving usable information for improved decision-making, action and positive change, besides labor and capital. Nevertheless, data by itself do little value to organizations. In other words, big data on its own are unlikely to be a source of competitive edge, since most firms have likely collected hordes of structured, unstructured or semi-structured data from various sources (Lamba and Singh, 2018a). It is imperative to have sophisticated data administration, data analytics and processing techniques to extract inherited insights (Beyer and Laney, 2012). Data are one of such immense resources, which are necessary but not

sufficient to create a BPDA capability. It is imperative for firms to be aware of the various resources that are required to build BPDA capability (Lamba and Singh, 2018b).

2.5.2 Managerial skills. MS are developed as a result of long years working experiences, which play a non-substitutable role for analytics projects as managers. The success of BDPA projects greatly depends on how well managers could infuse employees the common goals and assemble a team with right skills (Lamba and Singh, 2017; Dubey *et al.*, 2018). The essential quality to predict market behavior and the interpersonal skills to develop swift have been regarded as the critical parts to the successful use of BDPA for FP. Big data analytics managers should be enabled to work with functional managers, suppliers and customers, to coordinate big data-related activities, to anticipate the future business needs with the good sense of where to apply big data and to understand and evaluate the output extracted from big data (Gupta and George, 2016).

2.5.3 Technical skills. TS commonly refers to the know-how to possess specific skills and ability to extract intelligence from big data with the knowledge in statistics, computer and data science, as well as problem-solving skills and strong people skills (Lamba and Singh, 2016; Jeble *et al.*, 2018). In terms of developing TS, firms could hire new talented employees with BDPA capability or conduct some big data analytics training for current employees. Big data analysts need are supposed to have the rights skills to accomplish their jobs smoothly with the suitable education and work experience (Schoenherr and Speier-Pero, 2015). More specifically, these right skills involve competencies and proficiency in statistics analytics, data cleaning, extraction analytics, data mining, machine learning and master of programming paradigms (Davenport, 2014).

2.6 Organizational culture

Previous researchers have acknowledged the intangible resource of organizational culture is a source of sustained FP since it would be built over a long period and varies from organization to organization, which could not be duplicated by other competitors or coordinators (Teece, 2015; Jeble *et al.*, 2018). Along similar lines, recent work regarding big data has identified organizational culture as a critical success factor to inhibit an organization's ability to benefit from big data for analytics and predictive projects (Ross *et al.*, 2013), urging firms to develop data-driven culture (LaValle *et al.*, 2011; Ross *et al.*, 2013; Gupta and George, 2016). To fully realize the potential of big data origins from firms, it is critical and necessary to develop a data-driven organizational culture.

Organizational culture can be viewed as "corporate personality" as it encompasses collective values, beliefs, behaviors and principles of organizational members that contribute to an independent enterprise with unique environment (Needle, 2010). Though organizational knowledge would never wear out, but it tends to become outdated. In line with the data-driven culture, organizational members (including top decision-maker and executives, middle managers and lower-level employees) ought to concert efforts to exploit their existing knowledge and explore new knowledge that would upgrade them. Their effort needs to be in place to keep learning the latest knowledge from internal and external environment. It is essential because the competitive environment keeps changing in the economics, technology, management, politics and even society. Based on the works of Gupta and George (2016) and Ross *et al.* (2013), organizational culture is the key intangible resource to contribute to building BDPA capabilities.

Prior literatures have proposed several ways to classify organizational culture into either relation-oriented or transaction-oriented culture (McAfee *et al.*, 2002) or control and flexible orientation regarding organizational culture (Khazanchi *et al.*, 2007). Control orientation values the predictability and efficiency, leveraging core competencies, profile valuation, value–practice interactions and value congruence (Liu *et al.*, 2010; Dubey, Gunasekaran, Childe, Papadopoulos,

Luo, Wamba and Roubaud, 2017). In contrast, flexible orientation emphasizes innovation paradoxes, creativity, spontaneity and risk-taking (Liu *et al.*, 2010; Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud, 2017; Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba and Roubaud, 2017). Following with the works of Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud (2017) and Liu *et al.* (2010), our study adopted the paradoxical orientations of control and flexibility for the moderating effects of organizational culture study.

2.7 Firm performance

To fully measure the difference in the FP among organizations, we have considered two distinct factors, namely, MP and OP. Based on prior academic literature, FP comprises these specific actual outcomes of a firm: MP (market share, etc.), OP (profits, return on assets, etc.), shareholder return, customer service, social responsibility and even employee stewardship (Richard *et al.*, 2009; Upadhaya *et al.*, 2014). MP and OP are the two important distinct dimensions or components standard to account for organizational effectiveness or to measure the performance of a firm (Gupta and George, 2016; Rai and Tang, 2010; Wu *et al.*, 2015; Wang *et al.*, 2012). Consistent with the previous literature on FP, we select these two separate dimensions of FP in our study (i.e. MP and OP).

2.7.1 Market performance. In this study, we consider MP as an important role that acts on FP. The control variables to MP will be embodied in the abilities to explore market more quickly, to introduce new products or services into the market faster, and to gain higher success rate of new products or service and more market share than other competitors (Ji-fan Ren *et al.*, 2017).

2.7.2 Operational performance. In our study, we consider OP as another important part. The control variables of OP will be presented on the benchmark of productivity, profit rate, return on investment (ROI) and sales revenue. An organization with higher OP would mean more effective productivity, higher profit rate and ROI and more sales revenue than that of other competitor.

3. Theoretical framework and hypotheses development

In order to develop a theoretical framework to evaluate how BDPA and CERP act on FP, this study began by investing commonly cited resources that influence CERP and BDPA capabilities perception following DCV logic that explains an organization's competencies and competitiveness in dynamically changing environments. Resources and capabilities are the core components of DCV: resources refer to technology, people and organization whereas capabilities represent a special type of resource that aims to improve the productivity of other resources. By which, a firm could depend on it to effectively manage its all critical resources to achieve PF.

BDPA capability is one of the key organizational capabilities identified as the big competitiveness in the big data era with the help of CERP capability. The theoretical background identified three dimensions that support and reflect BDPA that features a higher-order construct, that is, data (D), MS and TS based on DCV. On top of that, CERP capability was frequently identified as a multi-dimensional construct with OF, PF and TF throughout our review and theoretical exploration. Further, we directly linked the relationship between BDPA and FP, CERP and FP (including MP and OP), respectively. Furthermore, we developed our hypotheses of these relationships (Figure 1).

3.1 Positive effect of cloud-based ERP on BDPA

Cloud-based ERP (CERP) links the internal departments of enterprise and the external enterprises across the supply chain, which shares a holistic view of all the data and

information that impacts enterprises' performance. Data in CERP are becoming increasingly voluminous in size, form and velocity from business and transactional activities. CERP systems are increasingly exposed to big data wherein the data analytics take place in a short moment of time with huge amount of data in the various form. Big data enables CERP to have a contextual view regarding all the processes. Big data in CERP system originates from organizational process details, purchase histories, business interactions, web behavior and even social media (Sastry and Babu, 2013). According to Babu and Sastry (2014) and McAfee *et al.* (2012), big data analytics require common and great use of predictive analytics to unfold potential rules or the relationships to explore current data and historical facts and even visualize the hidden pattern for the decision management in high-volume and front-line operational decisions and future probabilities and trends in market (Matthias *et al.*, 2017; Beatty and Williams, 2006). In other words, predictive analytics help firms to generate their weekly or even daily forecasts for material requirements planning for the sales goals in CERP system with the real-time analysis (John Lu, 2010; Babu and Sastry, 2014).

BDPA in CERP system provide forward-looking decisions to yield better operational effectiveness and more-informed market, improving the competitiveness of an enterprise among competitors and determining the likelihood of a future opportunity. It makes CERP system reflects not only what has happened, but also what is happening and will happen in the soon future for decision-making (Sistla and Babu, 2013; Salleh *et al.*, 2012; Duan *et al.*, 2013). From CERP system data, predictive analytics is the key branch of data mining and exploitation concerned with the optimization of the operational process and the prediction of future probabilities in the changing market (Snijders *et al.*, 2012). Following what the literature indicated, we hypothesize the first on as:

H1. CERP service is positively related to the BDPA.

3.2 Positive effect of BDPA capability on FP

BDPA capability is widely acknowledged to play a vital role in improving FP in the changing markets (Akter *et al.*, 2016; Wamba *et al.*, 2017). The literature provides plenty of evidences of a relationship between BDPA and FP, including productivity optimization, profit, ROI and sales revenue maximization on OP (Schroeck *et al.*, 2012; Gupta and George, 2016; Wamba *et al.*, 2017); and market share and new markets, be more quicker in responding advantages of new products or services into market than other competitors on MP (Ramaswamy, 2013; Gupta and George, 2016; Wamba *et al.*, 2017). More specifically, Srinivasan and Arunasalam (2013) concluded BDPA could enhance firms with a great benefit in healthcare of a firm by reducing the cost such as the fewer wastes and fraud and improving the quality of care such as operation and transaction safety and the efficacy of re-engineering and treatment. Thus, effectively exploiting these resources and capabilities into BDPA capability is phenomenal to maximize FP by facilitating the pervasive use of insights and support firms to achieve and sustain competitive advantages among competitors.

Drawing on DCV logic, we argued that superior FP (MP and OP) emerges from the effective exploitation of data, human such as MS and physical resources such as TS that are defined as valuable and so hard to replicate treasures of a firm. Validated by the BDPA literature, we argued that effective BDPA capability differentiates FP, creates firm precious competencies and advantages in the dynamically changing big data environment. Hence, we propose our second and third research hypotheses as:

H2. BDPA (BDPA) capability have a positive impact on the MP.

H3. BDPA (BDPA) capability have a positive impact on the OP.

3.3 Positive effect of cloud-based ERP on FP

CERP, as an integrated computer based application, has been increasingly concentrated toward by most firms and hosted in cloud platform over the internet over the last few years due to its capability to handle high-volume data sets in the centralized database, flexibility, scalability, friendly-use, low cost of setup, improved accessibility, lower upfront and operating costs, rapid implementation, cost transparency, higher security standards and free trials (Beheshti, 2006; Duan *et al.*, 2013; Salleh *et al.*, 2012). By the record, CERP features managing information for decision-makers at right time, faster response, smoothing and routinizing flow of data and information across departments and enterprises, supporting third-party software, developing wide database regarding supplier, manufacturer and customer behaviors for future market competences (Johansson *et al.*, 2015; Okezie *et al.*, 2012; Appandairajan *et al.*, 2012). Jain and Sharma (2016) found that adoption of CERP service had a critical impact on the day-to-day operations of a firm and simultaneously enhanced the efficiency of the operational processes. Yu *et al.* (2018) argued CERP provides enterprise effective interaction of cross-functional operation with the real-time integration of business operations.

In general, the authors found that CERP service helped most of the enterprises to lead more efficient business activities and new opportunities in the market armed by the seamless flow of integrated business operation and information (Dwayne Whitten *et al.*, 2012; Battleson *et al.*, 2016; Bruque Camara *et al.*, 2015; Gupta and George, 2016; Gupta *et al.*, 2018b). Hence, the literature leads to our fourth and fifth hypotheses as:

H4. CERP services have a positive impact on the MP of an organization.

H5. CERP services have a positive impact on the OP of an organization.

3.4 Moderating effects of organizational culture

Organizational culture correlates positively with the business performance that involves market share, product or service quality and responsivity, the source of competitive advantages in profit and sales (Jeble *et al.*, 2018; Deshpandé *et al.*, 1993). From the business perspective, organizational culture plays a vital role to support organizations in seeking competitive advantages for sustainable growth and thrive. As identified by many scholars (Hogan and Coote, 2014; Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud, 2017; Liu *et al.*, 2010; Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud, 2017), organizational culture classified by control orientation (rational hand hierarchical culture) and flexible orientation (group and development culture) play their roles on different effects on organizational performance, respectively. Control-oriented culture commonly designs disciplines and regulations, focusing innovation initiatives (i.e. long-term strategies and goals), applying its core competencies and meeting business budgets. On the other hand, flexible-oriented culture enables firm's creativity, empowerment and change vital for the exploration. Given flexibility-control would operate and originate from multiple levels. Control-oriented culture tends to descend from the top as the top management would come out with the strategy and goal, guidelines, disciplines and even constraints. By contrast, flexibility emerges in the model of bottom-up for most creative ideas or thoughts are popped up by the front-line subordinates. However, Khazanchi *et al.* (2007) argued that flexibility and control are not simple opposites and rather they contribute a more intricate paradox. Control is not the absence of flexibility and vice versa. In a nutshell, they would complement each other as the cross-fertilizations between the two orientations.

More specifically speaking, control-oriented culture emphasizes the predictability and efficiency, stability and productivity, cooperation, obeying disciplines and regulations and

focusing on innovation initiatives (Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud, 2017; Khazanchi *et al.*, 2007). That conforms to CERP systems with BDPA capability that enables organization to ensure the business activities intelligible, interoperable, normative and legitimacy for normal and high-efficiency process operation, predictable and high-productive for more competences regarding market competitions (Deshpandé *et al.*, 1993; Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba and Roubaud, 2017; Liu *et al.*, 2010; Khazanchi *et al.*, 2007). Firms with a high control orientation value efficiency, which is indeed a well-touted advantage for operation processing in CERP systems. In addition, focusing predictability features from control-oriented culture would be a high-level support for BDPA working, particularly in the market decision-making. Hence, the firm with a control orientation would be more likely to embrace CERP systems and BDPA capability. We argue that an enterprise with higher control orientation would be the one which shall probably focus on great operational and market benefit that is endowed with by such a seamless and timely BDPA capability on CERP platform and collaborate with internal and external partners, comparing with the lower control orientation competitors. Therefore, we suggest our hypotheses as:

H6. An organizational control orientation positively moderates the relationship between BDPA and MP.

H7. An organizational control orientation positively moderates the relationship between BDPA and OP.

H8. An organizational control orientation positively moderates the relationship between CERP and MP.

H9. An organizational control orientation positively moderates the relationship between CERP and OP.

By comparison, flexible orientation tends to refer to the group and development culture such as the creativity, innovation paradoxes, spontaneity, embracing changes and risk-taking (Liu *et al.*, 2010; Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud, 2017). Consequently, a flexible orientation may support aligning organizational strategies and goals in the direction of the new market (new product or service) and unique operating systems. On top of that, firms with the flexibility-oriented culture tend to leverage various resources in CERP systems to develop distinct and competitive capabilities to differentiate from their competitors gain more advantages from heterogeneity across the market (Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba and Roubaud, 2017). In doing so, BDPA passively related to CERP would be enhanced with a more direct effect on the performance of a firm as flexible orientation enables firms more creative, open for embracing new opportunities or changes in the dynamically changing environment. Thus, we may argue that flexible orientation would positively moderate the relationships between CERP/BDPA and OP and MP respectively. Hence, we hypothesize:

H10. An organization's flexible orientation positively moderates the relationship between cloud ERP and OP.

H11. An organization's flexible orientation positively moderates the relationship between cloud ERP and MP.

H12. An organization's flexible orientation positively moderates the relationship between BDPA and OP.

H13. An organization's flexible orientation positively moderates the relationship between BDPA and MP.

4. Research methodology

The research methodology used in our study includes: developing a theoretical framework based on DCV theory to understand the role of cloud-based ERP services and BDPA on the performance of a firm and empirically validating this theoretical framework by employing SEM. In the third section, we have presented our theoretical framework as above. We would discuss the empirical validity next.

4.1 Construct operationalization

Appropriate scales from our literature review were employed to develop the survey instrument. The operationalization of each construct, measurement and derivation is shown in Table AI.

4.2 Data collection

Our study employed a survey-based approach. An online survey was carried out to gather data to test our hypotheses and then qualify the role of CERP and BDPA on the performance of a firm. We designed a questionnaire that was administered to after-sales support executive, AVP/VP/EVP, consultant, corporate finance executive/analyst, director/CEO/founder, engineer, manager/senior manager, and the sales/marketing executive (Table I) throughout four types of cloud services and the cloud solutions (Table II) with total 231 respondents. These 231 fully filled questionnaires were applied for our final data collection and analysis, after continually modifying and improving its clarity and appropriateness base on respondents' inputs and feedbacks. Our target sample was those firms operating CERP with BDPA capability.

The key respondents we approached were not only involved directly in CERP but also interested in BDPA for they would be likely to provide the better response to our questionnaire. You could see the domain of our respondents and their work experiences

	Number of employees						
Role in company/institution	Less than 10	10–50	50–300	300–500	500–1,000	More than 1,000	Total
After-sales support executive	–	1	1	–	–	2	4
AVP/VP/EVP	–	1	1	5	2	7	16
Consultant	7	6	10	3	4	14	44
Corporate finance executive/ Analyst	1	2	2	1	1	11	18
Director/CEO/Founder	2	6	1	–	–	1	10
Engineer	1	3	2	3	7	30	46
Manager/Sr manager	3	4	7	8	11	51	84
Sales/Marketing executive	2	–	2	1	2	2	9
Total	16	23	26	21	27	118	231

Table I. Role of employee in the company/ institution and the number of employees

Type of cloud services	Cloud service user	Cloud service provider	Cloud consultant or researcher	Total
Software as a service (SaaS)	148	12	7	167
Platform as a service (PaaS)	16	1	1	18
Infrastructure as a service (IaaS)	10	2	3	15
Internal cloud	27	1	3	31
Total	201	16	14	231

Table II. Type of cloud services and the cloud solutions

in Table III, which would be well validated that our respondents ranged over a variety of fields. Table IV represents the age and qualification of the respondents. This helps to guarantee the quality of the better response from the respondents with different fields and stages for our subsequent data analysis as well. Hence, we could see data collection is an extremely important part for our later procedures regarding our study.

4.3 Data analysis and results

Our study puts efforts to assess the role of CERP and BDPA and even to explore the power of its combination on FP. Owing to the relationship between CERP and BPDA ant its joint efforts for a firm were not examined in the previous research, there would be a few specific theoretical foundations for reference to anticipate their associations on FP. However, the extant studies indicate partial least squares (PLS) makes sense to estimate a general model for an exploratory research (Gupta and George, 2016; Henseler *et al.*, 2014; Moshtari, 2016). And we supposed our study is a more exploratory research in nature. By similar argument, both almost chime in easily. Hence, we employed PLS–SEM performed by Warp PLS version 6.0 to test our model and research hypotheses reaping the benefits of effectiveness to explain and predict the target constructs from PLS–SEM (Hair *et al.*, 2016; Akter *et al.*, 2017).

Examining measurement model would be required before analyzing the PLS–SEM model. Variance inflation factors (VIF) is a way of identifying the risk of multicollinearity (Peng and Lai, 2012). VIF values of 5 or above would be considered to have a certain risk of multicollinearity, where we would improve our model. Our result Average block VIF showed a value of 4.966 (see Table V) and indicated that multicollinearity may not be a risk for our study. Although average block VIF values of 3 or below would be ideal fit value for PLS analysis, average path coefficient (APC) and average R^2 (ARS) would be mentioned regarding model fit indices for PLS as well. In Table V, APC (0.231, $p < 0.001$) and ARS (0.567, $p < 0.001$) show no evidence of fit problems. Hence, the results would be considered as a good fit to our model.

Table III.
Domain of work of the employees and their work experience

Domain of work	Years of work experience: Less than 1 year	1–3 years	3–5 years	5–10 years	More than 10 years	Total
Banking/Insurance/Financial services	5	5	9	11	8	38
Construction/Real estate/Infrastructure	–	2	1	3	5	11
Consulting	2	9	3	7	11	32
Education/research	1	6	9	6	3	25
Food and beverage	–	1	2	1	1	5
Government	–	1	3	2	3	9
IT services/Software	2	10	15	20	22	69
Manufacturing	–	2	2	6	15	25
Retail	1	4	3	8	1	17
Total	11	40	47	64	69	231

Table IV.
Age group of employees and their educational qualifications

Age group (in years)	Graduate	PhD	Post-graduate	Total
20–30	47	–	73	120
31–40	27	3	57	87
41–50	11	2	10	23
51–60	–	–	1	1
Total	85	5	141	231

Apart from APC, ARS and AVIF, Sympson's paradox ratio (SPR), R^2 contribution ratio (RSCR), statistical suppression ratio (SSR) and Nonlinear bivariate causality direction ratio (NLBCDR) are commonly used model fit indices for PLS. Concretely, these three indices would be regarded as causality assessment indices which aim to test our hypothesis are correct or not. SPR (0.715, the acceptable score), RSCR (0.913, the acceptable score and close to ideal score), SSR (1, the ideal score) and NLBCDR (0.785, the acceptable score) indicate that our theoretical model is appropriate for our study (see Table VI).

The result's combined loadings and cross-loadings is also one part of the measurement model in PLS–SEM analysis and used with statistical tools Warp PLS version 6 to see our model is accepted or rejected (model fitness test). From the 231 fully filled questionnaire response, the combined loadings and cross-loading are developed to show the constructs of column and the indicators of row, as the indicators of reliability and validity of our theoretical model. Based on the results in the Appendix, it could group our model to qualify for the convergent validity into reflective indicators and significant factors. Loadings value of > 0.50 would be grouped into significant factor. p-value of < 0.05 are satisfied for reflective indicators. Therefore, our results (see the Appendix) indicate that most of the constructs are within or close to acceptable range in terms of reliability.

Cronbach's α and composite reliability would be commonly used to test constructs reliability. In Table VII, the Cronbach's α values are 0.966 for BDPA, 0.961 for CERP, 0.93 for MP, 0.943 for OP, 0.942 for CO and 0.914 for FO. In general, Cronbach's α value of 0.7 and above is considered within the acceptable range (Gliner *et al.*, 2001). We note that all the composite reliability is shown to arrive at the threshold value of 0.7 as well (Tellis *et al.*, 2009). The average variances extracted (AVE) values satisfy the required value of > 0.5 (Hair *et al.*, 2006) for latent variable. The greater value of R^2 coefficient means the better fitness to data. BDPA, MP and OP could be well explained by the constructs. All these results in Table VII could indicate the reliability of our constructs is acceptable.

Discriminant validity (irrelevance) tests whether an indicator that are not supposed to be related to a construct are actually unrelated. The acceptable discriminant validity is the case

Table V. Model fit and quality indices

Average path coefficient (APC)	0.231, $p < 0.001$
Average R^2 (ARS)	0.567, $p < 0.001$
Average block VIF (AVIF)	4.966, acceptable if $\leqslant 5$

Table VI. Causality assessment indices

Sympson's paradox ratio (SPR)	0.715, acceptable if $\geqslant 0.7$, ideally $= 1$
R^2 contribution ratio (RSCR)	0.913, acceptable if $\geqslant 0.9$, ideally $= 1$
Statistical suppression ratio (SSR)	1.000, acceptable if $\geqslant 0.7$
Nonlinear bivariate causality direction ratio (NLBCDR)	0.785, acceptable if $\geqslant 0.7$

Table VII. Latent variable coefficients

	BDPA	CERP	MP	OP	CO	FO
R^2 coefficients	0.631	–	0.429	0.64	–	–
Adjusted R^2 coefficients	0.629	–	0.414	0.631	–	–
Composite reliability coefficients	0.968	0.963	0.938	0.95	0.947	0.925
Cronbach's α coefficients	0.966	0.961	0.93	0.943	0.942	0.914
Average variances extracted (AVE)	0.7	0.606	0.792	0.827	0.781	0.754
Variance inflation factors (VIF)	3.849	3.413	3.707	4.171	4.441	3.933

where square roots of AVE values are greater than the construct correlations (Hair *et al.*, 2006). Table VIII reveals the relationship among the constructs and the square root of AVEs. Results indicate that the constructs are positively correlated to each other, and square roots of AVEs are greater than the correlations values on the same column and row for that construct. Table VIII indicates that discriminant validity is acceptable for our paper.

Table IX indicates our hypotheses developed in Section 4 would be considered to be appropriate for our paper.

5. Discussion

5.1 Theoretical contribution

Our study is an early attempt to develop and explain the joint role of CERP and BDPA on the performance of a firm using the theoretical lens of DCV. From DCV's perspective, our study extends the current understanding of concepts and the influence of BDPA and CERP

Table VIII. Correlations among latent variables with square root of AVEs

	BDPA	CERP	MP	OP	CO	FO
BDPA	*0.837*					
CERP	0.794	*0.778*				
MP	0.747	0.7	*0.89*			
OP	0.765	0.732	0.821	*0.91*		
CO	0.699	0.7	0.706	0.72	*0.884*	
FO	0.723	0.693	0.695	0.707	0.835	*0.869*

Table IX. Results of hypotheses testing

Hypothesis	β and p-value	Supported or not supported
H1. Cloud-based ERP services is positively related to the big data predictive analytics	$\beta = 0.79$, $p < 0.01$	Supported
H2. Big data predictive analytics has a positive impact on the market performance of an organization	$\beta = 0.51$, $p < 0.01$	Supported
H3. Big data predictive analytics has a positive impact on the operational performance of an organization	$\beta = 0.48$, $p < 0.01$	Supported
H4. Cloud-based ERP services has a positive impact on the market performance of an organization	$\beta = 0.28$, $p < 0.01$	Supported
H5. Cloud-based ERP services has a positive impact on the operational performance of an organization	$\beta = 0.32$, $p < 0.01$	Supported
H6. An organization's control orientation positively moderates the relationship between BDPA and market performance	$\beta = 0.18$, $p < 0.01$	Supported
H7. An organization's control orientation positively moderates the relationship between BDPA and operational performance	$\beta = 0.01$, $p = 0.42$	Nota supported
H8. An organization's control orientation positively moderates the relationship between cloud ERP and market performance	$\beta = 0.02$, $p = 0.36$	Nota supported
H9. An organization's control orientation positively moderates the relationship between cloud ERP and operational performance	$\beta = 0.10$, $p = 0.06$	Not supported
H10. An organization's flexible orientation positively moderates the relationship between cloud ERP and operational performance	$\beta = 0.02$, $p = 0.36$	Not supported
H11. An organization's flexible orientation positively moderates the relationship between cloud ERP and market performance	$\beta = 0.02$, $p = 0.39$	Not supported
H12. An organization's flexible orientation positively moderates the relationship between BDPA and operational performance	$\beta = 0.02$, $p = 0.40$	Not supported
H13. An organization's flexible orientation positively moderates the relationship between BDPA and market performance	$\beta = 0.23$, $p < 0.01$	Supported

as organizational capabilities on FP (Teece *et al.*, 1997; Smith *et al.*, 2014; Lawson and Samson, 2001; Kraaijenbrink *et al.*, 2010). There exists remarkable contributions made by practitioners of CERP or BDPA to understand the effects of CERP or BDPA solely, but not from the prospective of integrated association of the two (Battleson *et al.*, 2016; Chen *et al.*, 2015; Akter *et al.*, 2016; Wamba *et al.*, 2015). We addressed the shortcoming by highlighting the joint effects of CERP and BDPA to improve the PF. Further, our empirical results using survey data from 231 executive-level technology respondents suggest that: for one, CERP is positively related to BDPA (*H1*), which supports our study on the joint effects of both; for another, BDPA directly affect MP and OP (*H2* and *H3*) in dynamically changing environment, the same in CERP aspects (*H4* and *H5*). Therefore, we could say our study further extend the extant CERP and BDPA literature regarding bringing organizations potential and sustainable development.

Our study also asserted the organizational cultures (i.e. control-oriented and flexibility-oriented) were not positively moderates the relationship between BDPA and operation performance (*H7* and *H12*), between CERP and MP/OP (i.e. *H8*/*H9* and *H10*/*H11*). The results are contrary to our expectations, but we supposed the relationship between organization culture and BDPA and CERP, respectively would happen to be not consistent to the previous literature (Schroeck *et al.*, 2012; Fosso Wamba *et al.*, 2017; Liu *et al.*, 2010; Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba and Roubaud, 2017). It would also be an interesting question that is worth pursing further for future research scholars.

Finally, another important contribution of our study is to develop a theoretically grounded construct of organization survey instrument to measure the organization's ability with CERP services and BDPA capability that is different from digital capabilities (i.e. IT capability). The constructs and its measures would give references to further researchers devoted to studying CERP and BDPA on the performance of an organization in terms of further the emerging research stream in that regard.

5.2 Managerial implications

Our study yields interesting insights for practice in business organizations for improving firm's competencies and competitiveness in a dynamically changing environment. Based on our current study highlighting the positive influence of CERP and BDPA on the performance of a firm, it attempts to enlighten business organizations that catching competitiveness in a changing market is not only about making hordes of investment, employing more talents with sophisticated skills and techniques, but also having access to CERP services as a well-established and cost-effective platform for data and information generation, sharing, processing and subsequent predictive analysis, BDPA capability where potential insights extracted from data and analysis acted upon and data-driven organizational culture (i.e. control-oriented and flexibility-oriented) where employees from top to ground have awareness to cultivate and process data-specific technologies and skills.

In addition to this, our study contained empirical validation of the role of CERP and BDPA on FP. It has advanced the understanding for top management and executives regarding the positive impacts in MP and OP from CERP and BDPA to enhance a firm's competitiveness and sustainability in the dynamically changing environment. Our study suggested that business firms implement CERP service and invest in very talent techniques and knowledge learning and sharing culture to build BDPA capability, which offers huge benefits to gain competitive advantages among competitors.

5.3 Limitations and directions for further research

Notwithstanding the insights on the positive impacts of CERP and BDPA for organizational performance for researchers and industry practitioners, some limitations and future research directions would be outlined. First, our study is the investigation of the role of

CERP and BDPA as organizational capabilities that impact on FP and bring competitive advantages for a firm. The final destination, we hope interested business organizations could understand and build CERP and BDPA capabilities for their firms. In such an attempt, further research may need to be explored through investigating the role of institutional pressures on implementing CERP systems and their commitment toward developing BDPA capability, which could help to make it possible to employ CERP systems with BDPA capability in firms. In this vein, our research concept is not only one scientific idea, but one kind of advanced firm operation type.

Second, both sets of data needed for the empirical validation in our study focused on the organizations from India. Furthermore, the study conducted the survey-based empirical validation at one point in time from 231 respondents. Hence, our study would be expanded by involving a broader sample outside of India, avoiding the limitation of our understanding of the role of CERP and BDPA on FP caused by gathering data from single source at a single point in time. It would be interesting for our study to see if the country-level differences would influence these relationships between CERP and FP, BDPA and FP, and CERP and BDPA.

Finally, our study relies on the survey-based approach for empirical validation. To advance better insights into CERP and BDPA capabilities, maybe the way of a mixed form approach could do better, such as telephone interview, semi-structured interviews with respondents. By which, the relationships between these constructs in our model could be further understood and lead to better empirical investigation.

6. Conclusion

This work developed a theoretical framework based on DCV theory to understand the role of CERP and BDPA on the performance of a firm. Drawing broadly on the DCV theory, we have conceptualized CERP and BDPA as organizational capabilities and tested the relationship between CERP and BDPA and their respective impacts on FP under the moderating effects of organizational culture. Through our empirical validation by employing SEM, it turned out that CERP which is positively related to BDPA has positive impacts on FP, and BDPA has the same positive impacts on FP, although the high or low control and flexible orientation do not positively moderate the impacts of BDPA on OP, CERP on MP and OP. By which, it supports to a certain degree to advance the understanding for business organizations to consider and build CERP and BDPA capabilities. Our study would be first theoretical framework to investigate and explain the joint impacts of CERP and BDPA on FP. And finally, we presented the empirical evidence that CERP and BDPA would be predictors of the organizational performance by developing a survey-based instrument. However, further research based on our limitations part would be explored to arrive to our final goal regarding convincing organizations to build CERP and BDAP capabilities.

References

Akter, S., Fosso Wamba, S. and Dewan, S. (2017), "Why PLS–SEM is suitable for complex modeling? An empirical illustration in big data analytics quality", *Production Planning & Control*, Vol. 28 Nos 11/12, pp. 1011-1021.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R. and Childe, S.J. (2016), "How to improve firm performance using big data analytics capability and business strategy alignment?", *International Journal of Production Economics*, Vol. 182, December, pp. 113-131.

Alaskari, O., Ahmad, M.M., Dhafr, N. and Pinedo-Cuenca, R. (2012), "Critical successful factors (CSFs) for successful implementation of lean tools and ERP systems".

Al-Mashari, M., Al-Mudimigh, A. and Zairi, M. (2003), "Enterprise resource planning: a taxonomy of critical factors", *European Journal of Operational Research*, Vol. 146 No. 2, pp. 352-364.

Appandairajan, P., Khan, N.Z.A. and Madiajagan, M. (2012), "ERP on cloud: implementation strategies and challenges", *IEEE International Conference on Cloud Computing Technologies, Applications and Management (ICCCTAM)*, *December*, pp. 56-59.

Armbrust, M., Fox, A., Griffith, R., Joseph, A.D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, I. and Zaharia, M. (2010), "A view of cloud computing", *Communications of the ACM*, Vol. 53 No. 4, pp. 50-58.

Babu, M.P. and Sastry, S.H. (2014), "Big data and predictive analytics in ERP systems for automating decision making process", *5th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, *June*, pp. 259-262.

Battleson, D.A., West, B.C., Kim, J., Ramesh, B. and Robinson, P.S. (2016), "Achieving dynamic capabilities with cloud computing: an empirical investigation", *European Journal of Information Systems*, Vol. 25 No. 3, pp. 209-230.

Beatty, R.C. and Williams, C.D. (2006), "ERP II: best practices for successfully implementing an ERP upgrade", *Communications of the ACM*, Vol. 49 No. 3, pp. 105-109.

Beheshti, H.M. (2006), "What managers should know about ERP/ERP II?", *Management Research News*, Vol. 29 No. 4, pp. 184-193.

Beyer, M.A. and Laney, D. (2012), *The Importance of "Big Data": A Definition*, Gartner, Stamford, CT, available at: www.gartner.com/doc/2057415

Boritz, J.E. (2005), "IS practitioners' views on core concepts of information integrity?", *International Journal of Accounting Information Systems*, Vol. 6 No. 4, pp. 260-279.

Bruque Camara, S., Moyano Fuentes, J. and Maqueira Marin, J.M. (2015), "Cloud computing, Web 2.0, and operational performance: the mediating role of supply chain integration", *The International Journal of Logistics Management*, Vol. 26 No. 3, pp. 426-458.

Chadwick, C., Super, J.F. and Kwon, K. (2015), "Resource orchestration in practice: CEO emphasis on SHRM, commitment-based HR systems, and firm performance", *Strategic Management Journal*, Vol. 36 No. 3, pp. 360-376.

Chen, C.S., Liang, W.Y. and Hsu, H.Y. (2015), "A cloud computing platform for ERP applications", *Applied Soft Computing*, Vol. 27, February, pp. 127-136.

Davenport, T. (2014), *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities*, Harvard Business Review Press, Boston.

Deshpandé, R., Farley, J.U. and Webster, F.E. Jr (1993), "Corporate culture, customer orientation, and innovativeness in Japanese firms: a Quadrad analysis", *The Journal of Marketing*, Vol. 57 No. 1, pp. 23-37, doi: 10.2307/1252055.

Duan, J., Faker, P., Fesak, A. and Stuart, T. (2013), "Benefits and drawbacks of cloud-based versus traditional ERP systems", *Proceedings of the 2012–2013 Course on Advanced Resource Planning*.

Duan, L. and Xiong, Y. (2015), "Big data analytics and business analytics", *Journal of Management Analytics*, Vol. 2 No. 1, pp. 1-21.

Dubey, R. and Gunasekaran, A. (2015), "Education and training for successful career in big data and business analytics", *Industrial and Commercial Training*, Vol. 47 No. 4, pp. 174-181.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Hazen, B., Giannakis, M. and Roubaud, D. (2017), "Examining the effect of external pressures and organizational culture on shaping performance measurement systems (PMS) for sustainability benchmarking: some empirical findings", *International Journal of Production Economics*, Vol. 193, November, pp. 63-76.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Luo, Z., Wamba, S.F. and Roubaud, D. (2017), "Can big data and predictive analytics improve social and environmental sustainability?", *Technological Forecasting and Social Change*.

Dubey, R., Luo, Z., Gunasekaran, A., Akter, S., Hazen, B.T. and Douglas, M.A. (2018), "Big data and predictive analytics in humanitarian supply chains: enabling visibility and coordination in the presence of swift trust", *The International Journal of Logistics Management*, Vol. 29 No. 2, pp. 485-512.

Dwayne Whitten, G., Green, K.W. Jr and Zelbst, P.J. (2012), "Triple-A supply chain performance", *International Journal of Operations & Production Management*, Vol. 32 No. 1, pp. 28-48.

Elmonem, M.A.A., Nasr, E.S. and Geith, M.H. (2016), "Benefits and challenges of cloud ERP systems – a systematic literature review", *Future Computing and Informatics Journal*, Vol. 1 Nos 1/2, pp. 1-9.

Esteves, J. and Pastor-Collado, J. (2001), "Analysis of critical success factors relevance along SAP implementation phases", *AMCIS Proceedings*, p. 197.

Françoise, O., Bourgault, M. and Pellerin, R. (2009), "ERP implementation through critical success factors' management", *Business Process Management Journal*, Vol. 15 No. 3, pp. 371-394.

Frisk, J.E. and Bannister, F. (2017), "Improving the use of analytics and big data by changing the decision-making culture: a design approach", *Management Decision*, Vol. 55 No. 10, pp. 2074-2088.

Gliner, J.A., Morgan, G.A. and Harmon, R.J. (2001), "Measurement reliability", *Journal of the American Academy of Child & Adolescent Psychiatry*, Vol. 40 No. 4, pp. 486-488.

Grover, V., Jeong, S.R., Kettinger, W.J. and Teng, J.T. (1995), "The implementation of business process re-engineering", *Journal of Management Information Systems* , Vol. 12 No. 1, pp. 109-144.

Gupta, M. and George, J.F. (2016), "Toward the development of a big data analytics capability", *Information & Management*, Vol. 53 No. 8, pp. 1049-1064.

Gupta, S. and Misra, S. (2016), "Moderating effect of compliance, network, and security on the critical success factors in the implementation of cloud ERP", *IEEE Transactions on Cloud Computing*, Vol. 99, p. 1.

Gupta, S., Kar, A.K., Baabdullah, A. and Al-Khowaiter, W.A.A. (2018a), "Big data with cognitive computing: a review for the future", *International Journal of Information Management*, Vol. 42, pp. 78-89.

Gupta, S., Kumar, S., Singh, S.K., Foropon, C. and Chandra, C. (2018b), "Role of cloud ERP on the performance of an organization: contingent resource based view perspective", *International Journal of Logistics Management*, Vol. 29 No. 2, pp. 659-675, available at: https://doi.org/10.1108/IJLM-07-2017-0192

Hair, J.F. Jr, Hult, G.T.M., Ringle, C. and Sarstedt, M. (2016), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage Publications, Thousand Oaks.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2006), *Multivariate Data Analysis*, 6th ed., Pearson Prentice Hall, Upper Saddle River, NJ.

Hansen, G.S. and Wernerfelt, B. (1989), "Determinants of firm performance: the relative importance of economic and organizational factors", *Strategic Management Journal*, Vol. 10 No. 5, pp. 399-411.

Hasibuan, Z.A. and Dantes, G.R. (2012), "Priority of key success factors (KSFS) on enterprise resource planning (ERP) system implementation life cycle", *Journal of Enterprise Resource Planning Studies*, Vol. 2012, p. 1.

Henseler, J., Dijkstra, T.K., Sarstedt, M., Ringle, C.M., Diamantopoulos, A., Straub, D.W. and Calantone, R.J. (2014), "Common beliefs and reality about PLS: comments on Rönkkö and Evermann (2013)", *Organizational Research Methods*, Vol. 17 No. 2, pp. 182-209.

Hitt, M.A., Xu, K. and Carnes, C.M. (2016), "Resource based theory in operations management research", *Journal of Operations Management*, Vol. 41, January, pp. 77-94.

Hogan, S.J. and Coote, L.V. (2014), "Organizational culture, innovation, and performance: a test of Schein's model", *Journal of Business Research*, Vol. 67 No. 8, pp. 1609-1621.

Jain, D. and Sharma, Y. (2016), "Cloud computing with ERP – a push business towards higher efficiency", *Annual Research Journal of SCMS Pune*, Vol. 4, pp. 140-155.

Jeble, S., Dubey, R., Childe, S.J., Papadopoulos, T., Roubaud, D. and Prakash, A. (2018), "Impact of big data and predictive analytics capability on supply chain sustainability", *International Journal of Logistics Management*.

Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R. and Childe, S.J. (2017), "Modelling quality dynamics, business value and firm performance in a big data analytics environment", *International Journal of Production Research*, Vol. 55 No. 17, pp. 5011-5026.

Johansson, B., Alajbegovic, A., Alexopoulo, V. and Desalermos, A. (2015), "Cloud ERP adoption opportunities and concerns: the role of organizational size", *48th IEEE Hawaii International Conference on System Sciences (HICSS), January*, pp. 4211-4219.

John Lu, Z.Q. (2010), "The elements of statistical learning: data mining, inference, and prediction", *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, Vol. 173 No. 3, pp. 693-694.

Khazanchi, S., Lewis, M.W. and Boyer, K.K. (2007), "Innovation-supportive culture: the impact of organizational values on process innovation", *Journal of Operations Management*, Vol. 25 No. 4, pp. 871-884.

Kim, M., Song, J. and Triche, J. (2015), "Toward an integrated framework for innovation in service: a resource-based view and dynamic capabilities approach", *Information Systems Frontiers*, Vol. 17 No. 3, pp. 533-546.

Kraaijenbrink, J., Spender, J.-C. and Groen, A.J. (2010), "The resource-based view: a review and assessment of its critiques", *Journal of Management*, Vol. 36 No. 1, pp. 349-372.

Lalsing, V., Kishnah, S. and Pudaruth, S. (2012), "People factors in agile software development and project management", *International Journal of Software Engineering & Applications*, Vol. 3 No. 1, pp. 117-137.

Lamba, K. and Singh, S.P. (2016), "Big data analytics in supply chain management: some conceptual frameworks", *International Journal of Automation and Logistics*, Vol. 2 No. 4, pp. 279-293.

Lamba, K. and Singh, S.P. (2017), "Big data in operations and supply chain management: current trends and future perspectives", *Production Planning and Control*, Vol. 28 Nos 11/12, pp. 877-890.

Lamba, K. and Singh, S.P. (2018a), "Dynamic supplier selection and lot-sizing problem considering carbon emissions in a big data environment", *Technological Forecasting and Social Change*, in-press, doi: 10.1016/j.techfore.2018.03.020.

Lamba, K. and Singh, S.P. (2018b), "Modeling big data enablers for operations and supply chain management", *The International Journal of Logistics Management*, Vol. 29 No. 2, pp. 629-658.

Lamba, K., Singh, S.P. and Mishra, N. (2018), "Integrated decisions for supplier selection and lot-sizing considering different carbon emission regulations in big data environment", *Computers and Industrial Engineering*, in press, doi: 10.1016/j.cie.2018.04.028.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2011), "Big data, analytics and the path from insights to value", *MIT Sloan Management review*, Vol. 52 No. 2, pp. 21-31.

Law, C.C.H. and Ngai, E.W.T. (2007), "ERP systems adoption: an exploratory study of the organizational factors and impacts of ERP success", *Information & Management*, Vol. 44 No. 4, pp. 418-432.

Lawson, B. and Samson, D. (2001), "Developing innovation capability in organisations: a dynamic capabilities approach", *International Journal of Innovation Management*, Vol. 5 No. 3, pp. 377-400.

Liu, H., Ke, W., Wei, K.K., Gu, J. and Chen, H. (2010), "The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems", *Journal of Operations Management*, Vol. 28 No. 5, pp. 372-384.

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D. (2012), "Big data: the management revolution", *Harvard Business Review*, Vol. 90 No. 10, pp. 60-68.

McAfee, R.B., Glassman, M. and Honeycutt, E.D. (2002), "The effects of culture and human resource management policies on supply chain management strategy", *Journal of Business Logistics*, Vol. 23 No. 1, pp. 1-18.

Makadok, R. (2001), "Toward a synthesis of the resource-based and dynamic-capability views of rent creation", *Strategic Management Journal*, Vol. 22 No. 5, pp. 387-401.

Matthias, O., Fouweather, I., Gregory, I. and Vernon, A. (2017), "Making sense of big data – can it transform operations management?", *International Journal of Operations & Production Management*, Vol. 37 No. 1, pp. 37-55.

Moshtari, M. (2016), "Inter-organizational fit, relationship management capability, and collaborative performance within a humanitarian setting", *Production and Operations Management*, Vol. 25 No. 9, pp. 1542-1557.

Needle, D. (2010), "Business in context: an introduction to business and its environment", Cengage Learning EMEA, London.

Okezie, C.C., Chidiebele, U.C. and Kennedy, O.C. (2012), "Cloud computing: a cost effective approach to enterprise web application implementation (a case for cloud ERP web model)", *Academic Research International*, Vol. 3 No. 1, pp. 432-443.

Peng, D.X. and Lai, F. (2012), "Using partial least squares in operations management research: a practical guideline and summary of past research", *Journal of Operations Management*, Vol. 30 No. 6, pp. 467-480.

Peng, G.C.A. and Gala, C. (2014), "Cloud ERP: a new dilemma to modern organisations?", *Journal of Computer Information Systems*, Vol. 54 No. 4, pp. 22-30.

Peng, G.C.A. and Nunes, M.B. (2013), "Establishing and verifying a risk ontology for surfacing ERP post-implementation risks", *Enterprise Resource Planning: Concepts, Methodologies, Tools, and Applications*, IGI Global, pp. 450-474.

Prajogo, D. and Olhager, J. (2012), "Supply chain integration and performance: the effects of long-term relationships, information technology and sharing, and logistics integration", *International Journal of Production Economics*, Vol. 135 No. 1, pp. 514-522.

Prescott, M.E. (2014), "Big data and competitive advantage at Nielsen", *Management Decision*, Vol. 52 No. 3, pp. 573-601.

Qian, X., Li, R., Cao, Y., Ni, Y. and Wu, X. (2016), "Modelling CF of tobacco industry based on PLC across the supply chain", *International Journal of Service and Computing Oriented Manufacturing*, Vol. 2 Nos 3/4, pp. 258-276.

Rai, A. and Tang, X. (2010), "Leveraging IT capabilities and competitive process capabilities for the management of interorganizational relationship portfolios", *Information Systems Research*, Vol. 21 No. 3, pp. 516-542.

Rajput, S. and Singh, S.P. (2018), "Identifying Industry 4.0 IoT enablers by integrated PCA-ISM-DEMATEL approach", *Management Decision*, in-press, doi: 10.1108/MD-04-2018-0378.

Ramaswamy, S. (2013), "What the companies winning at big data do differently", Bloomberg, June, available at: www.Bloomberg.com/news/2013-06-25/what-the-companies-winning-at-big-data-do-differently.html (accessed June 25, 2013).

Richard, P.J., Devinney, T.M., Yip, G.S. and Johnson, G. (2009), "Measuring organizational performance: towards methodological best practice", *Journal of Management*, Vol. 35 No. 3, pp. 718-804.

Ross, J.W., Beath, C.M. and Quaadgras, A. (2013), "You may not need big data after all", *Harvard Business Review*, Vol. 44 No. 12, pp. 1-9.

Saleh, M.F., Abbad, M. and Al-Shehri, M. (2013), "ERP implementation success factors in Saudi Arabia", *International Journal of Computer Science and Security*, Vol. 7 No. 1, pp. 15-30.

Salleh, S.M., Teoh, S.Y. and Chan, C. (2012), "Cloud enterprise systems: a review of literature and its adoption", PACIS 2012 Proceedings, Paper 76.

Sastry, H.S. and Babu, M.P. (2013), "Cluster analysis of material stock data of enterprises", *International Journal of Computer Information Systems*, Vol. 6 No. 6, pp. 8-19.

Schoenherr, T. and Speier-Pero, C. (2015), "Data science, predictive analytics, and big data in supply chain management: current state and future potential", *Journal of Business Logistics*, Vol. 36 No. 1, pp. 120-132.

Schroeck, M., Shockley, R., Smart, J., Romero-Morales, D. and Tufano, P. (2012), "Analytics: the real-world use of big data", *IBM Global Business Services*, Vol. 12, pp. 1-20.

Sistla, S.H. and Babu, M.P. (2013), "ERP implementation for manufacturing enterprises", *International Journal of Advanced Research in Computer Science and Software Engineering*, Vol. 3 No. 4, pp. 18-24.

Smith, A., Bhogal, J. and Sharma, M. (2014), "Cloud computing: adoption considerations for business and education", *IEEE International Conference on Future internet of Things and Cloud (FiCloud)*, *August*, pp. 302-307.

Snijders, C., Matzat, U. and Reips, U.D. (2012), " 'Big data': big gaps of knowledge in the field of internet science", *International Journal of Internet Science*, Vol. 7 No. 1, pp. 1-5.

Somers, T.M. and Nelson, K. (2001), "The impact of critical success factors across the stages of enterprise resource planning implementations", *Proceedings of the 34th Annual Hawaii IEEE International Conference on System Sciences*, January, p. 10.

Somers, T.M. and Nelson, K.G. (2004), "A taxonomy of players and activities across the ERP project life cycle", *Information & Management*, Vol. 41 No. 3, pp. 257-278.

Srinivasan, U. and Arunasalam, B. (2013), "Leveraging big data analytics to reduce healthcare costs", *IT Professional*, Vol. 15 No. 6, pp. 21-28.

Srivastava, D.K. (2014), "Big challenges in big data research", *Data Mining and Knowledge Engineering*, Vol. 6 No. 7, pp. 282-286.

Teece, D.J. (2015), "Intangible assets and a theory of heterogeneous firms", *Intangibles, Market Failure and Innovation Performance*, Springer, Cham, pp. 217-239.

Teece, D.J., Pisano, G. and Shuen, A. (1997), "Dynamic capabilities and strategic management", *Strategic Management Journal*, Vol. 18 No. 7, pp. 509-533.

Tellis, G.J., Yin, E. and Bell, S. (2009), "Global consumer innovativeness: cross-country differences and demographic commonalities", *Journal of International Marketing*, Vol. 17 No. 2, pp. 1-22.

Umble, E.J. and Umble, M.M. (2002), "Avoiding ERP implementation failure", *Industrial Management*, Vol. 44 No. 1, pp. 25-25.

Upadhaya, B., Munir, R. and Blount, Y. (2014), "Association between performance measurement systems and organizational effectiveness", *International Journal of Operations & Production Management*, Vol. 34 No. 7, pp. 853-875.

Utzig, C., Holland, D., Horvath, M. and Menorah, M. (2013), "ERP in the cloud is it ready? Are you?", *Perspective*, Booz & Company, pp. 1-9.

Vogel, R. and Güttel, W.H. (2013), "The dynamic capability view in strategic management: a bibliometric review", *International Journal of Management Reviews*, Vol. 15 No. 4, pp. 426-446.

Waller, M.A. and Fawcett, S.E. (2013), "Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management", *Journal of Business Logistics*, Vol. 34 No. 2, pp. 77-84.

Wamba, S.F., Akter, S., Edwards, A., Chopin, G. and Gnanzou, D. (2015), "How 'big data' can make big impact: findings from a systematic review and a longitudinal case study", *International Journal of Production Economics*, Vol. 41, January, pp. 77-94.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R. and Childe, S.J. (2017), "Big data analytics and firm performance: effects of dynamic capabilities", *Journal of Business Research*, Vol. 70, pp. 356-365.

Wang, G., Gunasekaran, A., Ngai, E.W. and Papadopoulos, T. (2016), "Big data analytics in logistics and supply chain management: certain investigations for research and applications", *International Journal of Production Economics*, Vol. 176, June, pp. 98-110.

Wang, N., Liang, H., Zhong, W., Xue, Y. and Xiao, J. (2012), "Resource structuring or capability building? An empirical study of the business value of information technology", *Journal of Management Information Systems*, Vol. 29 No. 2, pp. 325-367.

Wernerfelt, B. (1984), "A resource-based view of the firm", *Strategic Management Journal*, Vol. 5 No. 2, pp. 171-180.

Winter, S.G. (2003), "Understanding dynamic capabilities", *Strategic Management Journal*, Vol. 24 No. 10, pp. 991-995.

Wu, S.P.J., Straub, D.W. and Liang, T.P. (2015), "How information technology governance mechanisms and strategic alignment influence organizational performance: insights from a matched survey of business and IT managers", *MIS Quarterly*, Vol. 39 No. 2, pp. 497-518.

Yu, Y., Li, M., Li, X., Zhao, J.L. and Zhao, D. (2018), "Effects of entrepreneurship and IT fashion on SMEs' transformation toward cloud service through mediation of trust", *Information & Management*.

Appendix

Latent variable	Indicator	Measurement constructs	Journal paper considered
Organizational factors (OF)	OF1	Strategic goals and objectives	Gupta and Misra (2016)
	OF2	Communication	
	OF3	Implementation strategy	
	OF4	Business process re-engineering	
	OF5	Project management	
	OF6	Project budget	
	OF7	Organization resistance	
People factors (PF)	PF1	User involvement	Gupta and Misra (2016)
	PF2	Selection of vendor	
	PF3	Project team	
	PF4	Top management support	
	PF5	Training of user	
	PF6	Trust on vendor	
Technological factors (TF)	TF1	Selection of ERP package	Gupta and Misra (2016)
	TF2	IT infrastructure	
	TF3	Data integrity and system testing	
	TF4	Functionality	
Big data predictive analytics (BDPA)	Data (D)		Gupta and George (2016), Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud (2017), Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba and Roubaud (2017)
	D1	Access to very large, unstructured, or fast-moving data for analysis	
	D2	Integrate data from multiple internal sources into a data warehouse for easy access	
	D3	Integrate external data with internal to facilitate high-value analysis of business environment	
	Managerial skills (MS)		
	MS1	Big data analytics managers are able to work with functional managers, suppliers and customers	
	MS2	Big data analytics managers are able to coordinate big data-related activities	
	MS3	Big data analytics managers are able to anticipate the future business needs	
	MS4	Big data analytics managers have a good sense of where to apply big data	
	MS5	Big data analytics managers are able to understand and evaluate the output extracted from big data	
	Technical skills (TS)		
	TS1	Big data analytics training to employees	
	TS2	Hire new employees that already have the big data analytics skills	
	TS3	Big data analytics staff has the right skills to accomplish their jobs successfully	
	TS4	Big data analytics staff has suitable education to fulfill their jobs	

Table AI. Operationalization of Constructs

(*continued*)

Latent variable	Indicator	Measurement constructs	Journal paper considered
	TS5	Big data analytics staff holds suitable work experience to accomplish their jobs successfully	
Control orientation (CO)	CO1	Predictability and efficiency	Deshpande *et al.* (1993), Khazanchi *et al.* (2007), Liu *et al.* (2010), Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud (2017), Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba and Roubaud (2017)
	CO2	Leveraging core competencies	
	CO3	Profile valuation	
	CO4	Value–practice interactions	
	CO5	Value congruence	
Flexible orientation (FO)	FO1	Innovation paradoxes	Deshpandé *et al.* (1993), Khazanchi *et al.* (2007), Liu *et al.* (2010); Dubey, Gunasekaran, Childe, Papadopoulos, Hazen, Giannakis and Roubaud (2017), Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba and Roubaud (2017)
	FO2	Creativity	
	FO3	Spontaneity	
	FO4	Risk-taking	
Firm performance (FP)	Market performance (MP)		Gupta and George (2016)
	MP1	Exploring new markets more quickly than competitors	
	MP2	Introducing new products or services into the market faster than competitors	
	MP3	Success rate of new products or services has been higher than competitors	
	MP4	Market share has exceeded that of competitors	
	Operational performance (OP)		
	OP1	Productivity has exceeded compared to competitors	
	OP2	Profit rate has exceeded compared to competitors	
	OP3	Return on investment (ROI) has exceeded compared to competitors	
	OP4	Sales revenue has exceeded compared to competitors	

Table AI.

	BDPA	CERP	MP	OP	CO	FO	SE	*p*-value
D1	0.664	0.589	0.094	−0.405	−0.103	−0.077	0.058	< 0.001
D2	0.709	0.407	−0.098	0.113	−0.54	0.108	0.058	< 0.001
D3	0.739	0.388	−0.049	0.003	−0.228	−0.142	0.058	< 0.001
MS1	0.878	−0.004	−0.049	0.021	−0.183	0.047	0.056	< 0.001
MS2	0.902	0.061	−0.2	0.203	−0.294	0.188	0.056	< 0.001
MS3	0.907	0.071	−0.093	−0.01	−0.259	0.155	0.056	< 0.001
MS4	0.904	0.025	0.081	−0.14	−0.214	0.171	0.056	< 0.001
MS5	0.913	0.019	−0.008	−0.031	−0.135	0.085	0.056	< 0.001
TS1	0.816	−0.182	−0.04	0.015	0.236	−0.155	0.057	< 0.001
TS2	0.814	−0.31	−0.032	0.084	0.239	−0.144	0.057	< 0.001
TS3	0.87	−0.299	−0.014	0.049	0.407	−0.325	0.056	< 0.001
TS4	0.858	−0.135	−0.144	−0.084	0.282	−0.184	0.056	< 0.001
TS5	0.855	−0.28	−0.074	0.026	0.477	−0.292	0.056	< 0.001
OF1	−0.256	0.77	−0.215	0.254	−0.017	−0.01	0.057	< 0.001
OF2	−0.143	0.795	0.002	0.063	−0.163	0.014	0.057	< 0.001
0F3	0.195	0.78	0.217	−0.28	−0.015	−0.124	0.057	< 0.001
OF4	−0.117	0.794	0.068	0.051	−0.001	−0.106	0.057	< 0.001
OF5	−0.261	0.816	0.047	0.04	−0.004	0.037	0.057	< 0.001
OF6	−0.096	0.775	0.177	−0.206	0.136	−0.162	0.057	< 0.001
OF7	−0.11	0.802	0.166	−0.197	0.077	−0.061	0.057	< 0.001
PF1	−0.007	0.776	0.091	−0.255	0.109	−0.163	0.057	< 0.001
PF2	0.075	0.804	−0.062	0	−0.071	0.017	0.057	< 0.001
PF3	0.164	0.805	−0.202	0.016	0.037	−0.117	0.057	< 0.001
PF4	−0.152	0.803	−0.386	0.297	0.001	0.046	0.057	< 0.001
PF5	0.064	0.806	−0.199	0.134	−0.157	−0.013	0.057	< 0.001
PF6	0.103	0.807	−0.208	−0.078	−0.279	0.169	0.057	< 0.001
TF1	0.037	0.754	−0.184	−0.059	−0.048	0.168	0.057	< 0.001
TF2	0.034	0.629	0.209	−0.234	0.034	−0.115	0.059	< 0.001
TF3	0.281	0.747	0.048	−0.115	−0.24	0.124	0.058	< 0.001
TF4	0.151	0.75	−0.068	−0.133	0.072	0.105	0.058	< 0.001
MP1	0.024	−0.072	0.885	−0.01	−0.04	−0.05	0.056	< 0.001
MP2	0.058	−0.012	0.916	−0.015	−0.246	0.055	0.056	< 0.001
MP3	−0.035	−0.071	0.92	−0.077	0.081	−0.105	0.056	< 0.001
MP4	−0.147	−0.053	0.836	0.2	0.232	−0.179	0.057	< 0.001
OP1	0.046	0.178	−0.296	0.836	−0.41	0.258	0.057	< 0.001
OP2	−0.075	−0.028	−0.013	0.937	−0.07	0.016	0.056	< 0.001
OP3	−0.007	0.003	−0.073	0.932	0.01	−0.123	0.056	< 0.001
OP4	−0.038	−0.076	0.008	0.93	0.036	−0.105	0.056	< 0.001
CO1	−0.13	−0.047	0.047	−0.028	0.879	0.133	0.056	< 0.001
CO2	−0.038	−0.062	0.08	−0.026	0.889	−0.087	0.056	< 0.001
CO3	−0.054	−0.075	−0.074	0.081	0.895	−0.163	0.056	< 0.001
CO4	0.111	−0.02	−0.115	−0.13	0.889	−0.048	0.056	< 0.001
CO5	0.043	0.087	−0.24	0.061	0.867	−0.159	0.056	< 0.001
FO1	0.014	−0.079	0.066	−0.008	−0.067	0.817	0.057	< 0.001
FO2	−0.05	−0.053	−0.188	0.092	−0.172	0.922	0.056	< 0.001
FO3	−0.049	0.045	−0.056	−0.078	0.026	0.891	0.056	< 0.001
FO4	−0.147	−0.056	−0.012	0.059	−0.125	0.841	0.057	< 0.001

Note: Loadings are un-rotated and cross-loadings are oblique-rotated, both after separate Kaiser normalizations

Table AII.
Combined loadings and cross-loadings

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