Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture

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Abstract

The importance of big data and predictive analytics has been at the forefront of research for operations and manufacturing management. Literature has reported the influence of big data and predictive analytics for improved supply chain and operational performance, but there has been a paucity of literature regarding the role of external institutional pressures on the resources of the organization to build big data capability. To address this gap, this paper draws on the resource-based view of the firm, institutional theory and organizational culture to develop and test a model that describes the importance of resources for building capabilities, skills, and big data culture and subsequently improving cost and operational performance. We test our research hypotheses using 195 surveys, gathered using a pre-tested questionnaire. Our contribution lies in providing insights regarding the role of external pressures on the selection of resources under moderating effect of big data culture and their utilisation for capability building, and how this capability affects cost and operational performance.

Keywords: Big Data, Predictive Analytics, Institutional Theory, Resource Based View, Manufacturing Performance, PLS SEM

1. Introduction

The ability to access, analyse, and manage vast volumes of data with the support of robust information architecture – that is, big data predictive analytics (BDPA) – to improve the performance of manufacturing organizations has generated enormous interest among academia and industry (Matthias et al., 2017; Malomo and Sena, 2017; Srinivasan and Swink, 2018; Delen and Zolbanin, 2018; Aydiner et al., 2019). The information systems literature broadly conceptualizes BDPA as organizational capability (Srinivasan and Swink, 2018), to process large volumes and varieties of data with the velocity required to gain relevant insights, thereby enabling organizations to gain competitive advantage (Akter et al., 2016; Gupta and George, 2016; Fosso Wamba et al., 2015; Pauleen and Wang, 2017; Srinivasan and Swink, 2018). The term 'big data' is often used to describe massive, complex, and real-time data that requires sophisticated management, analytical and processing techniques to extract management insights (Gupta and George, 2016; Jin et al., 2016; Wang and Zhang, 2016; Wang et al., 2016; Sumbal et al., 2017; Khan and Vorley, 2017). The predictive analytics statistical models try to predict future behaviour based on the assumption that what has happened in the past will continue to happen in the future.

Chen et al. (2012) argue that BDPA can make a big impact on any sector including manufacturing. Other scholars note the popularity of BDPA tools only amongst manufacturing organizations that seek to improve their complex decision making and their manufacturing quality while reducing support costs by improving defect tracking and forecasting abilities (Dutta and Bose, 2015; Dubey et al., 2016). Lee et al. (2013) argue that with the use of predictive tools big data is transformed into useful information to achieve better enterprise control and optimization. Auschitzky et al. (2014) further argue drawing upon prior experiences of data-driven manufacturing practices that big data may be a recent wave, but that the practice of advanced analytics is grounded in years of statistical research and scientific application. Hence, BDPA can be a critical tool for realizing improvements in yield, particularly in any manufacturing environment in which process complexity, process variability, and capacity constraints are present (Zhong et al. 2016).

Despite the excitement for BDPA amongst academia and managers, exploiting BDPA for enhanced organizational performance is still one of the major challenges for both academics and practitioners (George et al., 2014; Kache and Seuring, 2017). Top management may be embracing BDPA to publicize their initiatives for satisfying stakeholders' expectations (Chen et al., 2012; Dutta and Bose, 2015) without being fully committed to BDPA-led decision making. Further, if the quality of the data is not controlled properly then the decision-making process guided by BDPA may even have negative consequences (Hazen et al., 2014; Janssen et al., 2017). Therefore, even though research has broadly discussed characteristics and the impact of BDPA on performance (organizational or operational performance) (see Gupta and George, 2016; Ren et al., 2017; Gunasekaran et al., 2017; Fosso Wamba et al., 2017; Srinivas and Swink, 2018; Wang et al., 2018; Aydiner et al., 2019), research on the influence of BDPA on manufacturing performance under the influence of external conditions is limited (Gunasekaran et al., 2017; Gunther et al., 2017). For instance, Gunther et al. (2017) argues that two debates in the information management literature which need to be addressed. Firstly, how organizations manage data access and secondly, how organizations are prepared to deal with external pressures arising from ethical concerns and regulatory norms. Only few studies utilize a theory-focused approach to explain how BDPA can help to achieve enhanced performance (see Chen et al., 2015; Gunasekaran et al., 2017; Srinivasan and Swink, 2018; Aydiner et al., 2019). Most of the studies have utilized dynamic capability view (Chen et al., 2015; Akter et al., 2016; Wamba et al., 2017) or organizational information processing theory (Srinivasan and Swink, 2018). However, a more holistic view – overcoming the issue of contradictory findings

– of BDPA and its associated capabilities has not been advanced. In summary, we can argue that the existing literature provides limited understanding of the organizational-level usage of BDPA as well as the related influence on manufacturing performance. To fill this gap, we address the following research questions: (1) *What are the antecedents of the intention of the organizations engaged in manufacturing activities to adopt BDPA?* (2) *How do these antecedents affect the cost performance/ operational performance of manufacturing organizations?*

We use an overarching theoretical lens based on three complementary theories: *institutional theory* (DiMaggio and Powell, 1983), *resource-based view* (RBV) (Barney, 1991) and *organizational culture* (Hewett et al. 2002; Khazanchi et al. 2007). Institutional theory sheds light on adoption of BDPA by addressing the interrelationships and coordination among stakeholders and the focal organization. RBV emphasizes the role of internal resources in influencing organization strategies and performance (Barney, 1991). Previous studies have attempted to integrate institutional theory and RBV to explain organizational decision making as independent motives for organizations (Oliver, 1997) and different roles of external pressures and internal resources as well as their relationships (Zhang and Dhaliwal, 2009; Zheng et al., 2013; Tatoglu et al. 2016). However, in the BDPA context it is not well-understood how external pressures and organizational culture can affect internal resource development, and in turn, the adoption of BDPA to enhance operational performance. Braganza et al. (2017) argues, following an RBV perspective, that big data related organizational resources can be exploited to gain competitive advantage when they meet VRIN (*value, rarity, imperfect imitability and non-substitutability*) requirements (Barney, 1991). However, the key challenge is that big data erodes the theory VRIN's (*value, rarity, imperfect imitability and non-substitutability*) assumptions (Braganza et al. 2017), as the core resource, data, is not rare. For instance, the core of big data is data which is generally utilized by organizations can be easily accessed by competitors as well (possibly with payment) (Braganza et al. 2017). Physical resources such as hardware, software, servers etc. are neither rare nor imperfectly inimitable. People with critical data skills such as data scientists or individuals with high level of statistical or computational skills are harder to locate. Yet, even these resources can be easily exploited, in a RBV sense, as they can be poached by competitors. Teo et al. (2003) argue that internet driven supply chain innovations are driven more by institutional rationale than technical reasoning. Yet, the findings of the prior studies on how institutional factors affect organization choice of selection of resources and innovation have been mixed (Liu et al. 2010). Hence, the moderating effect of *organizational culture* may help to resolve the inconsistency in previous studies (Greening and Gray, 1994; Hewett et al. 2002; Leidner and Kayworth, 2006; Kostova et al., 2008; Scott, 2008). Therefore, in this study we have synthesized these perspectives to provide a better understanding of how manufacturing organizations with a specific resource portfolio make decisions considering certain external pressures (Zhang and Dhaliwal, 2009; Zheng et al., 2013; Braganza et al., 2017). We answer our research questions based on a sample of 195 manufacturing firms, using PLS based structural equation modelling. To theoretically substantiate our empirical results, we integrate institutional theory, RBV and big data culture, because neither perspective can, on its own, explain direct performance implications of BDPA on organizational performance.

The rest of the paper is organized as follows. In the next section, we present our theoretical model and our research hypotheses. The subsequent sections consecutively describe the construct operationalization, the data collection method and the non-response bias test followed by the data analysis procedure and the results of model testing, and discussions. Finally, we conclude, with limitations and further research directions.

2. Theoretical Model and Hypotheses Development

Previous studies have tended to examine the impact of big data analytics (BDA)/ big data predictive analytics (BDPA) on an organization's overall performance (Chen et al., 2015; Akter et al., 2016; Gupta and George, 2016; Fosso Wamba et al., 2017; Gunasekaran et al., 2017; Srinivasan and Swink, 2018; Aydiner et al., 2019). The majority of these studies found that organizations using BDA/BDPA to take complex decisions are more competitive in the market place (Chen et al., 2015; Fosso Wamba et al., 2017; Srinivasan and Swink, 2018). However, Aydiner et al. (2019) in one of their recent studies have concluded that desired level of performance cannot be achieved in organizations which fail to respond effectively to relevant external pressures or environmental demand. Therefore, this study integrates three different perspectives: first, RBV (Barney, 1991; Grant, 1991; Amit and Schoemaker, 1993; Wu et al., 2006), second, institutional theory (DiMaggio and Powell, 1983; Heugens and Lander, 2009; Theodorakopoulos et al., 2015; Demirbag et al. 2007, 2017; Allen et al., 2018) and third, organizational culture (Khazanchi et al., 2007; Demirbag et al., 2007; Liu et al., 2010; Dubey et al., 2017) to examine the relationship between institutional factors and resources of the firm and cost performance/operational performance under moderating effect of big data driven culture (see Figure 1). RBV explains how an organization can achieve competitive advantage by creating bundles of strategic resources and/or capabilities. In BDPA, connectivity (a tangible resource) and information sharing (an intangible resource) can help to build BDPA capability (Gunasekaran et al., 2017). Gupta and George (2016) argue that tangible resources (basic resources, technology and data) and human skills (technical skills and managerial skills) under the moderating effect of big data driven culture help to build BDPA capabilities.

Following the tenets of institutional theory, firms operate within a social framework of norms, values, and taken-for-granted assumptions about what constitutes appropriate or acceptable economic behaviour (Oliver, 1997; Peng et al., 2009). Zukin and DiMaggio (1990) assume that the motives of human behaviour extend beyond economic optimization to social justification and social obligation. Oliver (1997) further argues that since individuals or organizations are partial captives of social convention, there is a tendency among the elements of the society to shape their decisions in alignment with social norms. DiMaggio and Powell (1983) and Oliver (1997) claim that conformity to social norms contributes to organizational success. Following, Tatoglu et al. (2016)'s arguments, we posit that despite the nuances in various institutional perspectives, embeddedness is a fundamental consideration while examining the adoption of BDPA at organizational level. Oliver (1997) argues that RBV suggests that inimitability is a mobility barrier, but that institutional barriers focus on the extent to which resources are politically/ culturally acceptable. Therefore, following this logic we can argue that institutional differences between different organizations impact all aspects of the organization's practices (Tatoglu et al., 2016). Thus by integrating these theories, we can explain how the organizational BDPA capability is built; and this capability is one of the antecedents of the cost performance and operational performance.

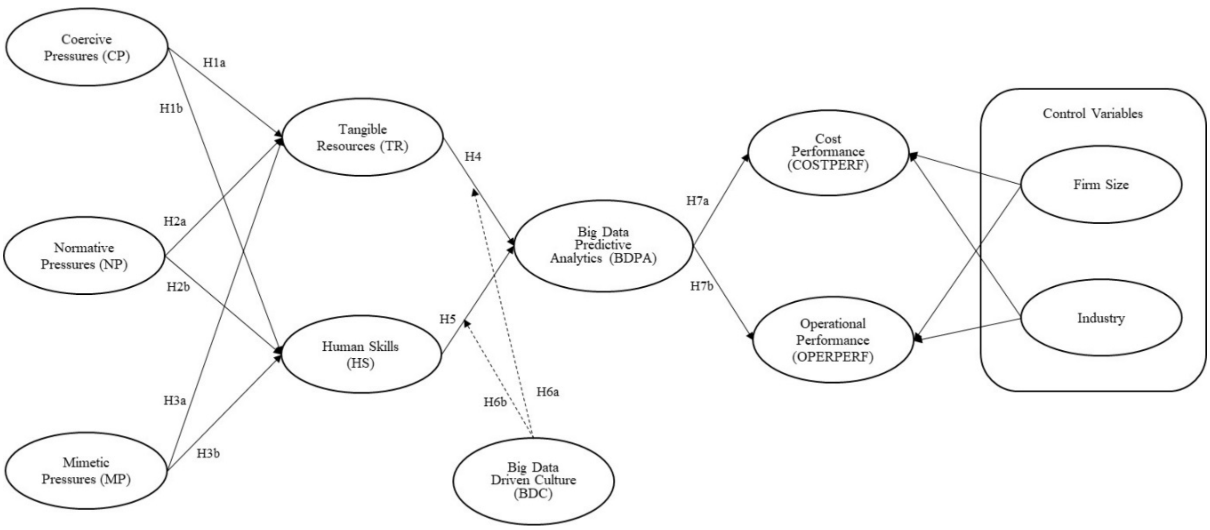

Figure 1: Theoretical Model

Hence, Figure 1 illustrates the conceptual model linking the antecedent factors (institutional factors and organizational resources), moderating construct (big data culture) and BDPA. In turn, BDPA affects the cost performance and operational performance of the manufacturing organizations. In addition, we utilise two control variables that may affect the performance measures. Appendix A, provides the definitions of constructs examined in this study.

2.1 Institutional forces and firm resources

Ciftci et al. (2019) argue that institutional theory has multiple strands: micro sociological approaches, which focus on internal organizational dynamics (c.f. DiMaggio and Powell, 1983) and macro level economic and socio-economic approaches that seek to establish association between a firm behaviour to wider societal realities. Demirbag et al. (2007, 2017) further argues that institutional theory has emerged as an alternative approach to examine the organizational behaviour in response to external influences. Following DiMaggio and Powell (1983), institutional theory assumes that individuals are motivated to comply with external social pressures whereas the RBV assumes that individuals are motivated to optimize available economic choices. Hence, institutional theory has several implications for RBV (see Oliver, 1997). Following Oliver (1997) and Hughes et al. (2017), we argue that institutional pressures affect positively firm resources, which further help building the BDPA organizational capability. Liang et al. (2007) argues that in contrast to other organizational theories such as transaction cost economics (TCE) and resource dependence theory (RDT), institutional theory posits that structural and behavioural changes in organizations are driven less by competition and desire for efficiency, but more by the need for organizational legitimacy. DiMaggio and Powell (1983) argue that this drive for legitimacy fosters organizations to embrace institutionalization, which eventually makes organizations similar to each other without necessarily making then more efficient, giving rise to institutional isomorphism. DiMaggio and Powell (1983) identify three types of institutional isomorphism, coercive, normative and mimetic, whereas Scott (2001) defines three components of the institutional environment: regulatory, cognitive and normative institutions that are motivated by coercive, mimetic and normative mechanisms, respectively.

2.1.1 Coercive pressure

Coercive pressure (CP) may arise from government regulations and policies from industry and professional networks and associations, or in the form of competitive necessity within an industry or market segment (DiMaggio and Powell, 1983; Liang et al., 2007; Thedorakopoulos et al., 2015; Demirbag et al., 2007, 2017; Ciftci et al., 2019). Demirbag et al. (2007) argue that CP emanates from formal and informal pressures exerted on organizations by other organizations upon which they are dependent. Following Liang et al. (2007) and Zheng et al. (2013) arguments, we argue in this paper that social pressures may influence the selection of technology and BDPA. Boyd and Crawford (2012) argue that legislation has already been proposed to curb the collection and retention of data, usually over concerns about privacy (e.g., the US Do Not Track Online Act of 2011). Features such as personalization allow rapid access to more relevant information, but they present difficult ethical questions and fragment the public in troubling ways. For, instance political and social issues may have a negative impact on the effectiveness of security policies, organizations are open to malicious damage from unsatisfied employees, and they are probably even more open to damage causes by satisfied but careful employees. Conforming to these institutional expectations and norms is critical for organization to maintain its legitimacy in the field, which in turn, ensures its access to important scarce resources (Liu et al. 2010). Liu et al. (2010) further argue that when an organization is deciding whether to adopt an innovation (like BDPA in our case), it will try to obtain information related to institutional expectations and norms, use the information to appraise the potential costs and benefits of adopting BDPA, and position itself accordingly to hedge against uncertainties (Choi and Eboch, 1998; Scott, 2008). Hence, organizations are obliged to select safer technologies, which can adhere to social pressures rather than economic benefits. Jackson and Schuler (1995) argue that institutional logic provides theoretical perspective to analyse the recruitment or selection process to comply with the legitimacy of organizations. Therefore,

H1a: Coercive pressure (CP) has significant impact on selection of tangible resources (TR).

H1b: Coercive pressure (CP) has significant impact on selection of human skills (HS).

2.1.2 Normative pressure

Normative pressure (NP) on focal organizations is the pressures that emanates from professionalization (Zheng et al., 2013). Within each industry, a pool of almost interchangeable employees is created through formal education and professional networks (DiMaggio and Powell, 1983; Liang et al., 2007; Zheng et al., 2013). Teo et al. (2003) argue that NP acts as an impetus for the adoption of interorganizational information systems. Liu et al. (2010) further argue that organizations – in order to avoid being locked out of cooperative relationships and to ensure access to organizational resources – will align with normative pressures and be inclined to adopt innovative technologies if this pressure materializes. Thus, due to similar orientation and disposition, these individuals shape organizational behaviour. In the BDPA era, organizations may be pressurised to embrace data driven decisions due to more managers with a technology and management background occupying the upper echelons (Gupta and George, 2016; Akhtar et al., 2018). Hence, we can argue that NP has significant influence on resources selection:

H2a: Normative pressure (NP) has significant impact on selection of tangible resources (TR);

H2b: Normative pressure (NP) has significant impact on building human skills (HS);

2.1.3 Mimetic pressure

Mimetic pressure (MP) results from the organizations' tendency to mimic others. Mimicking may result from poor understanding of technologies and poor direction. When goals are ambiguous or when the environmental uncertainty is high, organizations may model themselves after other organizations perceived to be legitimate or successful (DiMaggio and Powell, 1983). In the BDPA era, the majority of organizations may 'borrow' from a few successful peers by observing what they are doing and what they have to say on big data driven decision-making benefits (Srinivasan and Swink, 2018). As a rational response to the uncertainty, organizations tend to be based on BDPA decision-making benefits and translate their beliefs into actions. Hence, we hypothesize that

H3a: Mimetic pressure (MP) has significant impact on selection of tangible resources (TR);

H3b: Mimetic pressure (MP) has significant impact on building human skills (HS);

2.2 Firm resources and BDPA capability

Following RBV logic, resources are classified as physical capital, human capital, and organizational capital (Barney, 1991), and have been extended to include other resources, for instance financial capital, technological capital and reputational capital (Grant, 1991). Groβler and Grubner (2006) argue that resources are something that a firm possesses or has access to. They may be tangible, such as infrastructure, or intangible, such as information or knowledge sharing (Groβler and Grubner, 2006). Gupta and George (2016) have further classified resources into three categories: first, tangible resources, which include data, technology and basic resources such as time and investment; second, human resources, which include managerial skills and technical skills; and third, intangible resources, which include a data-driven culture and the intensity of organizational learning.

The literature on RBV has argued that organizational capabilities are defined as a higher order construct, which relies on the bundling of resources (Wu et al., 2006). Grant (1991) further argue that when resources are combined and utilized together they create capabilities. In BDPA studies, scholars argue that BDPA is an organizational capability, which explains how organization can leverage BDPA to achieve better organizational performance (Gupta and George, 2016; Gunasekaran et al., 2017). The BDPA capability can be created by combining strategic resources such as data connectivity and information sharing (Gunasekaran et al., 2017) and human skills and big data culture (Gupta and George, 2016) which can enhance operational performance (Srinivasan and Swink, 2018).

2.2.1 Tangible resources (TR)

Following RBV logic, we can argue that tangible resources can be acquired from the market. This may include financial resources (e.g., debt, equity) and physical assets (e.g., equipment and facilities) of the firm. Following Gunasekaran et al. (2017) and Gupta and George (2016) arguments, we further classified TR into three categories:

(i) Data connectivity

Data connectivity refers to a technological resource, which enables the effective sharing of information (Brandon-Jones et al., 2014; Gunasekaran et al., 2017). In addition, data connectivity facilitates improved decision-making and coordination (Davenport and Harris, 2007; Gunasekaran et al., 2017). Data connectivity and quality information sharing (Gunasekaran et al., 2017; Fosso Wamba et al., 2017) can be combined together to create BDPA.

(ii) Technology

Gupta and George (2016) argue that big data calls for novel technologies that are capable of handling volume, variety and velocity to extract valuable and authentic information. 80 percent of the stored data in RDBMS (relational database management systems) are in unstructured format. Consequently, organizations have started to move beyond RDBMS for storing and analysing data. In recent years' technologies, such as Hadoop have emerged which allow distributed storage and parallel processing of unstructured datasets. NoQSL (Not Only SQL) databases are another form of technologies, which have been used in recent years for storage and retrieving non-relational unstructured data.

(iii) Basic Resources

Besides data and technology, organizations need to make significant investments in their big data initiatives. Owing to the newness of big data and its related technology and tasks, most organizations are yet to explore the standard operating procedures to implement these initiatives. Therefore, it is likely that big data investments may not start yielding return on their investment immediately. It is important that organizations are persistent and willing to invest significant time to their BDPA initiatives to achieve desired success (Gupta and George, 2016). Gunasekaran et al. (2017) argue that big data assimilation is a three-stage process; hence, time is one of the crucial factor for realizing potential benefits from big data technology. Following Gupta and George (2016), we argue that investments and time are two important basic resources. Therefore,

H4: Tangible resources have a positive impact on BDPA.

2.2.2 Human skills

McAfee et al. (2012) argues that in order to meet the growing demand of the data driven world, new skills and new management styles are needed. Waller and Fawcett (2013) argue that BDPA requires different sets of skills. For instance, Waller and Fawcett (2013, p.79) have noted important skills for big data and predictive analytics professional as: *statistics, forecasting, optimization, discrete event simulation, applied probability, applied mathematical modelling, finance, economics, marketing and accounting*. Previous IT capability research has suggested technical and managerial skills as critical dimensions of human resources with respect to IT (Bharadwaj, 2000; Chae et al. 2014). Based on prior IT capability literature, Gupta and George (2016) argue that human resources are critical for building the BDPA capability. Human resources can be defined as a function of experience, knowledge, business acumen, problem solving abilities, leadership qualities and relationships with others (Wade and Hulland, 2004; Akhtar et al., 2018). For instance, technical “big data” skills refer to know-how required to use new technology to extract relevant management insights from big data. These skills include competencies in machine learning, data extraction, data cleaning, statistical analysis and understanding of programming paradigms such as MapReduce (Gupta and George, 2016). Waller and Fawcett (2013) noted that owing to newness of big data technology and the skills associated with it, organizations with big data- skilled employees are likely to have significant advantage over their competitors. However, the technical skills alone cannot provide competitive edge for long time since, big data skills may eventually get dispersed among individuals working in the same (or different) organizations, thereby making this resource ordinary across firms over time (Nonaka et al. 2000). Gupta and George (2016) argue that organization can build technical skills via hiring new talent and/ or by training their current employees, managerial skills are highly firm-specific and are developed over time by individuals. Hence, managerial skills are tacit and thus are heterogeneously dispersed across firms. Moreover, mutual trust and good working relationship between big data managers and other functional managers will likely enhance superior human big data skills, which may be difficult to copy by other organizations. Hence, we can hypothesize as,

H5: Human skills have a positive impact on BDPA.

2.2.3 Big data culture

Prior studies have increasingly tout that organizational culture plays an important role in shaping organizational strategies (i.e. Khazanchi et al., 2007; Demirbag et al., 2007; Liu et al., 2010; Dubey et al., 2017). Further, organizational culture influences human behaviour, motivation, knowledge transfer, team work, collaboration and organizational leadership (see, Allaire and Firsirotu, 1984; Marcoulides and Heck, 1993; Yong and Pheng, 2008; Kostova et al., 2008; Zu et al., 2010). Organizational culture refers to a collection of shared assumptions, values, and beliefs that is reflected in organizational practices and goals that helps its members to understand organizational functioning (Deshpande et al., 1993; Khazanchi et al., 2007; Liu et al., 2010). Organizational culture has been noted in various works as a source of competitive advantage (see Barney, 1995; Liu et al., 2010; Teece, 2015). Institutional theorists acknowledge that organizations exercise their own choice in responding to external pressures (Oliver, 1991; Demirbag et al., 2007; Zhang and Dhaliwal, 2009; Liu et al., 2010; Zheng et al., 2013; Braganza et al., 2017). For instance, Oliver (1991) argues that "*institutional theory can accommodate interest seeking, active organizational behaviour when organization's responses to institutional pressures are not assumed to be invariably passive and conforming across all institutional conditions*" (p. 146). Previous studies have noted that development and group culture and rational/ hierarchical cultures have differential effects on organizations interpretations of external events, and thus differentially affect their responses to the expectations and requirements of the environment (Deshpande et al., 1993; Khazanchi et al., 2007; Liu et al., 2010). The big data culture (BDC) or the lack of it may be one of the reasons that most of the organizations have failed to realize its potential benefits (LaValle et al., 2011). Along the same lines, Gupta and George (2016) have argued that BDC is critical for the success of big data initiatives in organizations. McAfee et al. (2012) and Ross et al. (2013) have noted that a big data driven culture has significant impact on big data ownership in the organizations. Shamim et al. (2018) argue that organizational culture has the ability to enhance a firm's ability to benefit from big data. Hence, it is logical to argue that the promotion of a culture of *collaboration*, *knowledge exchange* and *big data & predictive analytics* can promote data driven decision making capabilities. Therefore,

H6a/b: Big data culture (BDC) has a positive moderating effect on the paths connecting TR/HS and BDPA.

2.2.4 Big data and predictive analytics (BDPA) and cost performance/ operational performance

Many of the perspectives that nominated the early thinking concerning firm performance have their roots in traditional economic theory with an emphasis on market power and industry structure as determinants of firm performance (Wilkund, 1999; Hitt et al. 2001; Neely et al. 1995). These studies emphasize economies of scale and scope, the optimization of transactions costs across the channel partners to explain different firm-level strategies for performance. However, Neely et al. (1995) argue that modern performance measurement systems (PMS) is beyond traditional quantification of effectiveness and efficiency. PMS can provide important feedback information to managers to monitor performance, reveal progress, enhance motivation and communication, and diagnose problems (Waggoner et al. 1999; Kennerley and Neely, 2003). Srinivasan and Swink (2018) argue that by incorporating richer, more current information into operational decisions and by developing better solutions quickly, manufacturing organizations can avoid expensive actions such as overtime production, lost sales and excess inventories. Bayraktar et al. (2009) have tested empirically that information system practices have positive and significant impact on operational performance. Further, Gunasekaran et al. (2017) noted based on empirical results that organizations have successfully exploited BDPA to enhance their supply chain performance and organizational performance. Ayinder et al. (2019) found significant association between the level of BDPA adoption and business performance/ firm performance via business process performance. Because of these benefits, we argue that the BDPA enabled manufacturing activities enables the managers to lower operating costs, product quality and improve product delivery (availability). Hence:

H7a/b: Big data and predictive analytics (BDPA) is positively associated with: (a) cost performance (COST_PERF) and (b) operational performance (OPER_PERF).

2.3 Statistical Controls

To better account for the differences between organizations, we included firm size (FS) (log of firm sales in US $ millions) as big organizations have more resources to develop BDPA than small size organizations. Secondly, we controlled for industry using dummy variables to differentiate various industries (auto components manufacturers, cement manufacturers, chemical products and wood products) (Srinivasan and Swink, 2018).

3. Research design

To test our research hypotheses, we have collected data using a survey-based instrument by adopting appropriate measures from existing literature. The dimensions were measured on five-point Likert scales with anchors ranging from strongly disagree (1) to strongly agree (5) (Chen and Paulraj, 2004; Bayraktar et al., 2009; Gupta and George, 2016; Gunasekaran et al., 2017; Srinivasan and Swink, 2018). For measuring organizational performance, existing literature used objective and subjective measures. Objective measures included return on assets (ROA), market share, sales, export promotion, growth rates in domestic and sales growth rate (Hitt et al., 1982; Hitt and Ireland, 1985). Subjective performance measures include management's perceptions of productivity, profitability, market share, and customer satisfaction relative to competitors (Dess and Robinson, 1984). Objective measures were difficult to obtain in our study as participants did not want to share this sensitive information and rather restricted themselves to fill out perceptual scales. Furthermore, we could not get hold of objective data of our sample due to the size of the firms as well as the Indian context in which we collected the data. Emerging markets do not have the same level of data availability as developed markets (e.g. USA or UK). Before we finalized the instrument for data collection, we pre-tested the instrument in two stages following the good practice suggested by Chen and Paulraj (2004) and Dillman (2011). First, we requested eight experienced researchers to critique the wording of the questionnaire for ambiguity, clarity, and appropriateness of the measures used to operationalize each construct.

We further modified the wording of the questions in the survey instrument following inputs of experts. We e-mailed the survey instrument to 10 senior managers and consultants who are currently looking after their organizations' data analytics departments. These managers and consultants were asked to review critically the survey instrument for structure, readability, ambiguity and completeness. We included the suggestions from the consultants and managers in the final survey instrument. The constructs were operationalized as reflective constructs. Appendix B, lists the constructs, the items used for each measure, and the origin of each measure.

3.1 Data Collection

The sampling frames were defined differently across prior studies. Overall, previous work was rather consistent in the methods for data collection. Data were collected by surveying senior managers in all of the studies. The majority of the research utilized cross-sectional data. The simultaneous collection of data on coercive pressures, normative pressures, mimetic pressures, tangible resources, human skills, big data driven culture and manufacturing performance may cause the potential problem of simultaneity; that is, causality between independent exogenous constructs and endogenous constructs cannot be definitively determined. Sampling procedures followed clearly seen patterns. Sampling either focused on a narrow setting of one industry (e.g. Conant et. al, 1990; Liang et al., 2007) or broadly covered across industries (e.g., Hitt and Ireland, 1982; Li, 2000; Gupta and George, 2016; Gunasekaran et al., 2017; Srinivasan and Swink, 2018). There is no data source from previous research conducted on the same content and context as those of this study. Primary data was therefore imperative. Hence, important elements of this study were to identify the population and to design the appropriate sample for the survey, and to ensure that responses were free from bias by using reliable sampling. We used a cross-sectional e-mail survey of a sample of manufacturing companies located across India. The initial sample consisted of 375 firms derived from databases provided by CII Institute for Manufacturing and further validated using database of Dun & Bradstreet. To improve our response rate, we followed a modified version of Dillman's (2011) total design test method. The survey questionnaires were each sent to a key respondent. As a requirement for participation, respondents had to be functional heads associated with operations management, purchasing/procurement, production and quality management. Each survey included a cover letter, and we followed up with phone calls to the participants' offices. We believe this design is suitable for research in the light of India's unique social and cultural context. In India, business activities are largely based on personal relationships and incentive mechanisms may not yield better response, as argued in prior research (Baruch and Holtom, 2008).

We believe that personal relationships and support from over-arching organizations such as CII (Confederation of Indian Industries) and FICCI (Federation of Indian Chambers of Commerce and Industry) can help to improve to survey response. We were assisted by help from CII Centre of Manufacturing Excellence. The current study was on a key focus topic of the centre and thus we received encouraging support from the chairman who is an eminent industrialist in the country. On the personal request of the chairman, the secretary of the chairman distributed the questionnaires to the 375 firms we identified. The questionnaires were sent in the first week of March 2016. We received 195 complete and usable responses by the end of June 2016 resulting in an effective response rate of 52 % (195/375). We provide the respondents' (firm-level) demographic information in Table 1.

Table 1: Descriptive Statistics of Sample Frame (N=195)

Title	Number	Percentage
Annual Sales Revenue		
Under 10 Million USD	5	2.56
10- 25 Million USD	15	7.69
26- 50 Million USD	35	17.95
76-100 Million USD	48	24.62
101-250 Million USD	22	11.28
251-500 Million USD	24	12.31
Over 251 Million USD	46	23.59
Number of Employees		
0-50	6	2.93
51-100	6	4.88
101-200	13	9.27
201-500	8	5.37
501-1000	105	49.76
1001+	57	27.8
Industry		
Auto component manufacturers	60	30.77
Cement manufacturers	54	27.69
Chemical products	54	27.69
Wood products	27	13.85

3.2 Nonresponse bias

We tested for nonresponse bias through a comparison of early waves (respondents who returned their response within the first three weeks), late respondents (respondents who returned their response in the fourth week or later), and non-respondents (a subsample of 120 respondents was selected at random from the initial contact list) (Armstrong and Overton, 1977; Chen and Paulraj, 2004). We performed Student's t-tests on early and late waves on all variables. We found no significant difference between respondents and non-respondents (i.e., p>0.1)

4. Data analyses and results

In our study, we have used partial least squares (PLS) for data analysis (see, Peng and Lai, 2012; Henseler et al., 2014; George et al., 2016). However, in recent years some scholars have raised concerns over the use of PLS technique (see, Ronkko and Evermann, 2013; Guide and Ketokivi, 2015; Ronkko et al., 2016). In response to the criticism of traditional, PLS methods are due to them being composite-based, not factor-based (Kock, 2017). That is, in traditional PLS methods, latent variables are estimated as weighted aggregations of indicators without the inclusion of measurement errors (Henseler et al., 2014). The measurement errors usually serve as extra indicators that often complement the actual indicators; together, the actual indicators and measurement errors constitute factors. Kock (2017) further argues that without considering measurement errors the use of composites instead of factors leads to some known sources of bias. The path coefficients tend to weaken with respect to their corresponding true values. Thus, recent methodological developments building upon traditional PLS techniques have helped to bridge the gap between factor-based and composite-based structural equation modelling (SEM) techniques (Kock, 2015a; Sarstedt et al., 2016). Hence, we used WarpPLS 6.0, which is a popular PLS technique that has been recently used for path-analytical models (Kock, 2017).

4.1 Measurement model

Following Chen and Paulraj's (2004) suggestions, we used a three-stage continuous improvement cycle to develop measures that satisfied all the requirements for reliability, validity and unidimensionality. To assess the reliability of the constructs used in our study (see Figure 1), we used the average correlation among items in the scale (Cronbach, 1951; Nunally, 1978). As we can see from Table 3, the Cronbach's alpha values (α) for the items and scale were well above 0.6.

Initially, construct validity was assessed via exploratory factor analysis (EFA) using principal component analysis with Varimax rotation (Chen and Paulraj, 2004). Since the number of constructs was determined prior to analysis via extensive review of literature (see Figure 1), the exact number of factors to be extracted (nine factors in our case) was provided during analysis. The items that cross-loaded were discarded and then we repeated Varimax rotation until, we finally obtained parsimonious factors. Then we used confirmatory factor analysis (CFA) to assess construct validity and unidimensionality. Gerbing and Anderson (1988) noted that CFA provides a stricter and precise test of unidimensionality of latent constructs. In our study all, these constructs are made up of at least three items.

We note that all the individual factor loadings (λi) are greater than 0.5, the scale composite reliability coefficients (SCR) greater than 0.7 and average variance extracted (AVE) greater than 0.5 (see Table 2). This clearly supports that our constructs have adequate convergent validity.

Table 2: Loadings of the indicators variables (Cronbach's alpha, SCR and AVE)

Constructs	Items	λi	λi^2	Error	SCR	AVE
Coercive Pressures (CP) (α=0.93)	CP1	0.73	0.54	0.46	0.81	0.59
	CP2	0.68	0.46	0.54		
	CP3	0.88	0.77	0.23		
Normative Pressures (NP) (α=0.93)	NP1	0.78	0.61	0.39	0.75	0.51
	NP2	0.57	0.32	0.68		
	NP3	0.77	0.59	0.41		
Mimetic Pressures (MP) (α=0.92)	MP1	0.95	0.91	0.09	0.96	0.86
	MP2	0.90	0.81	0.19		
	MP3	0.93	0.87	0.13		
	MP4	0.92	0.85	0.15		
Tangible Resources (TR) (α=0.92)	TR1	0.80	0.64	0.36	0.95	0.72
	TR2	0.93	0.87	0.13		
	TR3	0.95	0.89	0.11		
	TR4	0.94	0.89	0.11		
	TR5	0.94	0.88	0.12		
	TR6	0.97	0.94	0.06		
	TR7	0.54	0.30	0.70		
	TR8	0.57	0.32	0.68		
Human Skills (HS) (α=0.92)	HS1	0.89	0.79	0.21	0.96	0.76
	HS2	0.90	0.81	0.19		
	HS3	0.91	0.84	0.16		
	HS4	0.95	0.90	0.10		
	HS5	0.88	0.77	0.23		

	HS6	0.87	0.76	0.24		
	HS7	0.66	0.44	0.56		
Big Data Culture (BDC) (α=0.92)	BDC1	0.69	0.48	0.52	0.75	0.50
	BDC2	0.74	0.55	0.45		
	BDC3	0.69	0.48	0.52		
Big Data and Predictive Analytics (BDPA) (α=0.63)	BDPA1	0.78	0.61	0.39	0.82	0.54
	BDPA2	0.81	0.65	0.35		
	BDPA3	0.81	0.65	0.35		
	BDPA4	0.49	0.24	0.76		
Cost Performance (COST_PERF) (α=0.68)	COST_PERF1	0.80	0.64	0.36	0.80	0.50
	COST_PERF2	0.57	0.33	0.67		
	COST_PERF3	0.73	0.53	0.47		
	COST_PERF4	0.71	0.51	0.49		
Operational Performance (OPER_PERF) (α=0.73)	OPER_PERF1	0.82	0.67	0.33	0.78	0.54
	OPER_PERF2	0.72	0.51	0.49		
	OPER-PERF3	0.66	0.44	0.56		

Table 3 indicates that square root of the AVE is greater than the all of the inter-construct correlations, providing evidence of sufficient discriminant validity (Fornell and Larcker, 1981; Chen and Paulraj, 2004).

Table 3: Inter-correlations among major constructs

	CP	NP	MP	TR	HS	BDPA	COST_PERF	OPER_PERF	BDC
CP	**0.77**								
NP	0.15*	**0.71**							
MP	0.29*	0.13*	**0.93**						
TR	0.15**	0.29*	0.17*	**0.85**					
HS	0.25*	0.20*	0.12*	0.21*	**0.87**				
BDPA	0.02***	-0.05***	-0.02***	-0.10***	-0.02***	**0.73**			
COST_PERF	0.28*	0.19**	0.24*	-0.09***	0.30*	0.07***	**0.71**		
OPER_PERF	0.24*	0.09***	0.08***	-0.12***	0.04***	0.01***	0.21*	**0.73**	
BDC	0.29*	0.21*	0.13**	0.30*	0.18**	-0.03***	0.29*	0.03***	**0.71**

Note: *The bold colour indicates that leading diagonal entries are square root of AVEs;*

** (p<0.001), ** (p<0.05), *** (p>0.1)*

Overall, we may argue that these statistics indicate that constructs of the model (see Figure 1) possess construct validity.

4.2 Common method bias (CMB)

In case of self-reported data, there is potential for common method biases (CMB) resulting from multiple sources such as consistency motif and social desirability (Podsakoff and Organ, 1986; Podsakoff et al., 2003). We conducted statistical analyses to assess the severity of the CMB in our data. Malhotra et al. (2006) further suggest performing CFA analysis, loading all items on a single factor, and examining the fit indices. The single factor is regarded as equivalent of a "methods factor" that indicates the presence of bias due to data collection. The fit for the single factor model was found to be poor (χ^2/df = 9.12; RMSEA= 0.333; NNFI=0.087; CFI= 0.151 and RMSR=0.513) and the $\Delta\chi^2$/df (7.43; $p<0.001$) from the hypothesized model is highly significant. Next, we tested for common method bias using the correlation marker technique (Lindell and Whitney, 2001). The unrelated variables were used to partial out the correlations caused by CMB. We further determined the significances of the correlations following Lindell and Whitney (2001) arguments. We found that the significance of the correlations did not change (see, Appendix C). Based on these results, we consider the potential effects of common method variance (CMV) to be non-substantial.

Causality is an important aspect that must be addressed before proceeding to hypotheses test (Abdallah et al., 2015; Guide and Ketokivi, 2015). Following Kock's (2015b) suggestions, we examined nonlinear bivariate causality direction ratio (NLBCDR). *The NLBCDR is a measure of the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in the proposed theoretical model* (Kock, 2015b, p. 52-53). The acceptable value should be $\geq$ 0.7. In our case, we note that NLBCDR=0.89 (approx.), which is greater than the critical value. We therefore can conclude that endogeneity is not a major concern. We further examined the model fit and quality indices (see, Appendix D).

4.3 Hypothesis testing

PLS does not assume a multivariate normal distribution. Hence, traditional parametric-based techniques for significance tests are inappropriate. PLS uses a bootstrapping procedure to estimate standard errors (SEs) and the significance of parameter estimates (Chin, 1998; Peng and Lai, 2012). We report the PLS path coefficients and *p*-values in Table 4. The estimated path coefficients are interpreted as standardized beta coefficients.

We tested hypotheses: H1a (CP→TR) (β=0.28, $p<0.001$), H1b (CP→HS) (**β=0.05, p=0.252**), H2a (NP→TR) (β=0.44, $p<0.001$), H2b (NP→HS) (β=0.27, $p<0.001$), H3a (MP→TR)

(β=0.40, p<0.001) and H3b (MP→HS) (β=0.24, p<0.001). We observed that except H1b, all our proposed hypotheses are supported. Similarly, the tangible resources (TR) (β=0.15, p=0.017) and human skills (HS) (β=0.28, p<0.001) are positively associated with BDPA. Thus we can argue that hypotheses (H4 and H5) are supported.

We further tested the moderating effect of BDC on the paths joining TR and BDPA (TR*BDC→BDPA) and HS and BDPA (HS*BDC→BDPA) (i.e. H6a/b). We found that BDC has positive and significant effects on the paths joining TR and BDPA (β=0.32, p<0.001) and HS and BDPA (β=0.45, p<0.001). However, our hypothesis H1b (CP→HS) is not supported (β=0.05, p=0.252).

Next, we observed that big data and predictive analytics (BDPA) is positively associated with cost performance (COST_PERF) (β=0.18, p=0.005) (H7a) and operational performance (OPER_PERF) (β=0.16, p=0.012) (H7b). Hence, we can argue that hypotheses (H7a/b) are supported.

Further, we observed that firm size is positively related to OPER_PERF (β=0.15, p=0.016) but not significantly associated with COST_PERF (β=-0.085, p=0.114). Similarly, the nature of industry is significantly associated with COST_PERF (β=0.19, p=0.003) but not significantly associated with OPER_PERF (β=0.08, p=0.140). To examine the robustness of our PLS results, we computed the p-values upon 1,000 and 1,500 bootstrapping runs.

Table 4: Structural estimates

Hypothesis	***Effect of***	***Effect on***	***β***	***p-value***	***Results***
H1a	CP	TR	0.28	<0.001	Supported
H1b	CP	HS	0.05	**0.252**	**Not supported**
H2a	NP	TR	0.44	<0.001	Supported
H2b	NP	HS	0.27	<0.001	Supported
H3a	MP	TR	0.40	<0.001	Supported
H3b	MP	HS	0.24	<0.001	Supported
H4	TR	BDPA	0.15	0.017	Supported
H5	HS	BDPA	0.28	<0.001	Supported
H6a	TR*BDC	BDPA	0.32	<0.001	Supported
H6b	HS*BDC	BDPA	0.45	<0.001	Supported
H7a	BDPA	COST_PERF	0.18	0.005	Supported
H7b	BDPA	OPER_PERF	0.16	0.012	Supported
	Control variables				
	Firm size	COST_PERF	-0.085	**0.114**	
	Firm size	OPER_PERF	0.15	0.016	

	Industry	COST_PERF	0.19	0.003	
	Industry	OPER_PERF	0.08	**0.140**	

Next, we have examined the explanatory power of the research model based on explained variance (R^2) of the endogenous constructs. The R^2 of the endogenous constructs of our model (see Figure 2), are TR (0.58), HS (0.23), BDPA (0.26), COST_PERF (0.38) and OPER_PERF (0.41) which are moderate (Chin 1998) (Table 5).

To evaluate the effect size of each predictor we used Cohen's f^2 formula (Cohen, 1988). According to Cohen (1988) f^2 values of 0.35, 0.15 and 0.02 are considered large, medium and small. Consequently, the effect sizes of CP on TR, 0.17, CP on HS, 0.21, NP on TR, 0.272, NP on HS, 0.123, MP on TR, 0.27, MP on HS, 0.104, TR on BDPA, 0.19, HS on BDPA, 0.21, BDPA on COST_PERF,0.32 and BDPA on OPER_PERF, 0.36 (Table 6).

Next, to evaluate the model's capability to predict, Stone-Geisser's Q^2 for endogenous constructs are TR (0.57), HS (0.26), BDPA (0.25), COST_PERF (0.36) and OPER_PERF (0.41), respectively which are greater than zero, indicating acceptable predictive relevance (Peng and Lai, 2012).

Table 5: R^2, Prediction and Effect Size

Construct	R^2	Q^2	f^2 in relation to				
			TR	HS	BDPA	COST_PERF	OPER_PERF
CP			0.17	0.21			
NP			0.272	0.123			
MP			0.27	0.104			
TR	0.58	0.57			0.19		
HS	0.23	0.26			0.21		
BDPA	0.26	0.25				0.32	0.36
COST_PERF	0.38	0.36					
OPER_PERF	0.41	0.41					

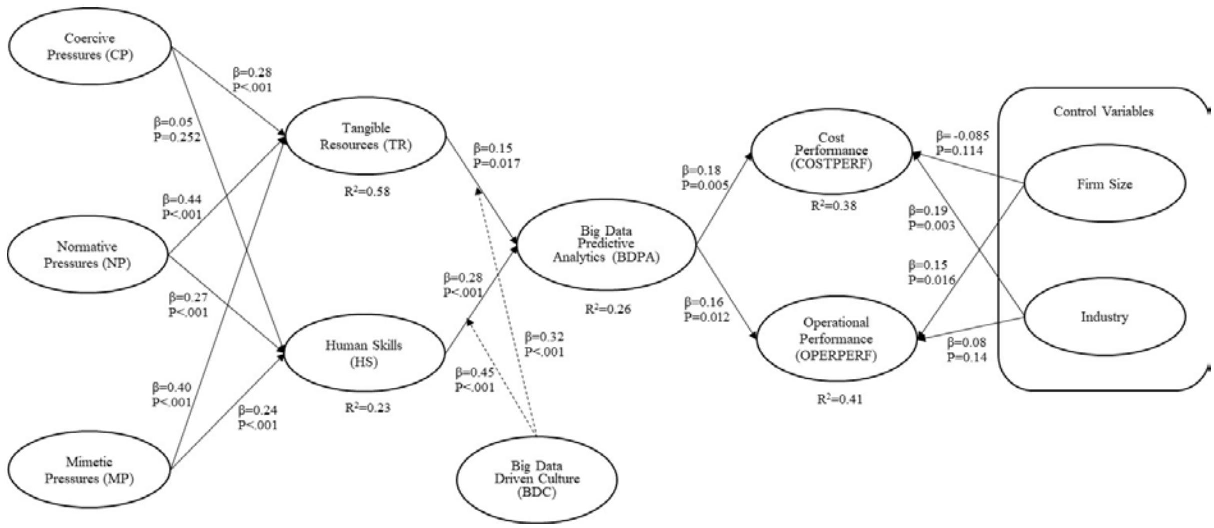

Figure 2: Final PLS Model

5. Discussion of Results and Implications for Research and Managers

The empirical results highlight that with regards to adoption of BDPA the institutional pressures of the manufacturing organizations directly affect the internal resources allocation and finally the adoption of BDPA. Dubey et al. (2016) argue that several years ago, when analytics capability was constrained by the complexity of the IT, the technology innovation and diffusion perspective was more appropriate for explaining the decision process of technology adoption such as ERP (Liang et al., 2007), e-government adoption (Zheng et al., 2013) or BDPA adoption (Gunasekaran et al., 2017). However, with the advance of IT, technology complexity is no longer a major concern for building analytics capability. Instead, inter organizational pressures heavily influence the decisions of manufacturing organizations, including BDPA adoption decisions. Under these circumstances, we argue that the institutional perspective is more relevant for understanding BDPA adoption for performance of manufacturing organizations. Previous studies (Akter et al., 2016; Gupta and George, 2016; Fosso Wamba et al., 2017; Fosso Wamba et al., 2017) have used RBV or dynamic capability view to explain the adoption of BDPA. However, RBV is criticized for being inattentive to contexts (Yang and Konrad, 2011). Oliver (1997) has argued that neither resource acquisition nor resource deployment are independent from the institutional context. Hence, to provide more insights, we integrated the institutional perspective and RBV to explain the adoption of BDPA. We have further outlined our main findings as:

Firstly, we have found that institutional pressures (i.e. CP, NP and MP) have significant effects on selection of tangible resources, extending thereby the study of Gupta and George

(2016). *Secondly*, we found that NP and MP have significant effects on HS. However, CP has no significant effect on HS. This finding can be explained by the argument that skills required for BDPA may not be sensitive to social pressures. Davenport and Harris (2007) argue that managers must improve data availability as the first step in building big data and predictive analytics capability. *Thirdly*, using institutional logic we can argue that importance of human resources that can effectively orchestrate various technologies, as well as possess both domain and data science skills. *Fourthly*, we found that big data culture has significant and positive moderating effects on the paths leading from TR/HS to BDPA. In particular these findings clearly support the previous studies arguing that organizational culture is one of the key factors influencing technology (information systems) adoption (see Khazanchi et al., 2007; Liu et al., 2010; Gupta and George, 2016). Moreover, our findings further extend Liu et al.'s (2010) findings, who suggest that integration of institutional perspective and organizational culture with RBV provides better explanation of adoption of innovative information systems (BDPA in our case). *Finally*, we found that BDPA has significant and positive effects on cost and operational performance, and this is in support of Srinivasan and Swink (2018) findings.

Contrary to our expectations, the present study found that firm size has no significant effect on cost performance. However, firm size has positive and significant effect on operational performance. We interpret these differential effects of the firm size as evidence that rapid change in manufacturing industry is meaningfully impending information sharing via connectivity and large firms are likely to gain more benefits from information derived from customer-sourced data related to changes in future product demands likely to result from changes in downstream inventories, promotion and sales. Supplier-sourced data can provide information on future supply shortages and excess resulting from changes in upstream inventories, capacities, and the status of orders and shipments. Hence, insights gained via BDPA can significantly improve operational performance. However, the size of the firm may not directly influence cost performance. Similarly, the nature of the industry has differential effects on cost and operational performance. This may be attributed to our samples, which we have gathered from auto components manufacturing industry, cement manufacturing industry, chemical products industry and wood products industry. Hence, to obtain deeper insights, we performed split sample analysis based on nature of the industry. The split method identified groups of firms into three segments (M1, M2 and M3): auto component manufacturers (n=60), cement manufacturers (n=54) and chemical products & wood products (n=81). Appendix E shows the PLS results. We observed no significant difference between these three models M1, M2 and M3, except that in case of M1 and M2, we have found that CP has positive and significant effects on HS. However, in case of M3, CP is not significantly associated with HS.

5.1 Theoretical contributions

The role of institutional theory and RBV for the adoption of technological innovations is well discussed in the literature (see Zhang and Dhaliwal, 2009; Zheng et al., 2013). What is less understood is how institutional pressures directly affect the selection of TR and HS in context to IT innovations and particularly BDPA adoption. Two key aspects of this study signify our main contribution to BDPA literature. First, our study is one of the few studies to integrate institutional theory, RBV, and the role of organizational culture in explaining the complex process of the BDPA adoption. Prior to this study, previous scholars have integrated institutional theory and RBV (Oliver, 1997; Zhang and Dhaliwal, 2009; Zheng et al., 2013; Tatoglu et al., 2016) and institutional theory and organizational culture (Kostova et al. 2008; Liu et al., 2010). Our study acts as the initial step and illustrates how these can be integrated to shed light upon BDPA adoption, and explains how external pressures affect internal resource configuration to achieve BDPA adoption for enhanced manufacturing performance. Secondly, our study highlights the effect of BDPA on cost performance and operational performance. Although Srinivasan and Swink (2018) in their study have studied the effects of analytics capability on cost performance (R^2=0.125) and delivery performance (R^2=0.186), our study argues that proper utilization of tangible resources and human resources under the effect of institutional pressures can provide better explanation. Finally, we identify big data culture as the key moderating construct, which enhances the effects of TR and HS on BDPA adoption. Although prior studies have noted the importance of organizational culture in adoption of innovative information systems, it was not clear how BDC could play an important role in adoption of the BDPA. Hence, our results provide an initial step for researchers to investigate how organizational culture can further explain the adoption of BDPA in flexible and controlled organizational structures.

5.2 Managerial Implications

Our research findings can offer useful guidance to management and to IT practitioners. Firstly, the role of institutional pressures offers useful insights in the selection of tangible resources, building the appropriate human skills and creating the appropriate big data culture. Conversely, if managers fail to respond to the external pressures, then the outcome realized from resources and big data capability may be limited. Thus, managers can develop appropriate strategies, which can shape their resource selection strategies within their organizations. By highlighting the tangible resources and human skills, we offer insights to big data managers, which can help them understand that leveraging big data requires not only investment and time, but also the appropriate human skills that can address the dynamic needs of the market. We offer insights into big data culture, an important source of competitive advantage, and how it can help to contribute to BDPA success. The most important observation, which we have noted in our study, is that the cognitive component of institutional pressures plays a significant role. From this perspective, we view institutional pressures as positive and beneficial to the resource selection decision, which plays a significant role in building big data capability to those manufacturing organizations that are struggling to reap benefits from investment and existing market opportunities.

6. Conclusion, limitations and further research directions

This study was triggered by the exponential rise in the interest in the BDPA in the literature on manufacturing and operations management. Despite the interest of both practitioners and academics, there is still lack of theory-based research on the role of BDPA in manufacturing performance. Following the call by Oliver (1997), we proposed a theoretical framework grounded in institutional theory and RBV to address the existing limitations of RBV and empirically investigate how resource selection guided by three components of institutional pressures can build big data capability, which in turn can help to achieve manufacturing performance. Our study has the following limitations. Firstly, although the RBV has attracted significant attention, we argue that the RBV suffers from context insensitivity as noted by Ling-Yee (2007). We further interpret context insensitivity as indicating that RBV is unable to identify the conditions in which resources or capabilities may be most valuable. Hence, in future, the current model can be extended using contingency theory regarding how internal and external conditions will influence manufacturing performance. Secondly, as with any survey-based research, our study has its own limitations such as CMB or endogeneity (Guide and Ketokivi, 2015). However, we took precautions to minimize the impacts of CMB and endogeneity; we argue that longitudinal data or multi-informants from a sampling unit may help to address the issue related to CMB. Thirdly, in our model we do not exclude the possibility that other factors that may mediate the influence of institutional forces. Fourthly, it may be useful to examine how the cognitive component can influence big data culture. To answer some of these questions, we suggest case-based research to generate more comprehensive theory surrounding big data capability. Finally, the sample of our research may limit the generalizability of our results. In order to avoid noise caused by sector differences, we purposely chose to study firms in manufacturing sector. However, we believe that these choices might have helped to enhance the internal validity of our study; they often limit the study external validity. Thus, the study findings should be applied to different contexts with caution under the light of its limitations. We acknowledge that generalizability troubles all survey-based research (including ours), because it is very difficult, if not impossible, to gather a sample that could well represent the whole population. Still, future research may be conducted over a longer period with samples from more industries, countries, and informants with more diverse backgrounds.

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Appendix A: Definitions of the main constructs

Constructs	Definitions
Coercive pressures (DiMaggio and Powell, 1983)	Coercive pressures occurs from both formal and informal pressures exerted on organizations by other organizations (e.g., buyers, government agencies, regulatory norms) due to expectations from society.
Normative pressures (DiMaggio and Powell, 1983, p. 152)	Normative pressures is defined as the collective struggle of members of an occupation to define the working conditions and their methods to work and in future guide the future professionals through legitimacy.
Mimetic pressures (DiMaggio and Powell, 1983)	Mimetic pressures results from mimicking other organizational actions.
Tangible resources (Gupta and George, 2016)	Tangible resources are the ones that can be sold or bought in a market. Examples include financial resources (e.g., debt or equity) and physical assets (e.g., equipment and facilities) of the firm.
Human skills (Gupta and George, 2016)	Human skills of human resources include technical skills and managerial skills relevant to big data and predictive analytics environment.
Big data culture (McAfee et al., 2012)	Big data culture is defined as the extent to which organizational members (including upper echelons, middle level managers and lower level employees) make decisions based on the insights extracted from big data.
Big data and predictive analytics (Gupta and George, 2016)	Big data and predictive analytics is defined as an organizational capability that allows the firm's to assemble, integrate and deploy it's big data-based resources.
Cost performance (Eckstein et al., 2015; Srinivasan and Swink, 2018)	Cost performance is defined as lowering of cost associated with manufacturing activities, inventories and transportation of raw materials and finished goods from source to the destination without compromising with other associated factors.
Operational performance (Eckstein et al., 2015; Srinivasan and Swink, 2018)	Operational performance is defined as improvement of product quality, service level and on-time delivery without affecting other associated factors.

Appendix B: Construct Operationalization, Derivation and Measures

Construct and Derivation	**Measures**
Coercive pressures (CP) *Liang et al., (2007); Dubey et al., (2016)*	(i) The data protection law requires our firm to use data safely. (ii) The industry association requires us to use data within the boundary of regulatory norms. (iii) The stakeholders of our firm want us to exploit data to improve decision making without interfering into privacy of any individuals, which may attract defamation to the firm.
Normative pressures (NP) *Liang et al., (2007); Dubey et al., (2016)*	(i) The extent to which your firm's suppliers use big data and predictive analytics for decision-making. (ii) The extent to which your firm's customers use big data and predictive analytics for decision-making. (iii) The extent to which industry associations' (such as CII or FICCI) promotion of big data and predictive analytics influences your firm to use big data and predictive analytics for decision-making.
Mimetic pressures (MP) *Liang et al., (2007); Dubey et al., (2016)*	(i) Our competitors who have adopted big data and predictive analytics have greatly benefitted. (ii) Our competitors who have adopted big data and predictive analytics are favourably perceived by the others in the same industry. (iii) Our competitors who have adopted big data and predictive analytics are favourably perceived by their suppliers and customers.

Tangible resources (TR) *Gupta and George (2016); Gunasekaran et al. (2016)*	*Data connectivity* (i) We have access to very large, unstructured and fast moving data for analysis. (ii) We integrate data from multiple internal sources into a data warehouse. (iii) We integrate external data with internal to facilitate high value analysis of our business environment. *Technology* (i) We have used parallel computing approaches (e.g. Hadoop) for data processing. (ii) We have used different data visualization tools. (iii) We have explored cloud-based services for processing data. *Basic resources* (i) We have allocated adequate funds for big data and predictive analytics project. (ii) We have enough time to achieve desired results from big data and predictive analytics.
Human skills (HS) *Gupta and George (2016)*	(i) We provide big data related training to our employees. (ii) We recruit new employees who have good exposure to big data and predictive analytics. (iii) Our big data analytics staff has the right skills to do the job successfully. (iv) Our big data staff has right education. (v) Our big data staff holds suitable years of experience in big data environment. (vi) Our big data and predictive analytics managers have strong understanding of business. (vii) Our big data and predictive analytics managers are able to coordinate effectively with all intra departments, suppliers and customers.

Big data culture (BDC) *Gupta and George (2016)*	(i) We treat data a tangible asset. (ii) We base our decisions on our data rather than on instinct. (iii) We are willing to override our own intuition when data contradict our viewpoints.
Big Data and Predictive Analytics *Srinivasan and Swink (2017)*	(i) We use advanced analytical techniques (e.g. simulation, optimization, regression) to improve decision-making. (ii) We easily combine and integrate information from many data sources for use in decision-making. (iii) We routinely use data visualization techniques (e.g. dashboards) to assist users or decision makers to understand complex information. (iv) Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement.
Cost Performance (COST_PERF) *Eckstein et al., (2015); Srinivasan and Swink (2017)*	(i) Manufacturing cost. (ii) Inventory carrying cost. (iii) Cost of transportation and handling. (iv) Cost of purchased goods and service.
Operational Performance (OPER_PERF) *Eckstein et al., (2015); Srinivasan and Swink (2017)*	(i) Product quality. (ii) Service level. (iii) On-time delivery.

Appendix C: Correlation Matrix with marker variable (MV) and other main constructs

	CP	NP	MP	TR	HS	BDPA	COSTPER	OPERPER	BDC	MV
CP	1.00									
NP	0.17	1.00								
MP	0.39	0.17	1.00							
TR	0.18	0.23	0.18	1.00						
HS	0.27	0.24	0.16	0.11	1.00					

BDPA	0.03	-0.08	-0.03	-0.09	-0.02	1.00				
COSTPER	0.18	0.29	0.23	-0.07	0.33	0.17	1.00			
OPERPER	0.34	0.11	0.09	-0.17	0.14	0.05	0.11	1.00		
BDC	0.22	0.24	0.17	0.22	0.16	-0.04	0.19	0.08	1.00	
MV	-0.01	-0.06	-0.06	-0.07	-0.10	-0.12	-0.05	0.02	-0.11	1.00

Appendix D: Model fit and quality indices

Model fit and quality indices	*Value from analysis*	*Acceptable if*	*Reference*
APC	0.268, $p<0.001$	$p<0.05$	Rosenthal and Rosnow (1991)
ARS	0.482, $p<0.001$	$p<0.05$	
AVIF	0.167, $p<0.001$	$p<0.05$	Kock (2015b)
Tenenhaus GoF	0.378	Large if ≥0.36	Tenenhaus et al. (2005)

Appendix E: Split sample analysis

	M1 (n=60) (β, p)	M2 (n=54) (β, p)	M3 (n=81) (β, p)
CP→TR	0.23, <0.001	0.21, <0.001	0.16, <0.018
NP→TR	0.22, <0.001	0.26, <0.001	0.14, <0.016
MP→TR	0.27, <0.001	0.32, <0.001	0.27, <0.001
CP→HS	0.24, <0.001	0.18, <0.017	**0.03, 0.321**
NP→HS	0.33, <0.001	0.27, <0.001	0.24, <0.001
MP→HS	0.22, <0.001	0.23, <0.001	0.25, <0.001
TR→BDPA	0.21, <0.001	0.16, <0.018	0.14, <0.016
HS→BDPA	0.26, <0.001	0.27, <0.001	0.24, <0.001
BDC*TR	0.26, <0.001	0.31, <0.001	0.27, <0.001
BDC*HS	0.38, <0.001	0.36, <0.001	0.28, <0.001
BDPA→COST_PERF	0.21, <0.001	0.17, <0.017	0.15, <0.016

BDPA→OPER_PERF	0.23, <0.001	0.16, <0.018	0.19, <0.001