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Abstract

The organizations engaged in sustainable development programmes are increasingly paying serious attention towards synergetic relationships between focal firms and their partners to achieve the goal of sustainable consumption and production (SCP) via big data and predictive analytics (BDPA). The study examines the role of BDPA in collaborative performance (CP) among the partners engaged in sustainable development programme to achieve the goal of SCP. The study further investigates the contingent effect of organization fit on the impact of BDPA on CP. We used variance based structural equation modelling (PLS SEM) to test research hypotheses using a sample of 190 respondents working in auto-components manufacturing organizations in India drawn from the ACMA and Dun & Bradstreet databases. The results indicate that BDPA has a significant positive impact on the CP among partners and the organizational compatibility and resource complementarity have positive moderating effects on the path joining BDPA and CP. The study contributes to the understanding of BDPA and collaboration literature in the context of sustainable development. These findings extend the dynamic capability view (DCV) to create a better understanding of contemporary applications of big data and predictive analytics capability, while also providing theoretically grounded directions to managers who seek to use information processing technologies to continuously improve the collaboration in supply chain networks. We have also noted some of the limitations of our study and identified numerous further research directions.

Keywords: *sustainable consumption, sustainable production, collaboration, inter-organizational fit, resource complementarity, sustainable operations*

1. Introduction

Sustainable development has attracted increasing attention from academia and practitioners (Tukker et al., 2010; Berg, 2011; Roy and Singh, 2017). Sustainable consumption and production (SCP) are often considered as two pillars of sustainable development (Moldan et al. 2012). SCP is now one of the most popular words in the management lexicon which gained popularity after the summit on sustainable development (UNEP, 2010). Despite much increasing attention from industry, sustainable development is still a pressing concern of the emerging economies (Huang et al., 2012). SCP may refer to "*the use of services and related products which respond to basic needs and bring a better quality of life while minimizing the use of natural resources and toxic materials as well as the emissions of waste and pollutants over the life cycle of the service or product so as not to jeopardize the needs of further generation*" (Norwegian Ministry of Environment, Oslo symposium, 1994). Dubey et al. (2016b), argue that SCP is one of the main goals of sustainable development which promotes resource & energy optimisation, better infrastructure, and access to basic amenities, green environment and decent jobs for everyone. The literature focusing on sustainable consumption (SC), sustainable production (SP) or SPC is rich (see Dubey et al., 2016b; Luo et al., 2017). Other studies like (e.g., Lin and Huang, 2012; Nazzal et al., 2013; Luthra et al., 2016; Dubey et al., 2016b; Luo et al., 2017) have examined the influence of antecedents such as attitudes towards sustainable consumption and production, learning, and product attributes, and external pressures under the mediating effect of top management perception to explain SPC. Despite accumulating contributions focusing on SPC, the existing literature has failed to resolve some of the unanswered questions related to SC/SP (Wang et al., 2011; Vinkhuyzen and Karlsson-Vinkhuyzen, 2014; Song and Wang, 2017; Song et al., 2017). However, in the era of large data or big data and the use of relevant technology to extract meaningful information, to address the unresolved questions remains no small challenge (Dubey et al., 2016a; Dubey et al., 2017). Organizations are often confronted with the key challenge of how to maintain business growth without compromising the environmental and social issues (Song et al. 2018). The complexity of decision making in a highly uncertain environment related to SCP behaviour is multiplied. As companies set out to evaluate the sustainable consumption and production impacts on the organization performance, they often face information asymmetry. Given the lack of complete information related to SCP behaviour, organizations seek more collaboration or alliances between partners in supply chain networks (SCN). The scholars in the previous studies have suggested improving visibility and integration among the supply chain partners to engage themselves for common goals (Vachon and Klassen, 2008; Ageron et al., 2012; Khan et al. 2016; Dubey et al. 2017). Based on recent debates surrounding the extraction and processing of valuable information from big data (see, Keeso et al., 2014; Dutta and Bose, 2015; Dubey et al., 2017; Song et al. 2017a; Gölzer and Fritzsche, 2017; Liu and Yi, 2017; Seele, 2017; Seles et al. 2018), we argue that big data provides unique opportunities to organizations to improve the visibility and integration in SCN.

Song et al. (2017) argue that both conceptual and empirical research on the influence of big data and predictive analytics (BDPA) on sustainable behaviour is still fragmented, and may not be adequate to compare and accumulate results to arrive at meaningful conclusions. Schoenherr and Speier-Pero (2015) argue that there is dearth of literature on BDPA, as most of the literature drawn from practitioner outlets and consultancy reports is repetitive and lacks rigorous scientific investigations. The existing literature clearly suggests that collaboration among partners in SCN plays a significant role in sustainable business development (Bocken et al. 2014); as well as confirming that BDPA can improve decision making (Schoenherr and Spier-Pero, 2015; Srinivasan and Swink, 2017; Zhao et al. 2017), visibility in SCN (Schoenherr and Spier-Pero, 2015; Gunasekaran et al. 2017; Srinivasan and Swink, 2017), agility (Schoenherr and Spier-Pero, 2015; Dubey et al. 2018) and enhanced sales and operations planning capabilities (Schoenherr and Spier-Pero, 2015). The role of collaboration in SCNs is highly significant (Vachon and Klassen, 2008; Cao and Zhang, 2011), however the role of BDPA on collaborative performance in SCN still needs to be examined. In this study we examine the association between BDPA and collaborative performance among the members in SCN and how organizational fit influences the association between BDPA and the collaborative performance.

We are investigating how lateral relations and vertical information systems can improve information processing capabilities (Galbraith, 1974; Zhu et al. 2018). Srinivasan and Swink (2017) argue that building lateral relations with supply chain network members can increase the availability of current and valuable information. Vertical information systems allow organizations to process data and extract useful information to adjust or develop new plans. Specifically, we note this as the first research question: *what is the effect of BDPA on collaborative performance?*

Holcomb and Hitt (2007) argue that the compatibility among organizations often plays a significant role in collaboration. This organizational compatibility among organizations and their resource complementarity is often referred as inter-organizational fit. In addition, Sarkar et al., (2001) argue that inter-organizational fit focuses on alignment between organizational systems in terms of organizational structures, the use of technology and the organisational norms. Resource complementarity may be understood to mean the extent to which strategic resources and organizational capabilities are shared between partners to achieve desired competitive advantage (Harrison et al. 2001). The existing literature suggests positive association between inter-organizational fit and synergetic components of the firm such as integration or collaboration, which includes conflict resolution, reducing transaction cost between a focal organization and its partners, exploring and exploiting better opportunities, minimizing formal paperwork and building trust and commitment among the partners (Moshtari, 2016; Jonkute and Staniskis, 2016). We consider collaboration as either a limiting or enabling factor associated with the success of SCP initiatives of the organizations. To an extent, organizations acquire data from partners in SCN to gain insights into changing market conditions. Galbraith (2014) argues that collaboration among partners as a way to increase information processing capacity. The availability of relevant, accurate and timely data from partners enables the firms to develop mechanisms to process and extract useful information. The insights gained via BDPA capability can highlight the opportunities for operational improvement and can help organizations to take suitable action (Keeso, 2014; Seles et al. 2018). Compatibility among participating organizations or partners and their resource complementarity may influence the level of collaborative performance (McLachlin and Larson, 2011). However, in the SCP context, the role of organizational fit is not well studied. Hence, we note this as our second research question: *what is the interaction effect of inter-organizational fit on the path connecting BDPA and collaborative performance?*

We answer our research questions based on 190 samples drawn from Indian auto components manufacturing organizations, using a variance-based SEM technique (PLS SEM). To theoretically substantiate our empirical results, we have firmly grounded our theoretical model in two independent organizational theories: the dynamic capability view (DCV) (Teece et al., 1997) and contingency theory (CT) (Donaldson, 2001). Eisenhardt and Martin (2000) argue that the resource based view (RBV) often fails to explain how organizations can gain competitive advantage using resources in dynamic situations. Teece et al. (1997) argue that DCV provides a better explanation for the organization's competitive advantage in changing environments. DCV can be defined as "*the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments*" (Teece et al. 1997, p. 516). However, Arend and Bromiley (2009) noted that, like RBV, the DCV suffers from context insensitivity. This suggests that DCV fails to identify the conditions in which resources or capabilities may be most valuable. Contingency theory (CT) addresses this notion. Hence, these perspectives may explain both the direct impact and the context in which BDPA is most effective. Our study provides theory-focused and empirically-tested results to those practitioners who are trying to explore how BDPA may help organizations to improve collaborative performance among partners engaged in sustainable development programmes to achieve SCP goals. Hence, this study extends the DCV beyond general organizational factors to address a rapidly emerging class of technologies. Our study is the first to provide empirical evidence of associations between BDPA, collaborative performance, compatibility and resource complementarity. The remainder of the manuscript is organized as follows. In Section 2, we provide the underpinning theories for our study. In Section 3, we present our theoretical framework and research hypotheses. In Section 4, we present our research design which includes construct operationalisation, sampling design and data collection. In Section 5, we present our discussion related to statistical analyses. Finally, we conclude with discussion of the results and implications of the results for theory and practice, limitations of our study and further research directions.

2. Underpinning Theories

2.1 Big Data

Big data has been the centre of attraction in recent years (Galbraith, 2014). Organizations in last two decades have increasingly based their decisions on large data (Galbraith, 2014; Fosso Wamba et al. 2015; Shukla and Tiwari, 2017). However, due to recent progress in terms of technology, generating and analysing data is fast and voluminous (Fosso Wamba et al. 2015; Chavez et al. 2017). Big data is often characterized by 5Vs (i.e., volume, velocity, variety, veracity and value) (Fosso Wamba et al. 2015). Chen et al. (2012) define big data as a complex process of storage, retrieval and processing of unstructured, semi-structured and structured data using suitable algorithms to extract useful information to improve the decision making skills. Minelli et al. (2012) define big data as the next generation of data warehousing and business analytics for delivering a higher level of performance. Waller and Fawcett (2013) further argue that, due to high complexity, big data often requires advanced techniques, as traditional statistical methods are only suitable for structured and limited data sets. Agarwal and Dhar (2014), further noted that due to the advent of advanced technology, big data is set to be one of the most significant drivers of the digital economy. Hence, big data has been defined as an umbrella term for any collection of large and complex datasets that are difficult to store, process and analyse with earlier methods (Dubey et al. 2017). In brief, a large amount of data is generated in a short span of a few hours, generated from a variety of sources which may exploited using processing technologies to extract useful information for decision making.

2.2 Big Data and Predictive Analytics

Big data and predictive analytics (BDPA) stems from classical multi-variate statistical techniques (Sivarajah et al. 2017). The large data sets often streaming continuously via sensor devices need to be reduced to an effective size followed by multiple regression analysis to establish the relationships. However, owing to the complexity associated with these data sets which represent heterogeneous sets of unstructured data, semi-structured data and structured data, the extraction requires fourth generation technology to process meaningful information (Chen et al. 2012; Zhang et al. 2017; Wu et al. 2017). Hence, we can draw the conclusion that BDPA is an emerging discipline which requires an inter-disciplinary approach which includes computer science, statistics, mathematics, psychology and sociology to analyse and to infer meaning. The BDPA requires a systematic approach to capture data, process and draw some interesting insights using mathematical models (Descriptive Analytics), develop a theoretical framework or model based on input variables to depict future behaviour of the outcome variables (Predictive Analytics) as well as developing a model to optimize or simulate outcomes based on variations in inputs (Prescriptive Analytics). Diagnostic analytics further helps in examining the causes by exploring the data and identifying underlying causes. It utilizes multi-variate statistical analyses to understand the overall nature of the data sets generated via sensor devices (Dubey and Gunasekaran, 2015).

2.3 Inter-organizational Fit

Steensma (1996) argues that there is pressing need for building skills and organizational capabilities and their effective utilization to gain competitive advantage. Successful synergy among organizations often hinges on alignment and effective sharing of strategic resources and organizational capabilities (Das and Teng, 1998). The literature in the area of supply chains (both commercial and humanitarian), has shown that the right fit and proper alignment between organizational elements of the focal organizations and their partners helps to improve coordination, helps to reduce variation in information sharing, and reduces risk (Moshtari, 2016). On the other hand mis-match in organizational structure or culture between focal organizations and their partners may reduce the degree of organizational compatibility (Naspetti et al. 2017). Mangla et al. (2017) argue that poor coordination among partners, cited as one of the barriers of SCP initiatives, may be due to the lack of common strategic objectives. Mangla et al. (2017) further argue that supply chain partners' characteristics in terms of organizational design often aligned with their organizational goals or their organizational cultures, which often act as a barriers in terms of information sharing among the partners engaged in SCP programmes. Next, the partners engaged in SCP programmes rely on strategic resource sharing which may be termed as resource complementarity. Scholars in previous studies argue that resource complementarity has a positive influence on collaboration (Harrison et al. 2001).

2.4 Collaborative Performance

The collaboration in SCN between focal organizations and their partners occurs in different forms, but in general it aims at achieving a common goal: to create transparency and visibility to reduce ripple effects in SCN. Gulati et al. (2012) argues that collaborations involve two aspects: cooperation and coordination. According to Simatupang and Sridharan (2002), collaboration refers to two or more organizations working together to plan and execute their actions. The collaboration between partners refers to a sharing of strategic resources among themselves (e.g., information, expertise and technology) (Fawcett and Magnan, 2004) or working closely to design and implement their operations (Cao and Zhang, 2011). Cao and Zhang (2011) further argue that despite the advantages of synergetic relationships, many partners often fail to exploit the potential benefits from such relationships. Following Dyer's (2000) arguments we can ascertain that supply chain collaboration is rooted in a paradigm of collaborative advantage. The collaborative paradigm argues that a supply chain is composed of a sequence or network of interdependent relationships fostered via strategic alliances and collaboration. Dyer and Singh (1998), argue that often the advantage resulting from collaborative or synergetic relationships, is reduced by the inherent tendency among the partners to maximize their own individual gains. Hence, the collaboration between two partners should not be viewed as zero-sum game. Instead it should be regarded as a positive-sum game.

3. Theoretical background and hypotheses development

By collaborating, partners help to achieve better cooperation and coordination to maximize the gains from SCP programmes (Mangla et al. 2017). Hampton et al. (2013) further argue that the use of big data with the help of advanced processing technology may help to improve the collaboration among the key participants. Although anecdotal or conceptual evidence suggest possible association between BDPA and collaboration among partners may enhance the success of SCP programmes, the empirical study of this has been limited. The relationship might be moderated by inter-organization fit: compatibility and resource complementarity. The direct or indirect effects are depicted in the Figure 1.

3.1 Direct effect of BDPA on collaborative performance

The BDPA has received wide recognition among scholars as an organizational capability which may help to improve the supply chain performance (Papadopoulos et al. 2017). Gunasekaran et al. (2017) argue that BDPA, as an organizational capability, may help to improve supply chain visibility and unleash powerful insights to understand the current situation and predict future possibilities. Collaboration in the SCN exist in a wide range of forms, but in general the common goal is to create visibility (Holweg et al. 2005). The visibility in supply chains via quality information sharing to help reduce risk is one of the main objectives of synergetic relationships between the focal organization and their partners (Brandon-Jones et al. 2014). On the other hand Srinivasan and Swink (2017) argue that organizations that invest in building analytics capabilities are likely to invest in visibility, because visibility provides the raw data upon which analytics systems and process operate. Thus, the visibility and BDPA can be seen as complementary. Hence, we hypothesize:

H1: BDPA has a positive impact on collaborative performance.

3.2 Moderating effects of compatibility and resource complementarity

The organizational compatibility refers to the degree of alignment among focal organizations and their partners in terms of their goal, missions and vision (Holcomb and Hitt, 2007). It further includes match in terms of their supply chain designs, the information systems used in SCN and their operational procedures (Sarkar et al. 2001). The organizational fit between focal organization and their partners has a positive impact on their synergetic or collaborative performance (Mitsuhashi and Greve, 2009). Unfortunately, partners engaged in SCP programmes may have differences with respect to their cultural or behavioural norms, which often leads to misunderstanding and miscommunication (Mangla et al. 2017). Organizations use diverse and complex procedures which may lead to poor collaboration among partners engaged in SCP programmes. Each organization tends to follow their own systems and procedures and expects their partners to adapt to their practices which may negatively influence the collaborative performance. Prior studies have suggested that organizations with more resources are more attractive as alliance partners (Ahuja, 2000). This may be due to that collaboration or alliances are often used to derive resources, so organizations that possess valuable resources have easier access to the alliance or collaboration opportunities. These phenomena can be explained using resource complementarity arguments which is considered as another aspect of the organizational fit. Resource complementary suggests that partners engaged in alliances may combine heterogeneous resources held by multiple partners (Holcomb and Hitt, 2007). The previous studies indicate that combined use of heterogeneous resources often helps in building better collaboration among partners (Harrison et al. 2001). Based on these observations we can argue that dependence on resources often creates better alliances between partners. By sharing of strategic resources and competencies, partners engaged in alliance formation are more likely to avoid opportunistic behaviour and improve trust and commitment. Hence, we hypothesize:

> *H2: The organizations' compatibility has a positive moderating effect on the path connecting BDPA and collaborative performance;*
>
> *H3: Resource complementarity has positive moderating effect on the path connecting BDPA and collaborative performance.*

3.3 Theoretical framework

Figure 1 illustrates the proposed model linking the BDPA with collaborative performance under the moderating effect of compatibility and resource complementarity. We provide definitions of the constructs used in the model in Table 1. To control for the confounding effect of the control variables, we have included temporal orientation in the analysis (see Figure 1). Building engagement among the partners in alliance formation or collaboration may take time and requires extensive investment to build trust and commitment among the partners. Hence, in building successful alliances or collaborations, a long-term orientation has been found to have positive influence on relationship performance (Morgan and Hunt, 1994).

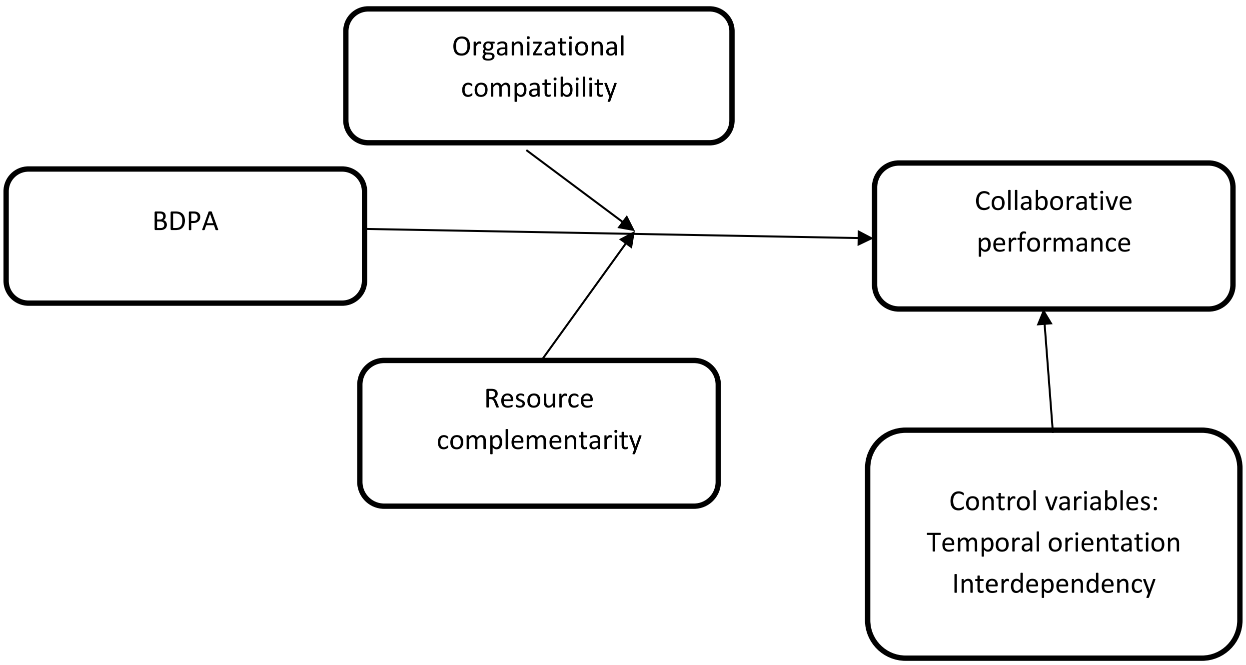

Figure 1: Theoretical Framework

Table 1: Definitions of the constructs

Construct	Definition
BDPA (Gupta and George, 2016; Dubey et al. 2017)	Big data & predictive analytics (BDPA) may be defined as an organizational capability which uses statistical knowledge to forecast future events based on the assumption that what has occurred in the past may have influence on future events.
Organizational compatibility (Holcomb and Hitt, 2007)	This refers to the alignment in terms of organizational structure, goal, mission and vision of the partners engaged in the alliance formation. Organizational compatibility is a desired characteristic for successful collaboration.
Resource complementarity (Harrison et al. 2001)	This refers to the ability to share heterogeneous resources and their organizational competencies to reduce opportunistic behaviours among the partners and build trust and commitment.
Collaborative performance (Krishnan et al. 2006)	This is the measure of the successful collaboration between partners by sharing resources and competencies.

4. Research Design

A pre-tested questionnaire was used to gather data to test research hypotheses. The instrument was pretested with the help of 7 academics and 15 senior managers drawn from manufacturing sector and consultants from reputed agencies. We asked 7 academics and 15 senior managers to provide their inputs. Based on inputs of these experts we modified our wording to improve the clarity and ensure that length of the questionnaire was appropriate. Finally, the questionnaire was ready for final data collection (see Appendix 2). Our target sample was those organizations drawn from the auto-component manufacturing sector in India.

4.1 Construct operationalisation

The constructs used in the model were operationalized as reflective constructs based on comprehensive literature review. In a reflective model, the latent constructs exist (in absolute sense) independent of measures. We further carried out some modifications in the existing scale to make it more suitable in our context of sustainable development (the scales used were drawn from prior studies which were used in a different context). The constructs listed in Appendix 1 were measured on a five-point Likert scale with anchors ranging from strongly disagree (1) to strongly agree (5).

BDPA

We reviewed existing literature drawn from reputable journals for developing the BDPA scale (Hart and Saunders, 1998). The seventeen items of the BDPA were identified from Gupta and George (2016) and Dubey et al. (2017). The seventeen items were further split into three reflective constructs: technical skills (TS) (six dimensions), managerial skills (MS) (six dimensions) and the data driven skills (DD) (five dimensions).

Collaborative performance

A four-item reflective scale was derived from existing studies (see, Krishnan et al. 2006; Wang et al. 2010; Moshtari, 2016). The four-item reflective construct was used to measure collaborative performance among the participating organizations in sustainable development or SCP programmes.

Organizational compatibility

A five-item reflective scale was derived from Moshtari (2016) and Sarkar et al. (2001) to measure organizational compatibility among the partners engaged in SCP programme.

Resource complementarity

A four-item reflective scale was derived from a review of existing literature (see, Cheung et al. 2010; Lambe et al. 2002; Moshtari, 2016). The scale was used to measure the degree to which partners engaged in a SCP programme were sharing their resources and competencies for successful collaboration.

Temporal orientation

A three-item reflective construct was developed on the basis of existing literature (see, Cannon et al. 2010; Marginson et al. 2010; Moshtari, 2016).

Interdependence

A two-item construct was developed based on literature (see, Brown et al. 1995; Moshtari, 2016).

4.2 Sample and Data Collection

We selected auto-component sector for following reasons. Firstly, the Indian auto-components sector is one of the fastest growing industries in terms of sales revenue but also responsible for carbon emissions (Gopal and Thakkar, 2016). Secondly, it is one of the major sources of direct and indirect employment creation. However, despite strong performance in last two decades, the industry has stiff competition from countries such as China, Malaysia, Indonesia, Vietnam and South Korea. For sustainable development the sector has made significant investment to reduce carbon footprints and improve the skills of the workers to enhance the productivity and improve quality of work life. We obtained a sampling pool of 738 auto-component manufacturing organisations situated in all four (north, south, east, and west) regions of India. Company information came from two databases: ACMA (the Automotive Components Manufacturers Association of India) and Dun & Bradstreet. A senior respondent from each organizations was identified to serve as a key informant. Following prior studies (Bowen et al. 2001; Menor and Roth, 2007; Dubey et al. 2017a), structured questionnaires along with a cover letter explaining the research, and a self-addressed pre-paid envelope were mailed to the senior managers who are or were part of the SCP programme of their respective organization, as revealed by our initial background research and selection of participants.

We made telephone calls to all potential participants after three weeks to ensure the package arrived and to clarify any questions about the research. After the first wave of mailing, 110 questionnaires were received. At five weeks, we again sent packages to those who had not responded. 80 questionnaires were subsequently returned for an overall response rate of 25.75%. Altogether, 190 completed questionnaires were received (please refer to Appendix 3 for demographics).

4.3 Non-response Bias

Many scholars argue that non-response bias (NRB) is an issue associated with survey-based research (Armstrong and Overton, 1977; Guide and Ketokivi, 2015). Although we do not claim that we have eliminated NRB in our study, we used a mix of classical and recent arguments to ensure that the effect of NRB on our data is limited. We conducted wave analysis on our data as suggested by Armstrong and Overton (1977). The comparisons between early and late responses showed no statistical differences at $p < 0.05$, indicating that NRB is not a significant threat to validity. Next, following Wagner and Kemmerling (2010), we also compared the demographics of the respondents and the non-respondents via Dun & Bradstreet and found that our sample is statistically homogenous with the broader population.

5. Data Analyses and Results

Following Kock's (2015) arguments, the Warp PLS 5.0 was used in our study to test the hypothesized relationships (as shown in Figure 1). The Warp PLS 5.0 relies on a variance-based PLS method. Although the PLS method has received criticisms (see, Guide and Ketokivi, 2015), still some established scholars argue that PLS is a preferred method for exploratory research in that the resulting parameter estimates are robust to artefacts that commonly arise from the employment of new or revised measures in new sample frames (Henseler et al. 2009; Hair et al. 2011, 2012, 2016; Peng and Lai, 2012; Henseler et al. 2014; Dubey et al. 2017a; Akter et al. 2017). Indeed, the proposed relationships between constructs in this study are guided by complementary yet distinct theories that are rarely examined in aggregate in the literature. Given these reasons, we chose PLS as the most suitable technique for data analysis in this study (Peng and Lai, 2012; Dubey et al. 2017a).

We followed two stages for model estimation as recommended by Peng and Lai (2012): firstly, examining validity and reliability of the measurement model and secondly, analysing the structural model. Appendices 4 and 5 present the output generated using two stages of PLS in the model with reflective constructs (see, Peng and Lai, 2012).

5.1 Measurement Model

To test the proposed theoretical model shown in Figure 1, we further examined each construct's properties: scale composite reliability and the average variance extracted (convergent validity) and correlation matrix between these constructs (discriminant validity) (Fornell and Larcker, 1981; Dubey et al. 2017a). Appendix 4 provides an overview of the factor loadings (λ), scale construct reliability (SCR), and average variance extracted (AVE) of the reflective constructs. All the thresholds were met: we found that the factor loadings were all greater than 0.5, the SCRs were calculated to be greater than 0.7, and the AVE for each construct was greater than 0.5 (Fornell and Larcker, 1981; Peng and Lai, 2012). Appendix 5 presents the correlations between paired constructs, and the leading diagonal of the matrix shows the square-root of the AVE of each construct. All measures indicate adequate discriminant validity (Fornell and Larcker, 1981; Peng and Lai, 2012).

5.2 Common Method Bias (CMB) and Endogeneity

Based on Podsakoff and Organ (1986), in the case of single-source data, there is potential for CMB. Hence, to address CMB in our study, we followed the suggestion of Podsakoff (2003) and performed Harman's one factor test to assess whether a single latent factor would account for all the theoretical constructs. The results from this test showed that the single factor explains 30.158 percent of total variance (see Appendix 6), demonstrating that CMB is not a significant concern.

Following guidance from a recent editorial note (Guide and Ketokivi, 2015) we understand that Harman's single factor test has its own limitations (c.f. Ketokivi and Schroeder, 2004). Thus, to ensure that CMB was not a major concern, we further used a method introduced by Lindell and Whitney (2001), a partial correlation technique which is often referred as the correlational marker technique, for controlling method variance using a marker variable that may be theoretically unrelated to the substantive variable in the study. Using this method, we first chose the four-item scale that measured collaborative performance, which provided the lowest positive correlation (r=-0.03) between the MV marker and other variables, to adjust the construct correlations and statistical significance (Lindell and Whitney, 2001). We did not observe any significant correlational value which changed to insignificant after further analyses.

Causality is an important issue which has been noted in recent scholarly debates (see Guide and Ketokivi, 2015). To address the causality issue is often considered a necessary step before performing hypotheses tests. In our study we conceptualized BDPA as an exogenous model variable to the collaborative performance but not the other way around, in accordance with the literature (Gunasekaran et al. 2017). Since the model is firmly grounded in existing theories, the causality may not be the major concern in our current study. Next, we performed Durbin-Wu-Hausman test (see, Davidson and MacKinnon, 1993). We observed that the parameter estimate for the residual was insignificant, suggesting that the BDPA is not the dependent variable but it is an independent variable in our current setting. We further tested the model fit and quality indices (see Appendix 7).

5.3 Hypothesis testing

Peng and Lai (2012) argue that PLS analysis does not assume normal distribution of the data, unlike in the case of CBSEM where normal distribution of the data is an essential criterion for hypotheses testing. The operations of the PLS are based on a bootstrapping technique to determine SEs and significance level of the parameter estimates (Hair et al. 2011; Peng and Lai, 2012). The beta (β) values of the paths and their corresponding p-values for the model (Figure 2) are reported in Table 3.

Table 3: Hypothesis testing results

Hypothesis	Effect of	On	β	p-value	Results
H1	BDPA	CP	0.51	p<0.01	supported
H2	BDPA*CO	CP	0.27	p<0.01	not-supported
H3	BDPA* RC	CP	0.34	p<0.01	not-supported

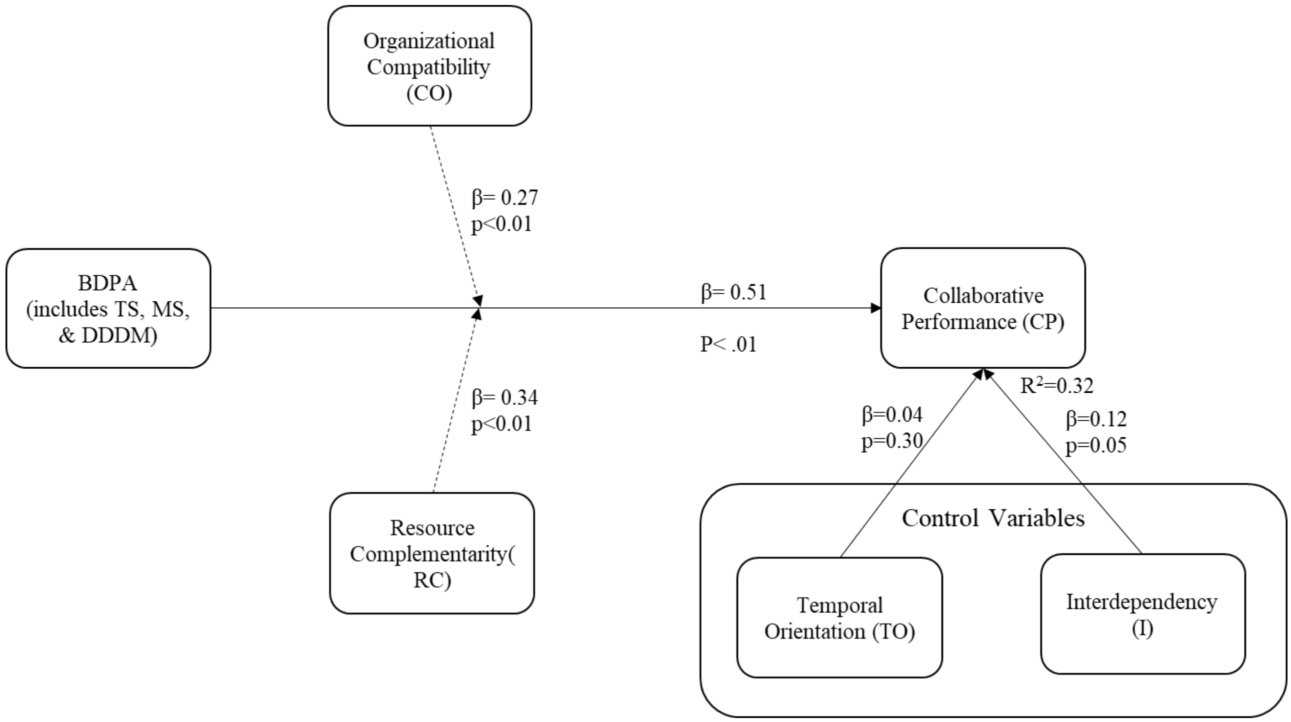

Figure 2: Final causal model

Table 3 examines the hypothesized relationships between BDPA and CP (H1). The interaction effects of CO and RC on the paths joining BDPA and CP are specified as H2 and H3 respectively. We found support for the prediction that BDPA is positively connected with CP (β=0.51; p<0.01). The control variables temporal orientation (TO) and interdependency (I) do not have significant effects in this model. We interpret these observations as evidence that rapid changes due to globalization in the auto-components manufacturing sector is not meaningfully affecting collaborative performance via BDPA and that temporal orientation and interdependency have little role to play in BDPA-CP relationship.

Next addressing H2 and H3 (Table 3) for the interaction effect of CO and RC on the path connecting BDPA and CP. We found support for H3 (β=0.27; p<0.01), which proposed a significant moderating effect of CO on the path connecting BDPA and CP. Similarly, we found support for H4 (β=0.34; p<0.01), which proposed significant moderating effect of RC on the path connecting BDPA and CP. Next, we evaluated the robustness of the PLS results. The p-values were obtained at 1000 and 1500 bootstrapping runs, which are consistent with the p-values upon bootstrapping runs.

We examined the explanatory power of our research model. For this we examined the explanatory power (R^2) of the endogenous construct (Figure 2). The R^2 for CP is 0.32 which is moderately strong (Chin, 1998). We further examined the f^2 value of the BDPA using Cohen's f^2 formula*. Consequently, the effect size of BDPA on CP is 0.276 (see Table 4) which is considered medium. Next, we have examined the model's capability to predict. Stone-Geiser's Q^2 for endogenous construct is 0.324 (see Table 4) for CP which is greater than zero, indicating acceptable predictive relevance (Peng and Lai, 2012).

Table 4: R^2, Prediction and Effect Size

Construct	*R^2*	*Q^2*	*f^2 in relation to*	
			SCRES	CA
BDPA	-	-	0.276	
CO	-	-		
RC	-	-		
CP	0.32	0.324		

*The f^2 values of 0.35, 0.15 and 0.02 are considered large, medium and small (Cohen, 1988).

6. Discussion

6.1 Theoretical Contributions

The current study further corroborates Wu and Pagell's (2011) arguments that organizations face multiple uncertainties due to complex and dynamic environments. Organizations often make their environmental related decisions surrounded by information asymmetry, evolving decision parameters which are often undefined and fast changing decision boundaries. Building upon the arguments of Vachon and Klassen (2008), our empirical findings highlight relational orientation (i.e., collaboration) as an informal governance between partners engaged in SCP programme. Based on recent debates surrounding extraction and processing of valuable information from big data, there exists a clear opportunity for organizations to improve visibility and integration (Keeso et al., 2014; Dubey et al., 2017). The role of BDPA on collaborative performance of the partners operating under complex and dynamic setting to achieve SCP goals, was not previously understood. Our study makes two important contribution to the literature by empirically testing the proposed model (see Figure 1), grounded in DCV. Firstly, our study found a significant positive relationship between BDPA and CP. This finding supports the arguments of previous scholars (Waller and Fawcett, 2013; Dutta and Bose, 2015). Secondly, our study resolves the debate under what context the BDPA positively impacts CP. We have examined the moderating influence of organizational fit (i.e. CO and RC) on the path connecting BDPA and CP. The results extend the findings of Holcomb and Hitt (2007) by examining the influence of BDPA on CP. The results suggest that the compatibility between organizations and their partner's cultures, missions, objectives, procedures or technical capabilities enhances the positive influence of the BDPA on the CP. Similarly, the Resource Complementarity among partners which has a positive moderating influence on the path connecting BDPA and CP suggesting that when reciprocal needs arise or when the partners share their resources or competencies, they reduce the opportunism and enhance the value of collaboration via BDPA.

We advance the existing literature by examining each possibility that may have significant influence on explaining the variation in CP in sustainable consumption and production context. Building on DCV, we tested the impact of BDPA on CP. Our study echoes the prior research findings on the critical role of BDPA on CP (Dutta and Bose, 2015). Organizations face an uncertain environment that requires them to make speedy decisions in ambiguous settings (Wu and Pagell, 2011).

6.2 Managerial Implications

The knowledge derived from this study supports practitioners to recognize the role of BDPA in improving the collaborative performance among the partners engaged in SCP programme. These findings further indicate that sharing strategic resources and competencies in terms of technical skills, managerial insights and building data driven culture and investing relationship management capability helps in successful alliance formation or collaboration. In other words, if the partners engaged in SCP programme do not share valuable resources, or do not invest in relationship management skills, the collaborative initiatives via BDPA may not work properly. Similarly, compatibility between organizations' cultures, missions, objectives, procedures or technical capabilities should be equally high for better results. This conclusion is consistent with Mangla et al.'s (2017) findings and Goal 12 of sustainable development of United Nations (http://www.un.org/sustainabledevelopment/sustainable-consumption-production/).

7. Conclusions, limitations and further research directions

Both the partners and the focal organization recognize the benefits of the collaboration. The stakeholders are demanding greater accountability and becoming less tolerant to the inefficiencies in the SCP programmes, and therefore strongly encouraging focal organizations and their partners to strongly collaborate (UNEP, 2017; Jonkute and Staniskis, 2016). This research furthers our understanding related to BDPA and alliance formation and collaboration literature specifically in context to SCP and the sustainable development goals. We have used our knowledge derived from organization science and operations management literature, as well as the insights gathered from the practitioner's reports or magazines to draw our empirical insights. The study furthers our understanding of BDPA and its role on collaborative performance under the moderating influence of the organization fit, which has been recently recommended in operations management literature (Waller and Fawcett, 2013; Dutta and Bose, 2015; Fosso Wamba et al. 2017). Methodologically, our study may be well considered alongside those few in which empirical methods are used for data collection and analysis in context of BDPA and SCP. More specifically, this study suggests that *compatibility* and *resource complementarity* have a moderating influence on the impact of BDPA on collaborative performance. Managers should understand that BDPA may be exploited as an organizational capability to create better visibility and enhance trust and commitment among the partners in SCP programmes. This further helps to improve the alliance formation or collaboration among the partners engaged in sustainable development. This necessitates the sharing of strategic resources and improving skills such as coordination and trust formation.

We believe that our study, like others, has its own limitations and the results obtained in our study should be interpreted cautiously under the lens of these specific limitations. The following limitations of our study may be addressed in future studies. Firstly, the study gathered cross-sectional data. Hence, a longitudinal data would further enrich our understanding by offering information on the causal relationships between dependent and independent variables. It could allow researchers or practitioners to investigate how collaborative performance among partners engaged in sustainable development or SCP programme can achieve collaborative performance via BDPA. In addition, longitudinal data may help to reduce common method bias (Ketokivi and Schroeder, 2004; Guide and Ketokivi, 2015) that undermines the validity of studies with the cross-sectional data.

Our study is confined to dyadic networks. However, the focal organization is collaborating with many organizations at once, which we have not explicitly taken into consideration in this study. We also recommend an examination of the impact of training, information exchange between the partners, reduction of behavioural uncertainty and commitment on the level of collaboration. To have deeper understanding about collaborative outcomes between focal organizations and the partners, a longitudinal multiple-case studies approach may be useful in this context (Eisenhardt, 1989; Voss et al., 2002; Childe, 2017).

The theoretical constructs of the proposed framework in this study are investigated at the inter-organizational level, but viewed only from the focal organization's perspective. Hence, future studies may gather perceptions from both sides of the collaborative relationship. This may shed some useful insights. Moreover, using the perception of single respondents should be considered as threat to common method bias (Ketokivi and Schroeder, 2004). Although we have adopted rigorous approach to check the impact of CMB on our study, future work could extend reliability by avoiding the use of single respondent data.

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Appendix 1: Construct operationalisation

Construct and Derivation	**Measures**
Technical skills adapted from Gupta and George (2016)	Training for our employees (TS1) We hired based on big data analytics skills (TS2) The big data analytics staff of our organization have right skills (TS3) The big data analytics staff of our organization have right education (TS4) The big data analytics staff of our organization have right experience for undertaking their jobs successfully (TS5) Our big data analytics staff are well trained (TS6)

Managerial skills (MS) adapted from Gupta and George (2016)	The big data analytics managers have the ability to understand and appreciate the needs of other managers (MS1) The big data analytics managers of our organization can work with other functional managers of their own organization (MS2) The big data analytics managers of our organization can coordinate big-data-related activities in ways that support other partners (MS3) The big data analytics managers of our organization can anticipate future challenges (MS4) The big data analytics managers of our organization have a good sense of where to use big data (MS5) The big data analytics managers of our organization 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)
Collaborative performance (CC) adapted from Krishnan et al. (2006); Wang et al. (2010); Moshtari (2016)	The objectives of the collaboration were met (CP1) The partners engaged in sustainable consumption and production initiatives seem to be satisfied with the overall performance of the collaboration (CP2) Our organization is satisfied with the overall performance of the collaboration (CP3) Our association with this partner has been a highly successful one (CP4)
Compatibility (CO) adapted from Sarkar et al. (2001)	There is a match in both organizations'' philosophies/ approaches to sustainable consumption and production (CO1) Both organizations share a similar organizational culture (CO2) Both organizations support each other's objectives (CO3) The technical capabilities of the two organizations are compatible with each other (CO4) The organizational procedures of the two organizations are compatible (CO5)
Resource complementarity (RC) adapted from Cheung et al. 2010; Lambe et al. 2002	The resources brought into the collaboration by each organization have been very valuable for the others (RC1) The resources brought into the collaboration by each organization have been significant in getting the job done (RC2) Both organizations have separate abilities that when combined enable to achieve goals beyond their individual reach (RC3) Both organizations have complementary strengths that are useful to the relationship (RC4)

Temporal orientation (TO) adapted from Cannon et al. (2010); Marginson et al. (2010)	Both organizations focus on long-term goals in their relationship (TO1) Both organizations expect to work together for a long time (TO2) Both organizations concentrate their attention on issues that will impact targets beyond the next (TO3)
Interdependency (I) Adapted from Brown et al. (1995)	It would be costly for our organization to lose its collaboration with this partner (I1) This partner would find it costly to lose the collaboration with our organization (I2)

Appendix 2: Questionnaire

Questionnaire ID: __________

This study is being carried out to gain insight about impact of big data and predictive analytics (BDPA) on collaborative performance among partners in supply chain network engaged for common sustainable consumption and production (SCP) goals. Collected data will be used only for academic purposes. We request your cooperation to spare 15 minutes to complete this survey. Thank you.

Name ……………………………………………………………….……………………

Name of the Organization……………………………………………………….

Designation…………………………………………………………………………

Gender (M/F)……………………………………………………………………….

Experience (Years)………………………………………………………………..

Address………………………………………………………………………………

Telephone……………………………………………………………………………

E-mail…………………………………………………………..………………

Instructions: Listed below are dimensions of big data and predictive analytics, organizational compatibility, resource complementarity, collaborative performance, temporal orientation and interdependency that may be applicable to your firm. Using the scale provided, please indicate your preference by selecting the relevant option.

(1)Strongly Disagree

(2)Disagree

(3) Neither Agree nor Disagree

(4 Agree

(5)Strongly Agree

Indicator	Survey Question	Rating				
TS1	Our organization provides necessary training to our employees related to big data analytics	1	2	3	4	5
TS2	Our organization hires people for big data and predictive analytics team based on their big data and predictive analytics skills	1	2	3	4	5
TS3	The big data analytics staff of our organization have the right skills	1	2	3	4	5
TS4	The big data analytics staff of our organization have the right education	1	2	3	4	5
TS5	The big data analytics staff of our organization have the right experience for undertaking their jobs successfully	1	2	3	4	5
TS6	Our big data analytics staff are well trained	1	2	3	4	5
MS1	The big data analytics managers have the ability to understand and appreciate the needs of other managers	1	2	3	4	5
MS2	The big data analytics managers of our organization can work with other functional managers of their own organization	1	2	3	4	5
MS3	The big data analytics managers of our organization can coordinate big-data-related activities in ways that support other partners	1	2	3	4	5
MS4	The big data analytics managers of our organization can anticipate future challenges	1	2	3	4	5
MS5	The big data analytics managers of our organization have a good sense of where to use big data	1	2	3	4	5
MS6	The big data analytics managers of our organization can interpret the analyses obtained using complex analyses and offer inputs which are useful for swift decision making	1	2	3	4	5
DDDM1	We consider data as an asset	1	2	3	4	5
DDDM2	We base most decisions on data rather than instinct	1	2	3	4	5
DDDM3	We are willing to override our intuition when data contradict our viewpoints	1	2	3	4	5
DDDM4	We continuously assess our strategies and take corrective action in response to the insights obtained from data	1	2	3	4	5
DDDM5	We continuously coach our people to make their decisions based on data	1	2	3	4	5
CP1	The objectives of the collaboration were met	1	2	3	4	5

CP2	The partners engaged in sustainable consumption and production initiatives, seem to be satisfied with the overall performance of the collaboration	1	2	3	4	5
CP3	Our organization is satisfied with the overall performance of the collaboration	1	2	3	4	5
CP4	Our association with this partner has been a highly successful one	1	2	3	4	5
CO1	There is a match in both organizations' philosophies/ approaches to sustainable consumption and production	1	2	3	4	5
CO2	Both organizations share a similar organizational culture	1	2	3	4	5
CO3	Both organizations support each other's objectives	1	2	3	4	5
CO4	The technical capabilities of the two organizations are compatible with each other	1	2	3	4	5
CO5	The organizational procedures of the two organizations are compatible	1	2	3	4	5
RC1	The resources brought into the collaboration by each organization have been very valuable for the others	1	2	3	4	5
RC2	The resources brought into the collaboration by each organization have been significant in getting the job done	1	2	3	4	5
RC3	Both organizations have separate abilities that when combined enable to achieve goals beyond their individual reach	1	2	3	4	5
RC4	Both organizations have complementary strengths that are useful to the relationship	1	2	3	4	5
TO1	Both organizations focus on long-term goals in their relationship	1	2	3	4	5
TO2	Both organizations expect to work together for a long time	1	2	3	4	5
TO3	Both organizations concentrate their attention on issues that will impact targets beyond the next	1	2	3	4	5
I1	It would be costly for our organization to lose its collaboration with this partner	1	2	3	4	5
I2	This partner would find it costly to lose the collaboration with our organization	1	2	3	4	5

Appendix 3: Demographic profiles

Title	Number	%
CEO	15	7.89
COO	40	21.05
Vice President	15	7.89
General Manager	65	34.21
Senior Manager	15	7.89
CIO	40	21.05

Appendix 4: Loadings of Indicator Variables (Scale Composite Reliability and Average Variance Extracted)

Note: TS- Technical skills; MS- Management skills; DD-Data driven skills; CP-Collaborative performance; CO-Compatibility; RC-Resource complementarity; TO-Temporal orientation; I: Interdependency

Items	*Factor Loadings (λ)*	*λ²*	*Error (Ei)*	*SCR*	*AVE*
TS1	0.79	0.62	0.38	0.97	0.67
TS2	0.83	0.7	0.3		
TS3	0.84	0.71	0.29		
TS4	0.81	0.66	0.34		
TS5	0.82	0.68	0.32		
TS6	0.8	0.64	0.36		
MS1	0.87	0.76	0.24		
MS2	0.89	0.8	0.2		
MS3	0.8	0.64	0.36		
MS4	0.9	0.81	0.19		
MS5	0.9	0.81	0.19		
MS6	0.72	0.52	0.48		

DD2	0.68	0.46	0.54		
DD3	0.77	0.6	0.4		
DD4	0.77	0.6	0.4		
CP2	0.95	0.9	0.1	0.96	0.9
CP3	0.94	0.88	0.12		
CP4	0.95	0.91	0.09		
CO1	0.57	0.32	0.68	0.81	0.47
CO2	0.75	0.56	0.44		
CO3	0.78	0.6	0.4		
CO4	0.71	0.5	0.5		
CO5	0.58	0.34	0.66		
RC3	0.98	0.95	0.05	0.98	0.95
RC4	0.98	0.95	0.05		
TO1	0.79	0.62	0.38	0.81	0.58
TO2	0.76	0.58	0.42		
TO3	0.74	0.55	0.45		
I1	0.64	0.41	0.59	0.71	0.55
I2	0.83	0.69	0.31		

Appendix 5: Correlations among major constructs

Note: BDPA- Big data & predictive analytics; CO-Compatibility; RC-Resource complementarity; TO-Temporal orientation; I: Interdependency; CP-Collaborative performance

	BDPA	*CO*	*RC*	*TO*	*I*	*CP*
BDPA	**0.82**					
CO	0.01	**0.95**				
RC	0.88	-0.02	**0.69**			
TO	-0.1	0.42	-0.13	**0.97**		
I	-0.03	0.45	-0.07	0.54	**0.76**	
CP	0.5	-0.03	0.25	-0.04	0.07	**0.74**

Appendix 6: Total Variance Explained

Item	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*		
	Total	*% of*	*Cumulative*	*Total*	*% of*	*Cumulative*
1	10.555	30.158	30.158	10.555	30.158	30.158
2	4.368	12.480	42.638			
3	3.916	11.189	53.827			
4	1.814	5.183	59.010			
5	1.683	4.808	63.818			
6	1.373	3.924	67.742			
7	1.278	3.652	71.394			
8	1.079	3.084	74.478			
9	1.067	3.050	77.528			
10	.987	2.819	80.347			
11	.874	2.497	82.845			
12	.739	2.112	84.956			
13	.701	2.003	86.960			
14	.631	1.802	88.761			
15	.531	1.516	90.278			
16	.481	1.374	91.651			
17	.457	1.306	92.958			
18	.313	.894	93.852			
19	.300	.857	94.709			
20	.291	.831	95.539			
21	.253	.722	96.262			
22	.224	.641	96.902			
23	.184	.524	97.427			
24	.160	.458	97.884			
25	.142	.406	98.290			
26	.123	.353	98.643			
27	.105	.300	98.944			
28	.097	.277	99.221			
29	.092	.263	99.484			
30	.089	.256	99.739			
31	.052	.148	99.888			
32	.028	.080	99.968			
33	.011	.032	100.000			
34	0.000	0.000	100.000			
35	0.000	0.000	100.000			

Appendix 7: Model fit and quality indices

Model fit and quality indices	Value from analysis	Acceptable if	Reference
APC	0.144, $p=0.011$	$p<0.05$	Rosenthal and Rosnow (1991)
ARS	0.317, $p<0.001$	$p<0.05$	
AVIF	0.298, $p<0.001$	$p<0.05$	Kock (2015)