Can Big Data and Predictive Analytics Improve Social and Environmental Sustainability?

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Abstract

Although literature indicates that big data and predictive analytics (BDPA) convey a distinct organisational capability, little is known about their performance effects in particular contextual conditions. Grounding our investigation in the dynamic capability views and organisational culture and based on sample of 205 Indian manufacturing organisations, we empirically investigate the effects of BDPA on social performance (SP) and environmental performance (EP) using variance based structural equation modelling (i.e. PLS). We find that BDPA has significant impact on SP/EP. However, we did not find evidence for moderating role of flexible orientation and control orientation in the links between BDPA and SP/EP. Our findings offer a more nuanced understanding of the performance implications of BDPA, thereby addressing the crucial questions of how and when BDPA can enhance social/environmental sustainability in supply chains.

Keywords: Big Data; Predictive Analytics; Dynamic Capability View; Supply Chains; Social Sustainability; Environmental Sustainability.

1. Introduction

Social sustainability and environmental sustainability are now well-established in the business lexicons (Berns et al. 2009; Sengers et al., 2016; Shrivastava and Guimaraes-Costa, 2017). Despite efforts from organisations to respond to external pressures from policy makers, consumers and internal pressures from leaders, the ground reality remains the subject of much debate (Mueller et al. 2009). Seuring and Mueller (2008) argue that the concept of sustainability has become increasingly important in supply chains. Hence, responding to the growing social and environmental demands on business operations is a primary challenge for businesses (Park-Poaps and Rees, 2010). This is because in recent years, organisations have increasingly outsourced manufacturing from low-wage countries. Frequently, this has gone together with a lack of acceptable environmental protection and appropriate working conditions (Mueller et al. 2009). Hartmann and Moeller (2014) further argue that due to irresponsible practices of supply chain partners which are often publicly exposed, consumers protest the focal organisations, and this has both financial and brand value implications. Our current study is therefore informed by the debate and centres around two main issues:

(i) Addressing social issues in supply chains: Following the United Nations International Labor Organization report (ILO, 2017), there are around 21 million people who are directly or directly

forced into slavery, despite the ILO's 1948 resolution banning slavery. The problem has often been undetected due to the extensive scope of the global supply chains.

(ii) Environmental issues: As the global population grows, developing or underdeveloped economies are committing themselves to rapid infrastructure growth, thereby putting tremendous pressures on the consumption of natural resources.

Wu and Pagell (2011) argue that the complexity of supply chain decision-making is multiplied when organizations address the uncertainty that surrounds environmental decisions, environmental issues due to the number of entities in the chain, and the interconnectedness of supply chain and ecological systems. As organisations set out to evaluate the environmental impact of their supply chains, they often do not have complete information on decision parameters or consequences. Hence, organisations are often constrained due to limited information and data about the environmental problems they face, how environmental issues interact and affect other dimensions of sustainability, and the consequences of such interactions. In fact, scholars have suggested improving transparency and integration among supply chain partners to engage themselves for common sustainability goals (Wolf, 2011; Ageron and Gunasekaran, 2012). However, due to information asymmetry in supply chains, the transparency and supply chain integration often remains unresolved. Barratt and Oke (2007) argue using resource based view (RBV) logic that supply chain connectivity (i.e. technology) and information sharing may enhance supply chain visibility. Hence, based on recent debates surrounding the extraction of valuable information from large data sets, we argue that big data and its application (BDPA) may offer a solution to these problems which often remain undetected due to lack of transparency in supply chains (Keeso, 2014; Wu et al. 2016; Wu et al., 2016).

Organizations are not only harnessing and analysing big data for improved transparency and decision-making, but also for improving collaboration (Waller and Fawcett, 2013; Schoenherr and Cheri, 2015; Hazen et al. 2014; Wang et al. 2016a; Kache and Seuring, 2017). Gold et al. (2010) observe that collaboration among partners in supply chains is used to meet sustainability goals, and to address environmental (Vachon and Klassen, 2008), social, and governance issues (Pagell and Wu, 2009). Despite the growing stream of literature which attempts to provide information on application of BDPA to improve environmental sustainability (Song et al. 2016, 2017; Zhang et al. 2017) and social sustainability (Song et al. 2017; Liu and Zhang, 2017), the literature offers mostly conceptual and anecdotal evidence. The existing literature has broadly discussed the characteristics and associations between big data application and green revolution (Wu et al. 2016), but to date no rigorous empirical testing exists. Furthermore, empirical research on the influence of BDPA capability on environmental and social sustainability is still in its infancy (Song et al. 2017). In fact, both conceptual and empirical research on impact of big data and predictive analytics on social sustainability and environmental sustainability is still fragmented, making it difficult to compare and accumulate results and arrive at meaningful conclusions. In this study, we particularly focus on two performance characteristics: *social performance* and *environmental performance*. Specifically, we address the first research question: *What are the effects of big data & predictive analytics on social performance and environmental performance?*

Gupta and George (2016) argue that research focusing on benefits of BDPA remains in an embryonic stage. The existing research on big data has focused on system infrastructure: data capture, storage, networking and distributed system parallel computing (Duan and Xiong, 201; Gupta and George, 2016). However, beside system infrastructure which will continue to progress, it is the time to focus on other critical resources, besides technology, which are needed to build firm specific "hard to imitate" BDPA capabilities (McAfee et al. 2012; Ross et al. 2013). McAfee et al. (2012) argue that data-driven decision-making culture is needed, where the senior executives make decisions based on data rather than gut feeling. Literature also states the importance of top management support (LaValle et al. 2011) and the appropriate technical and management skills (Waller and Fawcett, 2013) for the success of big data initiatives. However, research discussed so far mostly offers conceptual and anecdotal evidence. Hence, we address our second research question: *How do human (technical and managerial) skills and big data culture (organizational learning and data driven decision making) helps to build BDPA?*

Performance measurements are often crucial, but are not capable of fully capturing the complexity of real situation (Boyd et al. 2012; Eckstein et al. 2015). Thus, scholars have acknowledged that the performance of the BDPA hinges on contextual factors (Akter et al. 2016; Gupta and George, 2016; Wamba et al. 2017; Gunasekaran et al. 2017). Hence, we examine the contextual conditions under which BDPA is effective. This is in line with the methodological work of Sousa and Voss (2008) who suggest that research should not only aim to value practices, but rather to examine the specific conditions under which they are effective.

The moderating role of organizational culture has been found to be a key influencing factor in studies focusing on supply chain management practices and innovative information systems adoption (see Leidner and Kayworth, 2006; Khazanchi et al. 2007; Liu et al. 2010). Hence, we argue that organisations exposed to similar conditions may react differently to adopt BDPA due to the differences in their organisational cultures. However, so far literature has not explored the role of culture in the relationship between BDPA and social/environmental sustainability. Hence, our third research question is: *What are the effects of organisational culture on the relationships between BDPA and social/ environmental sustainability?*

We answer our research questions based on a sample of 205 Indian manufacturing firms, using structural equation modelling analysis. To theoretically substantiate our empirical results, we integrate two perspectives: dynamic capability view (DCV) (e.g. Teece et al. 1997) and contingency theory (Donaldson, 2001). These perspectives can, if combined, explain both the direct performance implications of BDPA, and the contextual conditions under which they are effective. From a managerial perspective, we offer theory-driven and empirically-tested guidance to those managers who are trying to explore how BDPA can help the organisation to achieve better sustainability results.

The paper is organised as follows. In Section 2, we synthesize the theoretical foundations of our study. In Section 3, we present our theoretical framework and research hypotheses. In Section 4 we present our research design which includes discussion on operationalisation of the constructs used in our theoretical framework, sampling design, data collection and non-response bias test. In Section 5 we present our discussion related to statistical analyses. We conclude with discussion of the results and the implications of the results for theory and practice, limitations of our study and further research directions.

2. Theoretical Background

2.1 Big data and predictive analytics

Literature has highlighted the role of data within *inter alia* business, engineering, education, and sociology (Duan and Xiong, 2015). Although data alone is ubiquitous (Duan and Xiong, 2015), extracting useful information from large data sets requires different analytical techniques. In the past, technical constraints limited the capacity of data scientists to collect, store and process data. With the recent advances in technology, generating and analysing data is fast and voluminous (Wamba et al., 2015). Big data is characterized by 3V's: volume, velocity and variety (Russom, 2011; Zhou et al. 2014; Duan and Xiong, 2015). Wamba et al. (2015) further characterized it as 5 V's: volume, velocity, variety, veracity and value. Here volume refers to the large amount of data generated. From a statistical point of view, the results of data analyses are statistically highly reliable with high sample size. With the recent advances in the technology, the rate at which data is generated is fast. This characteristic of the data is referred as velocity. Variety refers to the mix of different data sources in different formats: unstructured data, semi-structured data and structured data. Veracity refers to the inherent unpredictability of some data requires analysis of large data to gain reliable prediction and value refers to the extent to which one can derive economically worthy insights or benefits through extraction or transformation. Analysing big data using predictive techniques may offer many advantages and benefits (see Chen et al., 2014; Duan and Xiong, 2015; Wamba et al. 2015; Akter et al. 2016; Dubey et al. 2016; Wang et al. 2016b; Amankwah-Amoah, 2016; Matthias et al. 2017).

The power of big data is usually related to predictive analytics that uses statistical knowledge to forecast future events based on the assumption that what has occurred in the past may have influence on future events. The common predictive techniques that are often used by data scientists are: regression modelling, decision tree, Bayesian statistics, neural network, Support Vector Machine (SVM) and nearest neighbour algorithms (Oztekin, 2017). After acquiring the raw data from the various sources, cleaning, integration, and other steps are followed to make it ready for further analyses using appropriate predictive techniques.

2.2 Toward the conceptualization of a big data & predictive analytics (BDPA) capability

Wamba et al. (2017) defined BDPA as a higher-order organisational capability which relies on bundling of strategic resources. In a previous study, Akter et al. (2016) examined the effect that resources and BDPA capability have on organizational performance. Despite the increasing research on BDPA, empirical studies on BDPA conceptualisation are limited (George and Gupta, 2016; Akter et al. 2016; Wamba et al. 2017; Dubey et al. 2018). In this paper, we follow Teece et al. (1997) and argue that the BDPA can be conceptualised as a capability which is essential for an organization. This capability is based on existing environmental conditions under which the organization is functioning. The effective exploitation of this organisational capability may lead to the achievement of sustained competitive advantage.

Capabilities are created by the combination of resources, including human resources and technical and managerial skills. We define human resources as a function of the employees' experience, knowledge, business acumen, problem-solving abilities, leadership qualities and relationships with others (Hitt et al. 2001; Gupta and George, 2016). Skills (i.e. technical skills and managerial skills) required to build BDPA capability, organisational learning and data driven decision making culture may be the source of sustainable competitive advantage. These are briefly discussed next.

2.2.1 Technical skills

Technical skills refer to the know-how required to use new technology or algorithms to extract meaningful information from large data sets. Gupta and George (2016) argue that some of these skills include competencies in machine learning, data extraction, data cleaning, statistical analysis, and understanding programming tools such as MapReduce.

2.2.2 Technical skills

Managerial skills, unlike technical skills, are often acquired through long years of working (Gupta and George, 2016). Within the context of a firm's big data function, the intelligence gathered from the data may be of no use if the managers fail to understand the context in which the gathered insights can be useful. Hence, the ability to predict market behaviour is an essential quality which data analysts should possess. Secondly, interpersonal skills and the ability to develop trust may be critical to the successful use of BDPA in sustainable supply chains, in that such soft skills be valuable, rare, inimitable and non-substitutable (Mata et al., 1995; Kearns and Lederer, 2003).

2.2.3 Organizational Learning

Grant (1991) argued that sustained competitive advantage is based on the continuous process through which organisations explore, store, share, and apply knowledge. In a later study, Teece et al. (1997) suggested that in a dynamic environment, organizational learning is an important source of sustained competitive advantage. Nonaka et al. (2000) claimed that knowledge does not wear out, however with the passage of time it may become outdated due to the emergence of new technologies. Hence, organizations need to continuously adapt according to market demand. Those organizations that have the propensity for learning may remain competitive in the long run (Gupta and George, 2016). Hence, we argue based on existing literature that organizational learning may help to build BDPA capability to address issues related to social and environmental sustainability.

2.3 Organisational Culture

Khazanchi et al. (2007) argues that organisational culture refers to a collection of shared assumptions, values, and beliefs that is reflected in the organisational practices and the goals and that helps its organisational members to understand organisational functioning (White et al. 2003; Liu et al. 2010). In a previous study Deshpande et al. (1993) discussed how the organisational culture influences the way an organization responds to external events and makes strategic choices. Liu et al. (2010) showed that organisational culture has been classified either as relation- and transaction-oriented culture (e,g. McAfee et al. 2002) and flexibility-control orientation (e.g. Khazanchi et al. 2007). In the current research, following Liu et al.'s (2010) arguments we use flexibility-control orientation (FO-CO) in the Competing Value Model (CVM) proposed by Quinn and Rohrbaugh (1983).

3. Theoretical Model and Hypotheses Development

In this study, we follow the dynamic capability view (DCV), an extension of the resource based view (RBV) (Hitt et al. 2016). The DCV explains a firm's competitive advantage in changing environments (Teece et al. 1997). Hence, the DCV may be defined as the firm's ability to integrate, build and reconfigure internal and external competences to respond to rapid changing environments (Teece et al. 1997). We argue based on DCV logic that an organisation may create difficult to replicate capabilities to adapt to changing customer and technological opportunities. Akter et al. (2016) argues using DCV logic that BDPA can provide competitive advantage to an organisation in highly dynamic situation when due to lack of transparency the organisation, despite of having stock of strategic resources, often fails to translate into desired competitive advantage. Thus, DCV enables understanding of how BDPA can improve social and environmental sustainability.

Following DCV, we conceptualise BDPA as a higher order reflective construct. Here, we argue that the strategic resources and culture, that is, technical skills (TS), management skills (MS), organisational learning (OL) and data driven decision making (DDDM) build BDPA capability (Barney, 1991). Further, we directly link BDPA with social performance (SP) and environmental performance (EP), examining the role of BDPA in improving the two performance dimensions of sustainability. Furthermore, we develop our hypotheses on the contingent effects of the organisational culture (OC) (i.e. FO and CO).

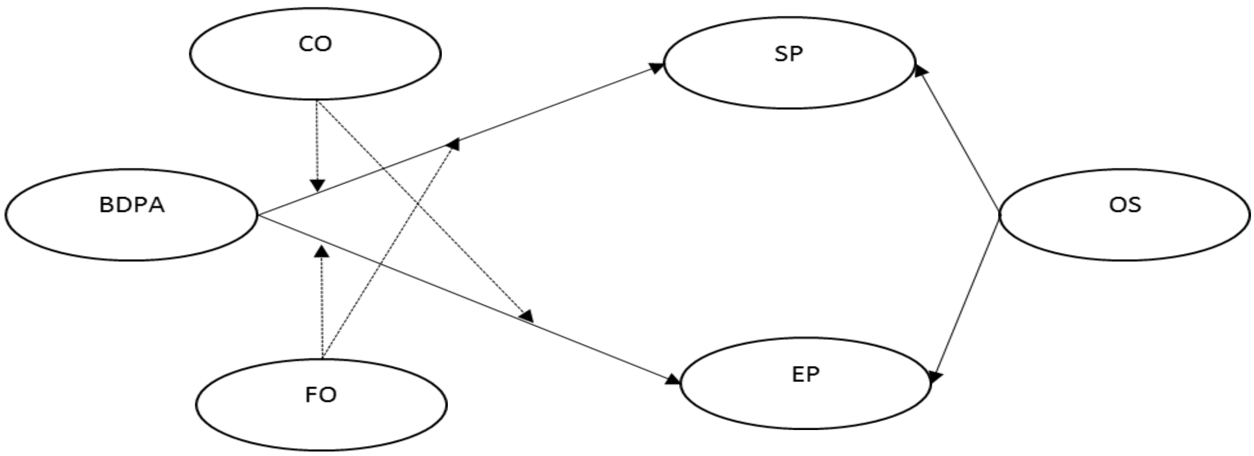

Figure 1: Theoretical Framework

3.1 Direct effect of BDPA on performance

Literature clearly suggests that social and environmental sustainability are not yet part of the popular lexicon of the BDPA in action. Keeso (2014) argues that the big data has enough potential to influence environmental study. In a special report (IGEL, 2014), the potential of the big data and its future impact on sustainability is presented following Gartner Hype Cycle. In a business report (see 3p Contributor, 2016), a real-life practice has been reported which suggests how Pirelli, the world fifth largest tyre manufacturing organisation with the help of SAP, a German software company, was able to resolve inventory related issues using real-time big data. The decision based on real-time big data allows Pirelli to plan its inventory which prevents tyres from reaching landfills and greenhouses gases from the atmosphere. In another case Koseleva and Ropaite (2017) noted the usefulness of the big data in energy efficient practices. Song et al. (2017) further discussed how big data can support organisational goal towards improving social and environmental sustainability. Hence, previous arguments provide conceptual and anecdotal evidence, with little empirical rigorous testing exists of such benefits. Although, some scholars have tested empirically the association between BDPA and market performance/ operational performance (Gupta and

George, 2016; Akter et al. 2016). In a similar vein, we can extend the previous attempt to test the direct impact of BDPA on social/ environmental performance. Hence, this evidence leads to our first and second research hypotheses as:

H1: The BDPA is positively related to perceived social performance.

H2: The BDPA is positively related to perceived environmental performance.

3.2 Moderating effect of organisational culture (OC)

Literature increasingly discusses OC as the guide for the organisational strategies (e.g. Khazanchi et al. 2007; Liu et al. 2010). Khazanchi et al. (2007) noted that flexibility-oriented and control-oriented cultures have different effects on the organisation's interpretations of external events, and thus differentially affect their responses to the expectations and requirements of the environment. Liu et al. (2010) argued that OC can impact managers' ability to process information, rationalise, and exercise discretion in their decision-making processes.

The DCV offers rational arguments related to selection and utilisation of the resources that are valuable, rare, difficult to copy, and non-substitutable which may lead to enduring organisation variation and supernormal profits (Barney, 1991). However, the DCV, being an extension of RBV (Teece et al. 1997; Hitt et al. 2016), has not looked beyond the properties of the resources and resource markets to explain enduring firm heterogeneity. We suggest that organisations with flexibility orientation may behave in a different manner to those with control orientation. Flexibility orientation allows organisation to be creative and risk-taker and open for embracing changes in the environment. Hence, following this logic we may posit that flexible orientation may strengthen the direct effect of BDPA on social/environmental performance. Organisations with flexible orientation may prefer to invest their resources in cultivating unique practices to differentiate themselves from other players in the field. Hence, we hypothesise it as:

H3: An organisation's flexibility orientation (FO) positively moderates the relationship between BDPA and perceived social/ environmental performance.

H3a: An organisation's flexibility orientation (FO) positively moderates the relationship between BDPA and perceived social performance.

H3b: An organisation's flexibility orientation (FO) positively moderates the relationship between BDPA and perceived environmental performance.

In contrast, control orientation emphasizes uniformity, coordination, efficiency, and close adherence to rules and regulations. Organisations with an emphasis on order, stability, and predictability (control orientation, that is) would limit the impact of BDPA. Hence, we hypothesise it as follows:

H4: An organisation's control orientation (CO) negatively moderates the relationship between BDPA and perceived social/environmental performance.

H4a: An organisation's control orientation (CO) negatively moderates the relationship between BDPA and perceived social performance.

H4b: An organisation's control orientation (CO) negatively moderates the relationship between BDPA and perceived environmental performance.

4. Research Design

A survey was employed to gather data to test our research hypotheses. Our target sample was those organisations operating in the manufacturing industry. Hence, for gathering data developing a psychometrically sound survey instrument was the most important stage.

4.1 Construct operationalisation

The survey instrument was developed by identifying measures from our literature review. All the constructs used in our theoretical framework are operationalised as reflective constructs. The operationalisation of each construct is shown in Table 1.

Table 1: Construct operationalisation

Construct and Derivation	**Measures**
Technical skills adapted from Gupta and George (2016)	We provide big data analytics training to our employees (TS1) We hired employees that already have big data and analytics skill (TS2) Our big data analytics staff have right skills to accomplish their jobs successfully (TS3) Our big data staff has the suitable education to fulfill their jobs (TS4) Our big data analytics staff have the suitable work experience to accomplish their jobs successfully (TS5) Our big data analytics staff is well trained (TS6)

Managerial skills (MS) adapted from Gupta and George (2016)	Our big data analytics managers understand and appreciate the needs of other members (MS1) Our big data managers can work with other functional managers (MS2) Our big data analytics managers can coordinate big-data-related activities in ways that support other partners (MS3) Our big data analytics managers can anticipate future challenges (MS4) Our big data analytics managers have a good sense of where to use big data (MS5) Our big data analytics managers can interpret the analyses obtained using complex analyses and offer inputs which are useful for swift decision making (MS6)
Data driven decision making culture (DDDM) adapted from Gupta and George (2016)	We consider data as an asset (DDDM1) We base most of the decisions on data rather than instinct (DDDM2) We are willing to override our intuition when data contradict our viewpoints (DDDM3) We continuously assess our strategies and take corrective action in response to the insights obtained from data (DDDM4) We continuously coach our people to make their decisions based on data(DDDM5)
Organisational learning(OL) adapted from Gupta and George (2016)	We can search for new and relevant knowledge (OL1) We can acquire new and relevant knowledge (OL2) We can assimilate relevant knowledge (OL3) We can apply relevant knowledge (OL4)
Flexible orientation (FO) adapted from Liu et al. (2010)	We value loyalty and tradition in our organization. The commitment runs high (FO1). Our people are willing to stick their necks and take risks (FO2). We are committed to innovation and development (FO3). Our organizations emphasize growth through developing new ideas (FO4).
Control orientation (CO) adapted from Liu et al. (2010)	Our organization follow formal rules and policies (CO1). Our organization value permanence and stability (CO2). Our organization is output driven (CO3). Our organization places high importance to accomplishing goals (CO4).
Social performance (SP) adapted from Yakovleva et al. (2012)	Total employment (SP1) Employee per enterprise (SP2) Average gross wages per employee(SP3) Male vs female full time employment (SP4)
Environmental performance (EP) adapted from Yakovleva et al. (2012)	Reduction of air emission (EP1) Reduction of waste water(EP2) Reduction of solid wastes(EP3) Decrease in consumption of hazardous/harmful materials(EP4) Improve an enterprise environmental situation (EP5)

4.2 Data collection

The survey was administered to managers in Indian manufacturing organisations that use big data to improve their decision-making skills, including thos who use data agencies and those who have developed in-house capabilities. A sample was drawn from the clients of Boston Consulting Group (BCG), a major consulting company which provides business solutions to many manufacturing, retail, pharmaceutical, oil & gas and 3 PL's organisations. We requested our contacts based in BCG India to randomly distribute our questionnaires to the directors, analytics head and senior managers of those manufacturing units where BCG in collaboration with CII (Confederation of Indian Industries) Institute for Manufacturing are working on a big data analytics project towards improving competitiveness of Indian manufacturing organisations.

We believe this design is suitable for research in the light of India's unique social and cultural context. In India, most of the manufacturing organisations are family owned enterprises. Hence, the personal liaisons are extremely important, instead of formal rules. Collecting data from Indian manufacturing firms for research is extremely difficult unless it is done through reputable agencies like CII. Hence, only with the help of CII and BCG could we access the key person of the big data analytics project of each organisation of interest. The key people whom we approached were not only involved directly in the big data analytics project but also interacted with functional head and top management team of their organisation. Hence, they are likely to provide better response to the questionnaire. We further requested each respondent to consult their team members or refer to their minutes of meetings to minimise reporting bias.

Of the 375 questionnaires distributed, 205 questionnaires were returned completed and usable for data analysis, showing an effective response rate of 54.67 percent. Next, we evaluated non-response bias using t-tests to compare the responding and non-responding organisations following Armstrong and Overton's (1977) suggestions. We noted that there are no significant differences ($p > 0.05$). Table 2 represent the demographic profiles of the respondents.

Table 2: Sample demographic (n=205)

Annual Sales Revenue (*Million USD**)*	*N*	*Percentage*
Under 10	15	7
10- 25	15	7
26- 50	35	17
76-100	48	23
101-250	22	11
251-500	24	12
Over 251	46	22
Number of Employees		
0-50	16	8
51-100	6	3
101-200	13	6
201-500	8	4
501-1000	105	51
1001+	57	28
Industry		
Auto component manufacturers	114	56
Cement manufacturers	10	5
Chemical products	54	26
Wood products	27	13

5. Data analyses and results

Henseler et al. (2014) argue that PLS (Partial Least Squares) estimates a more general model than covariance-based SEM and is less affected by model misspecification in some subparts of the model. Hence, we can argue that PLS is a suitable tool for exploratory research. Our study is more exploratory in nature as the existing literature is in a nascent stage (Gupta and George, 2016). Hence, we used WarPLS 5.0 version to test our model and our research hypotheses. Peng and Lai (2012, p. 469) argues that PLS is a prediction oriented and allows researcher to assess the predictability of the exogenous variables. Our study aims to assess the prediction or explanatory power of antecedent factor (i.e. BDPA). The relationship between BDPA and social/ environmental performance were not examined in the literature, therefore, there is no theoretical foundation anticipating their associations, which makes a PLS based modelling technique more appropriate for data analysis (Henseler et al. 2014). Moreover, PLS is suitable for estimating a complex structural equation model, as proposed in this model. In conducting the estimation, we followed the procedure advocated by scholars (i.e. Peng and Lai, 2012; Henseler et al. 2014; Moshtari et al. 2016). We evaluated the PLS model in two stages: examining the validity and reliability of the measurement model and analysing the structural model (see Peng and Lai, 2012; Moshtari et al. 2016).

5.1 Measurement model

We note that the scale composite reliability (SCR) are above 0.70, the Cronbach's alpha coefficients greater than 0.7 and each average variance extracted (AVE) is above 0.5 except BDPA which is 0.46 (see Appendix 1), indicating that the measurements are reliable and the latent construct account for at least 50 percent of the variance in the items. However, after dropping weak items (i.e. loadings less than 0.4), we further performed SEM analysis and obtained new results. The new AVE of the BDPA has improved significantly (see Table 3). As shown in Table 3, the loadings are in an acceptable range (Hair et al. 2006).

Table 3: Loadings of the Indicator Variables (Composite Reliability) (AVE)

Construct	Indicator	Factor Loadings	Variance	Error	SCR	AVE
BDPA	TS5	0.69	0.48	0.52	0.95	0.55
	TS6	0.58	0.34	0.66		
	MS1	0.70	0.50	0.50		
	MS2	0.62	0.38	0.62		
	MS3	0.75	0.56	0.44		
	MS4	0.75	0.57	0.43		
	MS5	0.78	0.61	0.39		
	MS6	0.81	0.65	0.35		
	DDDM1	0.80	0.64	0.36		
	DDDM2	0.75	0.56	0.44		
	DDDM3	0.76	0.58	0.42		
	DDDM4	0.73	0.53	0.47		
	DDDM5	0.72	0.52	0.48		
	OL1	0.76	0.57	0.43		
	OL2	0.78	0.61	0.39		
	OL3	0.82	0.67	0.33		
	OL4	0.82	0.67	0.33		
FO	FO1	0.92	0.84	0.16	0.84	0.63
	FO2	0.89	0.79	0.21		
	FO3	0.93	0.87	0.13		
	FO4	0.09	0.01	0.99		
SP	SP2	0.93	0.87	0.13	0.94	0.84
	SP3	0.93	0.86	0.14		
	SP4	0.90	0.81	0.19		
EP	EP1	0.81	0.65	0.35	0.96	0.85
	EP2	0.96	0.93	0.07		

	EP3	0.97	0.95	0.05		
	EP4	0.94	0.87	0.13		
CO	CO1	0.87	0.76	0.24	0.78	0.61
	CO2	0.87	0.75	0.25		
	CO3	0.73	0.54	0.46		
	CO4	0.64	0.41	0.59		

The leading diagonal entry of the Table 4 which represents square root of AVE is found to be greater than the inter-construct correlations. Hence, we can argue that our model demonstrates sufficient discriminant validity.

Table 4: Correlations among major constructs

	BDPA	SP	FO	CO	EP	OS
BDPA	0.74					
SP	0.01	0.92				
FO	0.38	0.26	0.79			
CO	-0.03	-0.04	-0.01	0.78		
EP	0.34	0.29	0.40	0.01	0.92	
OS	-0.09	-0.05	-0.12	-0.03	-0.06	1.00

5.2 Common method bias (CMB)

Ketokivi and Schroeder (2004) argue that it is almost impossible to address the CMB in survey research in an adequate manner unless one use multiple informants for each observational unit. Podsakoff et al. (2003) argue that CMB results from multiple sources such as consistency motif and social desirability. Hence, following Guide and Ketokivi (2015) we argue that our aim in this study is to take some remedy against self-reported data so that the CMB can be minimized. Firstly, we requested respondents not to respond according to personal experiences, but to get this information from minutes of company meetings or documentation. Next, we performed statistical analyses to assess the severity of CMB. We performed Harman's single-factor test. We observed that the maximum covariance explained the single factor is 41.86%, indicating that common method bias is not likely to contaminate our results.

5.3 Endogeneity test

Before testing the research hypotheses, we tested the endogeneity of the exogenous variable in our model. The BDPA is conceptualised as a variable exogenous to the SP and EP but not the other way around based on existing literature. The endogeneity is unlikely to be a concern in this context.

We also tested empirically whether the endogeneity was an issue by conducting the Durbin-Wu-Hausman test (Davidson and MacKinnon, 1993). We first regressed the BDPA on all moderation variables, SP, EP and control variable, then used the residual of this regression as an additional regressor in our hypothesized equations. The parameter estimate for the residual was not significant, indicating that the BDPA was not endogenous in our setting, consistent with the initial conceptualisation.

5.4 Hypothesis Testing

Henseler et al. (2014) argue that since PLS does not assume multivariate normal distribution, the traditional parametric-based techniques for significance tests are inappropriate. Instead, PLS based techniques uses bootstrapping procedure to estimate standard errors and the significance of parameter estimates (Chin, 1998; Peng and Lai, 2012; Moshtari, 2016). Figure 2 presents the estimates obtained from PLS analysis using WarpPLS 5.0. The $R^2=0.615$ indicates that model explains a significant amount of variance in social/ environmental performance. The hypothesis H1 (BDPA→SP) found support ($\beta=0.726$; $p<0.001$). This result supports several prior arguments that BDPA has enough potential to improve social performance (Song et al. 2017). Next, addressing hypothesis H2 (BDPA→EP) which found support ($\beta=0.854$; $p<0.001$). This result further supports the prior arguments of scholars (see Keeso, 2014; Song et al. 2017).

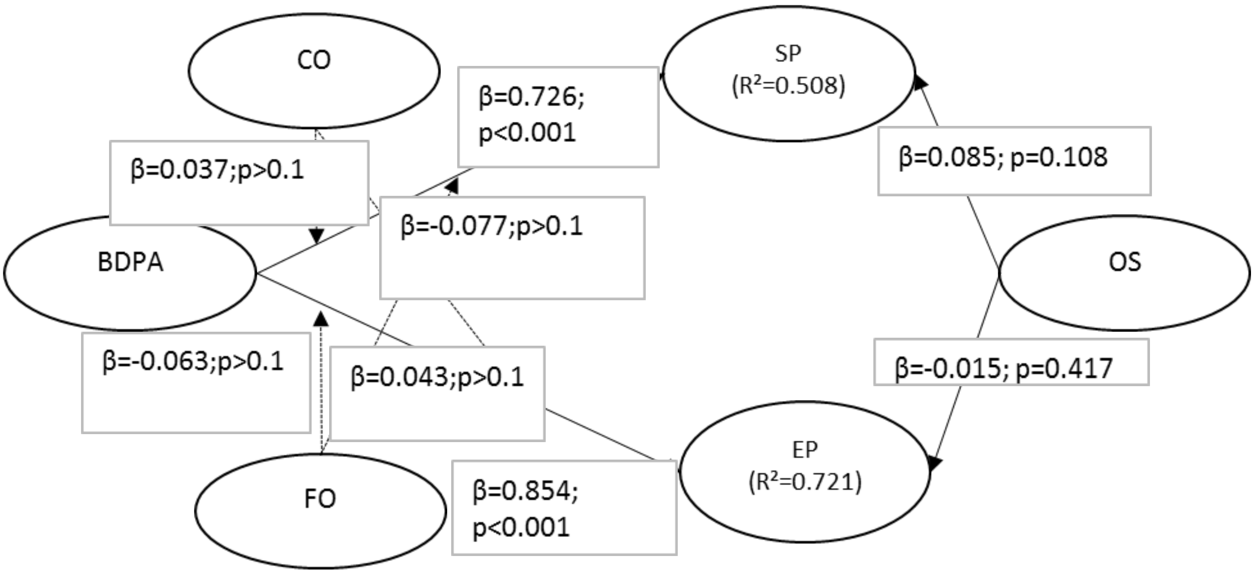

Figure 2: PLS Analysis of Results

H3a (FO*BDPA→SP) (β=0.063; p>0.1) and H4b (CO*BDPA→EP) (β=0.043; p>0.1), were found to be not supported. Similarly, H4a (CO*BDPA→SP) (β=0.037; p>0.1) and H4b (CO*BDPA→EP) (β=0.077; p>0.1), were found to be not supported. The organisational size (OS) included in the model as a control variable, is not significantly related to the SP and EP. We further summarised our PLS path coefficients and p-values were computed based on 500 bootstrapping runs. The estimated path coefficients are estimated as standardised beta coefficients of OLS (ordinary least squares). Table 5 presents the PLS path coefficients and their p-values.

Table 5: Structural estimates

Hypothesis	**Effect of**	**on**	**β**	**p**	**Result**
H1	BDPA	SP	0.726	<0.001	supported
H2	BDPA	EP	0.854	<0.001	supported
H3a	FO*BDPA	SP	0.063	>0.1	not supported
H3b	FO*BDPA	EP	0.043	>0.1	not supported
H4a	CO*BDPA	SP	0.037	>0.1	not supported
H4b	CO*BDPA	EP	0.077	>0.1	not supported

To further examine the explanatory power of the model, we examined the explained variance (R^2) of the endogenous constructs. Using R^2 to assess the structural model is consistent with the objective of PLS to maximize the variance explained in the endogenous variables. The R^2 for SP and EP are 0.508 and 0.721 respectively, which are moderately strong (Chin, 1998). To evaluate the effect size of each predictor, we use the Cohen f^2 formula. f^2 is equal to the increase in R^2 relative to the proportion of variance that remains unexplained in the endogenous latent variable. Following Cohen (1988), f^2 values of 0.35, 0.15, and 0.02 are large, medium and small. Consequently, the effect sizes of BDPA on SP, 0.526 and on EP, 0.725, were considered large. Finally, we examined the model's capability to predict, Stone-Geisser's Q^2 for endogenous constructs are 0.537 and 0.729 for SP and EP respectively, which are all greater than zero, indicating acceptable predictive relevance (Peng and Lai, 2012; Moshtari, 2016). We summarise our findings in Table 6.

Table 6: R^2, effect size and prediction

Construct	R^2	f^2	Q^2
SP	0.508	0.526	0.537
EP	0.721	0.725	0.729

6. Discussion

6.1 Implications for theory

Our empirical results highlight the importance of BDPA as an organisational capability to improve social and environmental performance in supply chains. The previous studies (see George and Gupta, 2016; Akter et al. 2016) considered BDPA as a formative construct. However, in our study we conceptualised BDPA as a reflective latent construct to eliminate complexity associated with the estimation of the formative construct (Henseler et al. 2014). Further, our data analysis suggests that BDPA is positively associated with SP/EP (H1 and H2). Together, these results imply that BDPA is one of the organisational capability which may help organisations to improve SP/EP. This result is found to be consistent with DCV (Teece et al. 1997). Song et al. (2017) argues that in dynamic situations, BDPA directly affect SP and EP. Hence, we may claim that our study results further extend the previous claim of scholars who believe that BDPA has enough potential to improve SP/EP (see Keeso, 2014; Song et al. 2017). The need for eradication of child labour, establishing equality among gender, better education, better living standards, access to safe drinking water, better health facilities, environmental protection and increasing demands for natural resources are forcing organisations to reconsider their business models and restructure their supply chain operations. In response to the pressing social and environmental challenges, scholars and proactive organisations have begun to create more sustainable supply chains. What has not been fully understood is how organisations deal with short-term pressures to remain socially and environmentally viable without compromising with their financial condition, while implementing these newly modelled supply chains. To this extend, scholars (Pagell and Wu, 2009; Wu and Pagell, 2011) have argued that visibility and coordination among partners in supply chains are considered as important antecedents of supply chain sustainability. Our study further extends these studies in that (i) we have examined the relationships between SP/EP, further our understanding related to supply chain sustainability, and (ii) we provide empirical justification for BDPA and its association with SP/EP in supply chains.

Contrary to our expectations, the organisational culture (i.e. FO and CO) does not have significant influence on the paths connecting between BDPA and SP/EP (i.e. H3a/H3b and H4a/H4b). Although the results were not consistent with previous findings (see Liu et al. 2010), we believe that the exact role of the FO and CO with BDPA and SP/EP remain an interesting question for further research. Furthermore, few studies provide insight into how OC may affect innovation adoption (e.g. Khazanchi et al. 2007; Liu et al. 2010). Complementing those studies, the present study suggests that the immediate motivation for BDPA adoption is based upon economic rationale rather than environmental or social motives..

Finally, given that the use of BDPA is prevalent in supply chain coordination tactics (Hazen et al. 2014; Wang et al. 2016; Gunasekaran et al. 2017), the current study reveals that the integration of DCV and OC is a promising paradigm for sustainable supply chain research. It contributes to a better understanding of a firm's choices around adoption of BDPA. Indeed, the applications of DCV in supply chain management is rather limited, whereas the literature in strategy has examined DCV for some time. Eckstein et al. (2015) urge researchers to examine supply chain management issues through the lens of DCV contingent to specific conditions. The present study, in part, answers this research call. From the perspective of DCV, the present study extends our current understanding of the influence of the strategic resources on building BDPA as an organisational capability. This finding supports previous studies (see Gupta and George, 2016; Akter et al. 2016).

6.2 Implications to practice

The findings of our study may offer practitioners guidelines for promoting the use of BDPA for enhancing social/ environmental sustainability in supply chains. Specifically, the firm despite any orientation (flexible or control) will have similar success. Hence, the OC may be an important moderating variable in context to adoption/ use of innovations that integrate partners in SCM. However, in the BDPA context the data driven decision making skills, organisational learning, technical skills and management skills are important antecedents of BDPA which is an important predictor of SP/EP.

Our results especially assist those managers who face constant dilemma on how and when BDPA can be used to improve sustainability in supply chains. Our study results suggest that firms which invest in right talent and build knowledge sharing culture, are more successful in building BDPA capability which may help eliminate complexities resulting in supply chains due to information asymmetry resulting from poor visibility. However, decision supported by BDPA helps to improve coordination among supply chain partners which plays an important role in achieving sustainability in supply chains.

Our results further assist managers who face a constant trade-off between requirements for social performance and environmental performance. The empirical results indicate that BDPA offers significant benefits to both social and environmental related initiatives in supply chains.

6.3 Limitations and directions for further research

Our study has following limitations. Firstly, the study gathered data at one point in time. A longitudinal study would enrich our understanding by offering information on the causal relationships between exogenous and endogenous constructs. It could further allow us to investigate how OC affects the implementation process of the BDPA adoption. Furthermore, the adoption of longitudinal data may reduce common method bias (Guide and Ketokivi, 2015) that undermines the study with data from single source at a single point of time.

Secondly, the current study focuses on managers' perceptions rather than actual performance. To ensure that the perception based measures can predict the actual outcome, we have conducted a strict operationalisation of the items development to improve the validity and compatibility of the indicators. However, it may be more interesting to use more objective data sets to predict the impacts of BDPA on SP/EP.

Thirdly, we used DCV logic to explain the adoption of BDPA. However, following Oliver (1997) arguments the DCV logic is often guided by economic rationality which focuses on the characteristics of resources and the strategic factor markets from which they are obtained to explain firm heterogeneity and sustainable advantage. The DCV has failed to examine the social context within which selection of the resources are imbedded. To address this limitation we attempted to introduce OC. However, we argue that the institutional pressures may offer better explanation to explain the motivation of the organisations which seek beyond economic rationality. Hence, future research can examine the adoption of BDPA using integration of institutional theory and DCV.

Finally, the demographic of our research sample may limit the generalisability of our findings. Hence, to avoid noise caused by the industry differences, we purposely chose to study only samples drawn from manufacturing industry. To avoid interference caused by personal background differences, we specifically chose those informants who held similar responsibilities in their respective organisations. Although these choices may enhance internal validity of current study, they further limit the present work's external validity. Thus, the research findings should be applied to other contexts with caution. Hence, we acknowledge that future research must include samples drawn from multiple industries, multiple geographies and conducted over a longer period.

Appendix 1: Initial Loadings of the Indicator Variables (Composite Reliability) (AVE)

Construct	Measurement	Factor Loadings	Variance	Error	SCR	AVE
BDPA	TS1	0.21	0.05	0.95	0.94	0.46
	TS2	0.07	0.01	0.99		
	TS3	0.24	0.06	0.94		
	TS4	0.16	0.03	0.97		
	TS5	0.69	0.48	0.52		
	TS6	0.58	0.34	0.66		
	MS1	0.70	0.50	0.50		
	MS2	0.62	0.38	0.62		
	MS3	0.75	0.56	0.44		
	MS4	0.75	0.57	0.43		
	MS5	0.78	0.61	0.39		
	MS6	0.81	0.65	0.35		
	DDDM1	0.80	0.64	0.36		
	DDDM2	0.75	0.56	0.44		
	DDDM3	0.76	0.58	0.42		
	DDDM4	0.73	0.53	0.47		
	DDDM5	0.72	0.52	0.48		
	OL1	0.76	0.57	0.43		
	OL2	0.78	0.61	0.39		
	OL3	0.82	0.67	0.33		
	OL4	0.82	0.67	0.33		
FO	FO1	0.92	0.84	0.16	0.84	0.63
	FO2	0.89	0.79	0.21		
	FO3	0.93	0.87	0.13		
	FO4	0.09	0.01	0.99		
SP	SP1	0.25	0.06	0.94	0.87	0.65
	SP2	0.93	0.87	0.13		
	SP3	0.93	0.86	0.14		
	SP4	0.90	0.81	0.19		
EP	EP1	0.81	0.65	0.35	0.96	0.85
	EP2	0.96	0.93	0.07		
	EP3	0.97	0.95	0.05		
	EP4	0.94	0.87	0.13		
CO	CO1	0.87	0.76	0.24	0.78	0.61
	CO2	0.87	0.75	0.25		
	CO3	0.73	0.54	0.46		
	CO4	0.64	0.41	0.59		

Appendix 2: Single Factor Harman's Test

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.489	41.863	41.863	15.489	41.863	41.863
2	5.311	14.355	56.218			
3	3.094	8.362	64.580			
4	2.255	6.095	70.675			
5	2.143	5.793	76.468			
6	1.618	4.373	80.841			
7	1.135	3.068	83.909			
8	.961	2.597	86.506			
9	.831	2.245	88.751			
10	.649	1.754	90.505			
11	.581	1.571	92.076			
12	.444	1.200	93.276			
13	.392	1.060	94.336			
14	.318	.859	95.195			
15	.308	.833	96.028			
16	.249	.674	96.702			
17	.205	.553	97.255			
18	.193	.522	97.777			
19	.164	.442	98.219			
20	.141	.381	98.600			
21	.122	.329	98.929			
22	.095	.257	99.186			
23	.077	.209	99.395			
24	.063	.172	99.566			
25	.057	.154	99.720			
26	.046	.123	99.843			
27	.024	.066	99.909			
28	.024	.065	99.974			
29	.010	.026	100.000			
30	3.775E-16	1.020E-15	100.000			

31	1.970E-16	5.325E-16	100.000			
32	8.443E-17	2.282E-16	100.000			
33	4.150E-17	1.122E-16	100.000			
34	2.621E-17	7.084E-17	100.000			
35	-1.490E-17	-4.026E-17	100.000			
36	-1.123E-16	-3.034E-16	100.000			
37	-1.189E-15	-3.214E-15	100.000			

Extraction Method: Principal Component Analysis.

References

Ageron, B., Gunasekaran, A., & Spalanzani, A. (2012). Sustainable supply management: An empirical study. *International Journal of Production Economics*, *140*(1), 168-182.

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: a systematic review and agenda for future research. *Electronic Markets*, *26*(2), 173-194.

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

Amankwah-Amoah, J. (2016). Emerging economies, emerging challenges: Mobilising and capturing value from big data. *Technological Forecasting and Social Change*, *110*, 167-174.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 14(3), 396-402.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99-120.

Barratt, M., & Oke, A. (2007). Antecedents of supply chain visibility in retail supply chains: a resource-based theory perspective. *Journal of Operations Management*, *25*(6), 1217-1233.

Berns, M., Townend, A., Khayat, Z., Balagopal, B., Reeves, M., Hopkins, M., & Kruschwitz, N. (2009). Sustainability and Competitive Advantage. *MIT Sloan Management Review*, 51(1), 19-26.

Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications*, *19*(2), 171-209.

Chin, W.W. (1988). The partial least squares approach for structural equations modelling. G.A. Marcoulides, ed. *Modern Methods for Business Research*. Mahwah, NJ: Lawrence Erlbaum Associates, London, pp. 295-336.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Erlbaum.

Davidson, R., & MacKinnon, J. G. (1993). Estimation and inference in econometrics.

Deshpandé, R., Farley, J. U., & Webster Jr, F. E. (1993). Corporate culture, customer orientation, and innovativeness in Japanese firms: a quadrad analysis. *The Journal of Marketing*, 57(1), 23-37.

Donaldson, L. (2001). *The contingency theory of organizations*. Sage.

Duan, L., & Xiong, Y. (2015). Big data analytics and business analytics. *Journal of Management Analytics*, *2*(1), 1-21.

Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F., & Papadopoulos, T. (2016). The impact of big data on world-class sustainable manufacturing. *The International Journal of Advanced Manufacturing Technology*, *84*(1-4), 631-645.

Dubey, R, Luo, Z, Gunasekaran A, 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.*

Gold, S., Seuring, S., & Beske, P. (2010). Sustainable supply chain management and inter-organizational resources: a literature review. *Corporate Social Responsibility and Environmental Management*, *17*(4), 230-245.

Grant, R. M. (1991). The resource-based theory of competitive advantage: implications for strategy formulation. *California management review*, *33*(3), 114-135.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B., and Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, 70, 308-317.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064.

Hartmann, J., & Moeller, S. (2014). Chain liability in multitier supply chains? Responsibility attributions for unsustainable supplier behavior. *Journal of Operations Management*, *32*(5), 281-294.

Hazen, B.T., Boone, C.A., Ezell, J.D., and Jones-Farmer, L.A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72-80.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W. & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, *17*(2), 182-209.

Hitt, M. A., Bierman, L., Shimizu, K., & Kochhar, R. (2001). Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective. *Academy of Management Journal*, *44*(1), 13-28.

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

ILO (2017). http://www.ilo.org/wcmsp5/groups/public/---dgreports/---nylo/documents/statement/wcms_547544.pdf (date of access: 11th April, 2017).

Kache, F., and Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of big data analytics and supply chain management. *International Journal of Operations and Production Management, 37*(1), 10-36.

Kearns, G. S., & Lederer, A. L. (2003). A resource-based view of strategic IT alignment: how knowledge sharing creates competitive advantage. *Decision Sciences*, *34*(1), 1-29.

Keeso, A. (2014). *Big data and environmental sustainability: A conversation starter*. Working paper 14-04, Smith School Working Paper Series (http://www.smithschool.ox.ac.uk/library/working-papers/workingpaper%2014-04.pdf) (Date of access: 15th April, 2015).

Ketokivi, M. A., & Schroeder, R. G. (2004). Perceptual measures of performance: fact or fiction? *Journal of Operations Management*, *22*(3), 247-264.

Khazanchi, S., Lewis, M. W., & Boyer, K. K. (2007). Innovation-supportive culture: The impact of organizational values on process innovation. *Journal of Operations Management*, *25*(4), 871-884.

Koseleva, N. and Ropaite, G. (2017). Big Data in Building Energy Efficiency: Understanding of Big Data and Main Challenges. *Procedia Engineering*, 172, 544-549.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, *52*(2), 21.

Leidner, D. E., & Kayworth, T. (2006). Review: a review of culture in information systems research: toward a theory of information technology culture conflict. *MIS quarterly*, *30*(2), 357-399.

Liu, H., Ke, W., Wei, K. K., Gu, J., & 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*, *28*(5), 372-384.

Liu, X., & Zhang, C. (2017). Corporate governance, social responsibility information disclosure, and enterprise value in China. *Journal of Cleaner Production*, *142*, 1075-1084.

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS quarterly*, 19(4), 487-505.

Matthias, O., Fouweather, I., Gregory, I., & Vernon, A. (2017). Making sense of big data – can it transform operations management? *International Journal of Operations and Production Management, 37*(1), 37-55.

McAfee, A. (2002). The impact of enterprise information technology adoption on operational performance: An empirical investigation. *Production and Operations Management*, *11*(1), 33-53.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data. *The management revolution. Harvard Business Review*, *90*(10), 61-67.

Moshtari, M. (2016). Inter-Organizational Fit, Relationship Management Capability, and Collaborative Performance within a Humanitarian Setting. *Production and Operations Management*, *25*(9), 1542-1557.

Mueller, M., Dos Santos, V. G., & Seuring, S. (2009). The contribution of environmental and social standards towards ensuring legitimacy in supply chain governance. *Journal of Business Ethics*, *89*(4), 509-523.

Nonaka, I., Toyama, R., & Konno, N. (2000). SECI, Ba and leadership: a unified model of dynamic knowledge creation. *Long Range Planning*, *33*(1), 5-34.

Oliver, C. (1997). Sustainable competitive advantage: Combining institutional and resource-based views. *Strategic Management Journal*, 18(9), 697-713.

Oztekin, A. (2017). Big Data Analytics for Creating a Marketing Strategy in Healthcare Industry. *Annals of Operations Research,* 1-XX (accepted).

Pagell, M., & Wu, Z. (2009). Building a more complete theory of sustainable supply chain management using case studies of 10 exemplars. *Journal of Supply Chain Management*, *45*(2), 37-56.

Park-Poaps, H., & Rees, K. (2010). Stakeholder forces of socially responsible supply chain management orientation. *Journal of Business Ethics*, *92*(2), 305-322.

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management*, *30*(6), 467-480.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903.

Quinn, R. E., & Rohrbaugh, J. (1983). A spatial model of effectiveness criteria: Towards a competing values approach to organizational analysis. *Management Science*, *29*(3), 363-377.

Ravichandran, T., Lertwongsatien, C., & Lertwongsatien, C. (2005). Effect of information systems resources and capabilities on firm performance: A resource-based perspective. *Journal of Management Information Systems*, *21*(4), 237-276.

Ross, J. W., Beath, C. M., & Quaadgras, A. (2013). You may not need big data after all. *Harvard Business Review*, *91*(12), 90-98.

Russom, P. (2011). Big data analytics. *TDWI best practices report, fourth quarter*, 1-35. (https://vivomente.com/wp-content/uploads/2016/04/big-data-analytics-white-paper.pdf) (Date of access: 10th April, 2017).

Schoenherr, T. & Cheri, S-P. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics,* 36(1), pp. 120-132.

Sengers, F., Wieczorek, A.J., & Raven, B. (2016). Experimenting for sustainability transitions: A systematic literature review. *Technological Forecasting and Social Change*, DOI: http://doi.org/10.1016/j.techfore.2016.08.031

Seuring, S., & Müeller, M. (2008). Core issues in sustainable supply chain management–a Delphi study. *Business strategy and the environment*, *17*(8), 455-466.

Shrivastava, P., & Guimaraes-Costa, N. (2017). Achieving environmental sustainability: The case for multi-layered collaboration across disciplines and players. *Technological Forecasting and Social Change*, 116, pp. 340-346.

Song, M. L., Fisher, R., Wang, J. L., & Cui, L. B. (2016). Environmental performance evaluation with big data: Theories and methods. *Annals of Operations Research*, 1-14.

Song, M., Cen, L., Zheng, Z., Fisher, R., Liang, X., Wang, Y., & Huisingh, D. (2017). How would big data support societal development and environmental sustainability? Insights and practices. *Journal of Cleaner Production*, *142*, 489-500.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18 (7), 509-533.

Vachon, S., & Klassen, R. D. (2008). Environmental management and manufacturing performance: The role of collaboration in the supply chain. *International Journal of Production Economics*, *111*(2), 299-315.

Waller, M. A., & 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*, *34*(2), 77-84.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & 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*, *165*, 234-246.

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

Wang, Y., Kung, L., & Byrd, T. A. (2016b). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*. http://doi.org/10.1016/j.techfore.2015.12.019.

White, M., Hill, S., McGovern, P., Mills, C., & Smeaton, D. (2003). 'High-performance' Management Practices, Working Hours and Work–Life Balance. *British Journal of Industrial Relations*, *41*(2), 175-195.

Wolf, J. (2011). Sustainable supply chain management integration: a qualitative analysis of the German manufacturing industry. *Journal of Business Ethics*, *102*(2), 221-235.

Wu, J., Guo, S., Li, J., & Zeng, D. (2016). Big Data Meet Green Challenges: Big Data Toward Green Applications. *IEEE Systems Journal*, *10*(3), 888-900.

Wu, Z., & Pagell, M. (2011). Balancing priorities: Decision-making in sustainable supply chain management. *Journal of Operations Management*, *29*(6), 577-590.

Yakovleva, N., Sarkis, J., & Sloan, T. (2012). Sustainable benchmarking of supply chains: the case of the food industry. *International Journal of Production Research*, *50*(5), 1297-1317.

Zhang, Y., Ren, S., Liu, Y., & Si, S. (2017). A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. *Journal of Cleaner Production*, *142*, 626-641.

Zhou, Z. H., Chawla, N. V., Jin, Y., & Williams, G. J. (2014). Big data opportunities and challenges: Discussions from data analytics perspectives [discussion forum]. *IEEE Computational Intelligence Magazine*, *9*(4), 62-74.

Other references

3p Contributors (2016). How Big Data Can Make Your Company More Sustainable. Triple Pundit: people, planet and profit (Feb 10th 2016). http://www.triplepundit.com/2016/02/big-data-can-make-company-sustainable/ (date of access: 16th April, 2017).