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Impact of Big Data & Predictive Analytics on Supply Chain Sustainability: A Contingent Resource Based View

Abstract

Purpose- The main purpose of this paper is to develop a theoretical model to explain the impact of big data and predictive analytics (BDPA) on sustainable business development goal of the organization.

Design/methodology/approach- We have developed our theoretical model using resource based view (RBV) logic and contingency theory (CT). The model was further tested using PLS-SEM (partial least squares- Structural Equation Modelling) following Peng and Lai (2012) arguments. We gathered 205 responses using survey based instrument for PLS-SEM.

Findings- The statistical results suggest that out of four research hypotheses, we find support for three hypotheses (H1-H3) and we did not found support for hypothesis H4. Although, we did not find support for H4 (moderating role of supply base complexity (SBC)). However, in future the relationship between BDPA, SBC and sustainable supply chain performance measures remain interesting research questions for further studies.

Originality/value- This study makes some original contribution to the operations and supply chain management literature. We provide theory-driven and empirically-proven results which extend previous studies which have focused on single performance measures (i.e. economic or environmental). Hence, by studying the impact of BDPA on three performance measures we have attempted to answered some of the unresolved questions. We also offer numerous guidance to the practitioners and policy makers, based on empirical results.

Keywords- Big Data & Predictive Analytics (BDPA), Resource Based View (RBV), Contingency Theory (CT), Partial Least Squares (PLS), Structural Equation Modelling (SEM), Supply Base Complexity (SBC), Sustainability, Supply Chain Management (SCM).

Paper type- Research

1. Introduction

In the recent years, big data analytics has been considered as the next big thing for organizations to gain competitive advantage (Wamba et al. 2015; Akter et al. 2016). With the increasing digitalization of every aspect of business and government, large datasets are available for analysis. Big data has been defined primarily with 5 Vs: volume, variety, velocity, veracity and value (Wamba et al. 2015). Big data analytics is a field which consists of big data, analytical tools and techniques to derive actionable insights from the big data for delivering sustainable value, improving business performance and providing competitive advantage (Wamba et al., 2017). Predictive analytics is defined as the process of discovering meaningful patterns of data using pattern recognition techniques, statistics, machine learning, artificial intelligence and data mining (Abbott, 2014).

Big data and predictive analytics (BDPA) is an emerging field which uses various statistical techniques and computer algorithms to derive insights, patterns from large datasets. Analytics is considered as the next big frontier of innovation, competition, and productivity (Manyika et al., 2011, p.1). While next generation information technology techniques (such as smart phones, digital devices, scanning devices, cloud computing, internet of things etc.) help in improving productivity, these generate variety of large datasets which help in building analytics capabilities for the firms.

Business firm's primary goal is to make profits for long term economic sustainability. With globalization, improved communication and arrival of social media, firms are competing as never. Despite, the challenging business environment, going forward keeping profit alone as a goal may not be sustainable considering long term impact of commercial activities on environment and society. Thus, in addition to profit maximization, social and environmental sustainability goals are necessary for businesses as per (Elkington, 1994). Environmental Sustainability has gained significant attention in recent years due to growing concern for environment. Extreme weather, rising temperature, scarcity of natural resources – all these call for a different strategy towards environment (Winston, 2014). To preserve natural resources for future generations, sustainability needs to be considered in every aspect of business, supply chains and executive decision making.

Businesses strive for creating value for the stakeholders such as shareholders and society. Although, living conditions in most developed and developing countries have improved, there are several regions which are challenged to meet their basic needs. Brundtland and Khalid (1987) have acknowledged the need for attention to social issues along with environmental concerns in their report to United Nations. There are several measures designed to assess economic and environmental performance of the firm, however social performance does not get measured due to intangible nature of these issues and complexity in assessment (Mani et al., 2014). There are several instances when organizations in developed countries have come under scrutiny due to untenable social practices of their suppliers located in distant regions (Goldberg and Yagan, 2007; Plambeck and Yatsko, 2012). With improved communication, awareness about social sustainability is improving amongst manufacturing companies (Wu and Pagell, 2011). As a result, many companies have started publishing their corporate social responsibility reports that share company's track record on social issues. Automobile industry is one of the fastest growing in India and provides large scale employment (Chandra Shukla et al. 2009). This industry generates significant level of carbon footprint across entire product life cycle which includes manufacturing process, movement of goods across supply chain and use of automobiles by consumer (Luthra et al. 2016). Thus environmental, social and economic impact of automobile industry is significant (Kushwaha and Sharma, 2016). The supply chains of the automotive industry are highly complex (Thun and Hoenig, 2011). Hence, the major challenges of the automotive industry supply chains are visibility, cost containment, risk management, increasing customer demands and globalization. The information sharing among the partners in complex supply chains network is highly challenging (Wu and Pagell, 2011).

Considering the revolutionary role of big data analytics in several domains, there has been trend of research in big data and sustainability for firms in auto industry (Bughin et al. 2010). However, most of these studies offers conceptual and anecdotal evidences. The empirical studies focusing on big data and predictive analytics (BDPA) capability and its impact on sustainability three dimensions (i.e. environment, social and economic) is scant. There are some studies which have attempted to study the impact of big data and predictive analytics on environmental sustainability (Keeso, 2014; Bin et al., 2015; Koo et al., 2015; Braganza et al., 2016; De Gennaro et al., 2016; Lokers et al., 2016; Pan et al., 2016; Wolfert et al., 2017; Koseleva and Ropaite, 2017). Similarly, the impact of the BDPA on organizations economic performance has attracted significant contributions (see Akter et al., 2016; Gupta and George, 2016; Ren et al., 2016; Wamba et al., 2016; Gunasekaran et al., 2017). Hence, the studies focusing on the impact of BDPA on three dimensions of sustainability in combination is still underdeveloped. To address the gap, our current study draws on RBV and contingent RBV theories to explain the role of BDPA on three dimensions of the sustainability. We have derived two research questions to address our stated research gap as:

RQ1: What are the resources that are needed to build a BDPA capability?

RQ2: How these resources and capability impact three dimensions of sustainability?

We have organized our paper as follows. In the second section, we have discussed underpinning theories and concept used for building our theoretical framework. In the third section, we have proposed our theoretical model and research hypotheses. In the fourth section, we have presented our research design. In the fifth section, we have presented our statistical analyses. In the sixth section, we have presented our discussion based on statistical results followed by theoretical contributions, managerial implications, limitations and further research directions.

2. Underpinning Theories

2.1 Resource Based View (RBV)

The Resource based view theory (RBV) has gained significant importance in strategic management literature following Barney (1991) seminal works. Barney (1991) argues that a firm may derive its competitive advantage from the resources and capabilities that a firm possesses which may be valuable, rare, imperfectly imitable, and not substitutable (VRIN). These resources and capabilities can be viewed as bundle of tangible and intangible assets, including firm's management skills, its organizational processes and routines, the information and knowledge it controls as summarized in Table 1 below (Barney, 1991; Barney et al., 2001).

Table 1: Classification of Resources

Resource type	Examples	Source
Physical capital resources	Physical technology used, plant and equipment, geographic location, access to raw materials	Barney (1991); Williamson (1975)
Human capital resources	Training, experience, judgment, intelligence, relationships, insight of individual managers and workers	Barney (1991); Becker (1964)
Organizational capital resources	Firm's reporting structure, planning, controlling and organizing systems etc.	Barney (1991); Tomer (1987)

Grant (1991) argues that, an organization may create capabilities by combining these strategic resources which may be difficult for the competitors to imitate. However, developing capabilities for long term sustenance of the firm requires a long-term plan, well defined business processes and complex patterns of close coordination between people and other resources where organizational members are critical components (Dubey et al., 2017; Grant, 1991). Toyota's unique lean system is difficult to replicate for several competitors despite plenty of literature available on lean (Iyer et al., 2009). Similarly, McDonald's capability to integrate different business functions is a source of its competitive advantage (Grant, 1991). Many times, firms create innovative products with their management and technical skills. Both these skills are valuable and rare. Innovative product developed by a firm, gives them a first mover advantage for some time (Barney, 1991). However, soon competition catches up by imitating such products to capture market share. Apple has introduced several innovative products which were soon imitated by competitors. As more firms can imitate the product, segments which were once profitable will be subject to intense competition (Grant, 1991). Whereas, certain resources or capabilities (e.g. company culture, business processes, continuous learning culture within organization, unique information systems or innovative capabilities of the firm) are relatively difficult to imitate.

2.2 Contingent Resource Based View (CRBV)

RBV explains how organizations can achieve competitive advantage by possession of certain resources or capabilities (Barney, 1991; Grant, 1991). Resources can be procured from the market whereas capabilities (such as learning culture or management skills) need to be developed within the firm (Brush and Artz, 1999), thus process of building capabilities is more complex than acquiring resources in general. RBV theory has traditionally focused only on the competitive implications of internal organizational resources and capabilities (Aragón-Correa and Sharma, 2003), however this theory is unable to identify conditions in which resources or capabilities provide competitive advantage (Ling-Yee, 2007). Influence of external factors or conditions has not been considered in the resource based view theory. In general, the contingency theory argues that superior organizational performance is a result of the proper alignment of internal and external variables (Burns and Stalker, 1961; Lawrence and Lorsch, 1967). Contingent RBV argues that ability of firms possessing resources and capabilities achieving competitive advantage is dependent on certain conditions (Aragón-Correa and Sharma, 2003). Thus, the contingency theory helps to address the somewhat static nature of RBV (Brandon-Jones, et al., 2014).

2.3 Big data

Big data is defined as datasets that are too large for traditional data processing systems and therefore require new technologies to handle them (Waller and Fawcett, 2013). Since the arrival of the internet and digital economy, big data is set to be one of the most significant disruptors in technology (Agarwal and Dhar, 2014). Considering high volumes, variety of data, it requires advanced and unique storage, management, analysis and visualization technologies (Chen et al., 2012). Big Data cannot be defined just by volume of data, but also by high velocity, diverse variety, exhaustive in scope, and relational in nature (Kitchin, 2014). Big data has been defined as an umbrella term for any collection of large and complex datasets that are difficult to store, process, analyze with earlier methods (Huang and Chaovalitwongse, 2015). Traditional database management technologies are unable to scale up to the demand of storage, analysis or management of such large volumes of continuous data from a variety of data sources. Visionary companies such as Google, Amazon, Wal-Mart, Netflix, have developed unique ways of tapping value from these high speed, large datasets. A new field of analytics has emerged in recent years, which uses computer science, advanced data storage and management techniques and statistics concepts. This field is based on finding out patterns within data, correlation among dependent and independent variables.

2.3.1 Big data analytics

Many economic transactions such as banking, e-commerce and social transactions are moving online. Large scale data is created from these applications. With the availability of big data and major advancements in techniques that derive intelligence from data, several new research questions and opportunities are created (Agarwal and Dhar, 2014). Big data analytics has its roots in the earlier data analysis methodologies using statistical techniques such as regression, factor analysis etc. It includes data mining from high speed data streams and sensor data to get real time analytics (Chen et al., 2012). Thus, it is an interdisciplinary field which uses the knowledge of computer science, data science, statistics and mathematical models. It consists of a systematic process of capturing and analyzing business data, developing a statistical model to explain the phenomenon (Descriptive Analytics), developing a model to predict future outcomes based on variable inputs (Predictive Analytics) as well as developing a model to optimize or simulate outcomes based on variations in inputs (Prescriptive Analytics). It leverages statistical techniques such as regression, factor analysis, multivariate statistics and knowledge of mathematics for developing equations (Dubey and Gunasekaran, 2015).

In the present era, researchers and people are not concerned with what happened or why it happened commonly known as descriptive analytics but the main issue of concern is to find out the answer to questions like what is happening at present and what is likely to happen in the future commonly known as Predictive Analytics and what actions should be taken to find out the optimal results basically known as Prescriptive Analytics. Therefore, business analytics may be further classified into Descriptive, Predictive and Prescriptive Analytics (Bose, 2009).

2.3.2 Predictive analytics

Predictive analytics is the most useful technique for getting insights from data about what can happen in future from available big data. It is defined as the process of discovering meaningful patterns of data using pattern recognition techniques, statistics, machine learning, artificial intelligence and data mining (Abbott, 2014). Also, referred as advanced analytics, it simply means application of data analytics techniques to answer questions or solve problems (Bose, 2009). It is a further progression of Business Intelligence (BI) and data mining combined with statistical techniques. Business Intelligence processes help analysis of internal and external data to enable business executives to make intelligent decisions. The questions and variables are developed by experts in the field of study whereas in case of predictive analytics, selection of model and relationship are data driven (Abbott, 2014).

2.4 Big Data & Predictive Analytics (BDPA) Capability

According to RBV logic, when firm integrate and deploy strategic resources, they develop capabilities which are distinct from other competitors (Bharadwaj, 2000; Barratt and Oke, 2007; Brandon-Jones et al. 2014). Several firms have developed infrastructure to gather large datasets, analyze them and use them either for making operational decisions or predictions. This additional information helps them to gain market share or improve profitability. This ability to assemble, integrate and deploy firm's big data specific resources is defined as big data and predictive analytics (BDPA) capability (Gupta and George, 2016). There is no dearth of recent literature which explains significance of data science. Drawing on the RBV logic, Gupta and George (2016), have identified tangible (data, technology and other basic resources), human (managerial and technical skills) and intangible (organizational learning and data driven culture) resources as building blocks of BDPA capabilities.

2.4.1 Tangible Resources

According to Barney (1991) and Grant (1991), tangible resources include capital, buildings, IT infrastructure, networks, connectivity, data sources etc. These resources are necessary for engineers to develop analytics solutions. There is a recent trend of investments into big data and relevant technologies. However, investments alone may not provide the competitive advantage from big data. It is important that in addition to these investments, firms devote enough time to their big data analytics projects to accomplish their objectives (Mata et al. 1995; Wixom and Watson, 2001; Gupta and George, 2016). These resources will not provide competitive advantage on their own but these are required as a foundation for building capabilities. Thus, availability of data, technology, time and money are some of the basic resources towards the BDPA objectives (Gupta and George, 2016).

2.4.2 Human Resources

In addition to investments in basic resources required for big data analytics projects, firm needs human resources with skills in big data analytics technology as well as management skills to run the projects effectively (Bharadwaj, 2000; Chae et al., 2014; Mata et al., 1995; Gupta and George, 2016). A firm's human resources consists of its employee's experience, knowledge, business acumen, problem solving skills, leadership qualities, relationships with others (Barney, 1991; Ross et al.,1996).

Technical skills: Big data analyst, commonly referred as data scientist needs to possess specific skills and knowledge in statistical analysis, machine learning and business acumen to understand business problems, articulate research problems, problem solving skills, strong communication and people skills (Davenport, 2014). According to Davenport (2014), many large firms are augmenting their existing analytical staff with data scientists who possess higher order IT capabilities and ability to manipulate big data technologies.

Management skills: Technical skills may be developed through training or hiring from the market, whereas managerial skills are rare and highly firm specific (Mata et al., 1995). Management skills are important for analytics projects as managers play an important role in leading and culture building role (Davenport, 2014). Success of analytics projects depends on how well managers can assemble a team with right skills and align team members towards common goals. Managers need to possess good communication and relationship building skills as they need to deal with internal and external stakeholders for the project.

2.4.3 Intangible Resources

Unlike tangible resources, intangible resources are not documented on the firm's financial reports (Grant, 2010). Prior studies have identified organization culture as a source of sustained firm performance (Barney, 1986; Barney, 1995; Teece, 2015). Organization culture built over a period differs from company to company and it's hard to replicate. It's hard for competitors to replicate close coordination and trust based relationship across supply chains required for imitating Toyota Production System or McDonalds functional capabilities to integrate different functions within the chain (Grant, 1991). On similar lines, recent work in big data has confirmed organization culture as critical success factor for big data initiatives (Lavalle et al., 2011). For realizing full potential of big data owned by firms, it is critical that firms develop data driven culture (Gupta, 2015; McAfee et al., 2012; Ross et al., 2013).

External environment keeps changing with changes in the political, economic, social, technological, environmental or legal environment. Employees of the organization need to upgrade themselves with the latest knowledge in their field and push the boundaries towards developing new knowledge. Significance of continuous learning within an organization is well understood by many competitive firms. They invest into training their workforce regularly. The only way to retain sustainable competitive advantage for the firm is to learn faster than their competitors (De Geus, 1988; Stata, 1989; Pedler et al., 1991) and its needs to keep pace with the change in its external environment (Garratt, 1987, p.54; Revans, 1982). Thus, in line with prior studies data driven culture (McAfee et al., 2012; Ross et al., 2013; Gupta and George, 2016) and organizational learning (De Geus, 1988; Garratt, 1987; Grant, 1996; Gupta and George, 2016) are key intangible resources that contribute towards BDPA capabilities.

2.5 Sustainable Business Development (SBD)

United Nations Brundtland Commission published report "Our Common future" in 1989 seeking "Development meeting the needs of the current generation without compromising the ability of future generations to meet their needs". UN efforts have given a much-needed impetus at political level for sustainable development. It has evolved over a period to blend and balance environmental, economic and social goals (Virakul, 2015). Sustainability means different things to different organizations. Some organizations may be striving for financial self-sustainability, whereas another may be committed to financial-social objectives or another may be focusing entirely on environmental sustainability (Swanson and Zhang, 2012). Nevertheless, sustainability has become part of common business nomenclature in recent years. It is increasingly being used as a measure of a firm's overall performance. ISO 26000 provides guidance on how businesses and organizations can operate in a socially responsible way. This means acting in an ethical and transparent way that contributes to the health and welfare of society.

2.6 Sustainable Supply Chain Performance Measures

Dubey et al. (2016) have developed a framework to assess impact of world class sustainable manufacturing practices (WSCM) on environmental, social and economic sustainability of the firm. They have identified various practices (leadership, regulatory pressure, supplier relationship management, employee involvement, customer relationship management, TQM, TPM, lean) that contribute towards WCSM to achieve economic, social and environmental sustainability. Wilson (2015) in their study of a leading UK based retailer firm, have found that the retailer has enhanced their economic bottom-line by adopting TBL.

2.7 Supply Base Complexity (SBC)

Complexity in the general business environment can be defined as having many factors and issues to deal with to conduct the business (Duncan, 1972; Miller and Friesen, 1983; Smart and Vertinsky, 1984). Complexity increases with the increase in number of factors and issues the manager must deal with. The greater the complexity, the managers end up spending more time in solving issues than to deal with important issues of strategic concern (Amit and Schoemaker, 1993). To get cost and quality advantage, large manufacturers and retailers source their materials globally. They make extensive use of sea, air and ground transportation for logistics purpose. Transporting large quantities by ships give significant cost and quality advantage. However, with addition of each global supplier, the materials manager must deal with uncertainty posed by distance, geography, culture and increased management work. This is termed as supply base complexity (SBC). It is defined by factors related to number of suppliers (scale complexity), delivery lead time (delivery complexity), differences between suppliers (differentiation complexity) and their different geographic locations (geographic dispersion complexity) (Vachon and Klassen, 2002; Choi and Krause, 2006; Caridi et al., 2010; Brandon-Jones et al. 2014). Well defined business processes, database and state of the art information system including BDPA capabilities helps firms to get visibility and transparency to reduce the complexity. Firms get visibility of real time demand, inventory and delivery status across supply chain, which helps in reducing uncertainty. This facilitates one or more members of supply chain to respond to changes in timely manner (Brandon-Jones et al., 2014). Manufacturing firms based in India being members of local or global supply chain, their performance is interlinked with SBC.

3. Theoretical Framework and Hypotheses Development

The foundation of our theoretical framework comprises of two elements: RBV and SBC (Figure 1). To answer our first research question, we have grounded our arguments in RBV. Although, numerous studies have attempted to explain BDPA using RBV (Gupta and George, 2016) and dynamic capability view (Akter et al. 2016). However, the dynamic capability view (DCV) and contingent resource based view (CRBV) are the further extensions of the RBV to address the criticisms of some antagonists who believes that RBV is static in nature or suffers from context insensitivity. In the present study, we further built upon Akter et al. (2016) and Gupta and George (2016) to include the moderating role of SBC. The complexity in supply chains increases with the increase in supplier's base as there are additional relationships to manage, alongside additional information and product flows to oversee (Bozarth et al. 2009). Hence, the geographical dispersion and differences in suppliers in terms of cultural differences generates complexity in supply chains. Thus, we argue that moderating role of SBC may positively enhance the effect of the BDPA on three performance measures of sustainable supply chain.

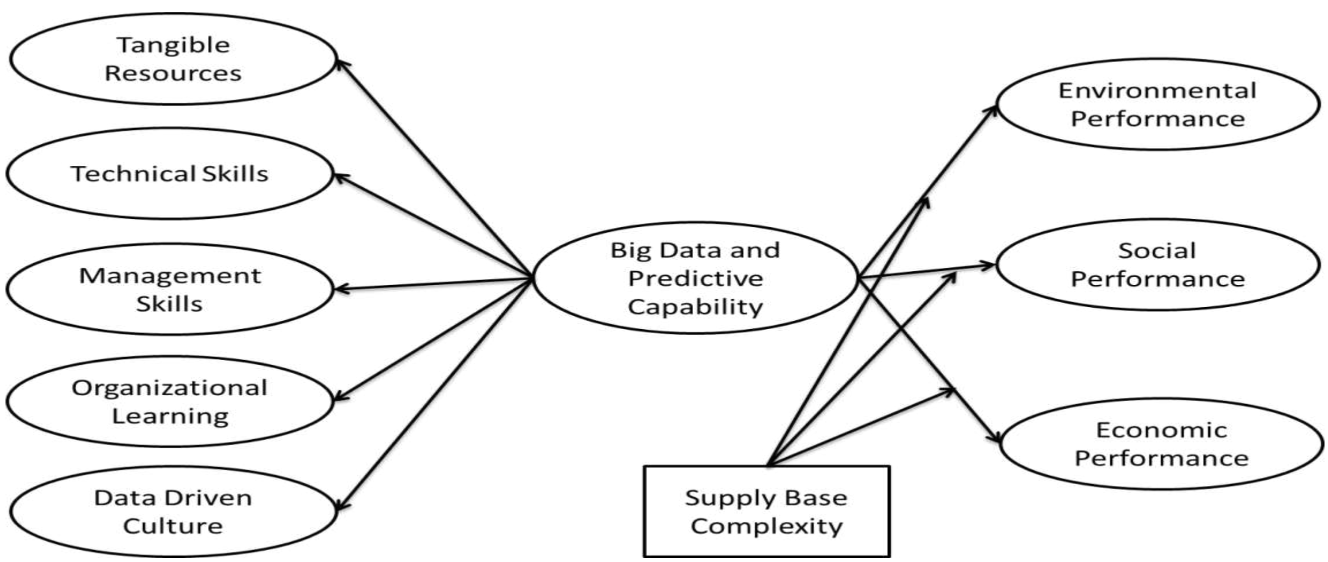

Figure 1: Theoretical Framework

3. 1 Impact of Big Data & Predictive Analytics (BDPA) on Environmental Performance

Environmental concerns have been a topic of discussion at different levels from local government bodies to international forums such as United Nations as the effects of global warming caused by carbon emissions are quite visible. In 1987, United Nations Brundtland commission proposed long term strategies for achieving sustainable development by the year 2000 and beyond. Those objectives remain unfulfilled. This commission defined sustainable development as the one that seeks to meet the needs and aspirations of the present without compromising the ability to meet those of the future (Brundtland and Khalid, 1987). The impact of carbon emissions arising from various manufacturing, logistics and supply chain activities are clearly visible in form of global warming leading to melting of ice layers and rising sea levels. Environmental sustainability objectives such as reducing carbon footprint can be achieved through programs such as "reduce, reuse and recycle". Consumers are increasingly concerned with ethical and environmental issues that affect their purchasing decisions (Laroche et al., 2001, Trudel and Cotte, 2009). This is leading to carbon-labeling which provides product's impact on environment (Svensson and Wagner, 2015). In recent studies (see Zhao et al. 2017; Xie et al. 2017; An et al. 2017) scholars have attempted to study the impact of big data and predictive analytics on reducing the negative effects of carbon emissions. Hence, we hypothesize it as:

H1: BDPA has positive impact on environmental performance (EP);

3.2 Impact of Big Data & Predictive Analytics (BDPA) on Social Performance

In addition to the planet, the second area of concern is society in which firms operate, i.e. social sustainability. While the standard of living is improving in many countries, some societies are challenged in meeting basic needs. There are several challenges ahead of us in terms of equity, gender equality, child labor, malnutrition and sustainable working conditions etc. Brundtland and Khalid (1987) in their report to United Nations on sustainable development call for social equity between generations as well as equity within generations. Developmental goals should not ignore interest of future generations and other societies sharing the planet. For measuring economic performance of the firm, there are many economic indicators available in the balance sheet and stock markets. Environmental performance is being measured with help of GRI (Global Reporting Initiative) or ISO 14001 Environmental Management System (EMS). However, social dimension of sustainability has not received enough attention due to challenges in getting tangible outcomes and very complex human issues involved (Mani et al., 2014). There are numerous cases where the firms in developed countries have come under scrutiny for unethical practices of their suppliers located elsewhere. The big data in the form of social media like twitter, face book and other forms of unstructured data creates significant level of awareness about wages, employment conditions, equity, safety and living conditions are created amongst various stakeholders (Lindsey et al. 2013). This is leading to recognition by firms the significance of social and environmental responsibility and its influence on their performance (Porter and Linde, 1995; Zadek, 2004). Thus, socially sustainable manufacturing and sourcing practices are getting better. Firms are contributing in the form of raising living standards for the society, improving workplace conditions, eliminating waste and using resources efficiently etc. (Mani et al., 2015). Many companies have started publishing their corporate social responsibility reports that share company's track record on social issues. Consumers and stakeholders expect firms to be responsible towards profitability, good environment and ethical behavior (Ashby et al., 2012). Song et al. (2017) argues that BDPA has enough potential to improve social sustainability. Hence, we hypothesize it as:

H2: BDPA has positive impact on social performance (SP);

3.3 Economic Sustainability

The primary focus of business firms is to remain profitable for a long-term survival. Firms operate in a highly competitive marketplace where every other firm wants to gain market share (Svensson and Wagner, 2015). Due to globalization, improved information and communication technologies and creative destruction, average lifespan of the firms is reducing drastically in recent years (Foster and Kaplan, 2001). Economic success is measured by profitability, competitiveness, cost reduction and brand equity (Svensson and Wagner, 2015). Business firms need to be profitable to be able to provide returns to stakeholders. They need to remain competitive by continuous improvement of their product or service and reducing costs. A measurement model has been suggested by Svensson and Wagner (2015) for economic, social and environmental sustainability. In previous studies (see Gupta and George, 2016; Akter et al. 2016) have noted based on empirical studies that BDPA has positive influence on economic performance. Hence, we hypothesize as:

H3: BDPA has positive impact on economic performance (ECOP)

3.4 The Moderating Role of Supply Base Complexity (SBC)

Drawing upon contingent RBV (Aragón-Correa and Sharma, 2003), moderating role of SBC on the relationship between BDPA capability of the firm and its economic, social and environmental performance is discussed. BDPA capability can be created by bundling of resources such as tangible, human resource and intangible resources (Gupta and George, 2016). Brandon-Jones et al., (2014), argues that the scale complexity which is a result of several suppliers, has strong moderating effect on the relationship between supply chain visibility and firm performance. Barratt and Oke (2007) further established the relationships between supply chain visibility, improved firm performance and sustainable competitive advantage. We argue that SBC may have moderating effect on the links connecting BDPA capability and environment, social and economic sustainability performance of the organization. Hence, we hypothesize it as:

H4a: Supply base complexity (SBC) has positive moderating effect on the path connecting BDPA and EP

H4b: Supply base complexity (SBC) has positive moderating effect on the path connecting BDPA and SP

H4c: Supply base complexity (SBC) has positive moderating effect on the path connecting BDPA and ECOP

4. Research Design

In this study, all measurement items were derived from existing literature and were adapted to fit BDPA context. Survey design was pretested with the help of four experienced researchers and academicians working in the field of big data analytics. Based on feedback received, the questionnaire was modified to make it more objective and clear. Then the questionnaire was emailed to senior managers from manufacturing companies in Indian automobile industries from CII database. All exogenous and endogenous constructs in the model are operationalized as reflective. Responses were measured on a five point Likert scale ranging from strongly disagree (1) to strongly agree (5).

4.1 Constructs Operationalization

We used survey based instrument to test our theoretical model. The instrument was developed by identifying measures based on extensive review of existing literature. Some modifications were made to existing scale to make those more suitable in context to BDPA study. All the exogenous and endogenous constructs was operationalized as reflective constructs.

Table 2: Operationalization of Constructs

Construct	Type	Relevant Literature	Measures
Tangible Resources	Reflective	Barney, 1991; Grant, 1991; Gupta, 2015; Mata et al. 1995; Wixom and Watson, 2001	a) We have allocated adequate funds for big data and predictive analytics project (BR1) b) We have enough time to achieve desired results from big data and predictive analytics (BR2)
	Reflective	Barney, 1991; Grant, 1991; Davenport, 2014; Gupta, 2015	a) We have access to very large, unstructured and fast moving data for analysis (D1) b) We integrate data from multiple internal sources into a data warehouse (D2) c) We integrate external data with internal to facilitate high-value analysis of our business environment (D3)
Technology	Reflective	Davenport, 2014; Gupta and George, 2016.	a) We have explored or adopted parallel computing approaches (e.g. Hadoop) to big data processing (T1) b) We have explored or adopted different data visualization tools (T2) c) We have explored or adopted cloud based services for processing data and doing analytics (T3) d) We have explored or adopted open-source software for big data and analytics (T4) e) We have explored or adopted new forms of databases such as NoSQL (Not only SQL) for storing data (T5)
Technical Skills	Reflective	Mata et al., 1995; Carmeli and Tishler,	f) We provide big data related training to our employees (TS1)

Construct	Type	Relevant Literature	Measures
		2004; Gupta and George, 2016.	g) We hire new employees that already have the big data & predictive analytics skill (TS2) h) Our big data & predictive analytics staff has right skills to accomplish their jobs successfully (TS3) i) Our big data & predictive analytics staff has suitable education to fulfill their jobs (TS4) j) Our big data & predictive analytics staff is well trained (TS5)
Management Skills	Reflective	Davenport, 2014; Gupta and George, 2016.	a) Our big data & predictive analytics managers understand and appreciate sustainable business development needs of other functional managers, suppliers and customers (MS1) b) Our big data & predictive analytics managers can coordinate big data & predictive analytics related activities in ways to support other functional managers, suppliers and customers (MS2) c) Our big data & predictive analytics managers can work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business (MS3) d) Our big data & predictive analytics managers can anticipate the future business needs of the other functional managers, suppliers and customers (MS4) e) Our big data & predictive analytics managers have good sense of where to use big data (MS5) f) Our big data & predictive analytics managers can understand and

Construct	Type	Relevant Literature	Measures
			evaluate the output generated from big data (MS6)
Organizational Learning	Reflective	De Geus, 1988; Garratt, 1987; Grant, 1996; Bhatt and Grover, 2005; Gupta and George, 2016	a) We can search for new and relevant knowledge (OL1) b) We can acquire new and relevant knowledge (OL2) c) We can assimilate new and relevant knowledge (OL3)
Data Driven Culture	Reflective	Laney, 2001; Mcafee et al., 2012; Ross et al., 2013; Davenport and Dyché, 2013; McAfee et al., 2012, Davenport and Patil, 2012)	a) We treat data as a tangible asset (DD1) b) We base our decisions on data rather than instinct (DD2) c) We are willing to override our own intuition when data contradict our view points (DD3)
Social Performance	Reflective	Elkington, 1991; Svensson and Wagner, 2015; Wilson, 2015; Dubey et al, 2016.	a) Our firm believes in gender equality (SP1) b) Our firm pays significant attention to the mortality rate of the daily wage workers children (SP2) c) Our firm believes in poverty reduction (SP3) d) Our firm pays significant attention to the nutritional status of the meal served in the canteen (SP4)
Environmental Performance	Reflective	Elkington, 1991; Svensson and Wagner, 2015; Wilson, 2015; Dubey et al, 2016.	a) Our organization has adopted adequate measures for reduction of air emissions (EP1) b) Our organization has adopted adequate measures for re-cycling waste water (EP2) c) Our organization has adopted adequate measures to prevent discharge of solid waste (EP3) d) Our organization has adopted adequate measures to prevent consumption of hazardous harmful toxic materials (EP4)

Construct	Type	Relevant Literature	Measures
Economic Performance	Reflective	Elkington, 1991; Svensson & Wagner, 2015; Wilson, 2015; Dubey et al, 2016.	a) Decrease of cost for materials purchasing (ECOP1) b) Decrease of cost for energy consumption (ECOP2) c) Decrease of fee for waste treatment (ECOP3) d) Decrease of fee for waste discharge (ECOP4)
Supply Base Complexity	Reflective	Barratt and Oke, 2007; Brandon-Jones et al., 2014; Gunasekaran et al., 2017	a) The supply chain network involves a lot of players (SCBC1) b) The supply chain network is complex (SCBC2) c) Suppliers in this supply chain are of the same size (SCBC3) d) Suppliers in this supply chain have the same level of technical capability (SCBC4) e) We depend on on-time delivery from suppliers in this supply chain network (SCBC5) f) We can depend on short-lead times from suppliers in this supply chain (SCBC6)

4.2 Data Collection

For this study, a simple random sampling method was used. An email survey of a sample of auto component manufacturing companies from CII database was conducted. The initial sample consisted of 635 manufacturing firms located in the Pimpri-Chinchwad industrial area. Each survey included an email request and was followed up with emails, and one or more phone calls. Survey emails were sent to key functional heads from above mentioned manufacturing companies, from logistics, operations management, materials management departments and are aware of role of big data analytics. We have received 215 responses however, only 205 responses were complete and usable, resulting in effective response rate of 32.28%. Most of the respondents (45%) are in large auto component manufacturing companies with sales revenue above $100 million and more than 500 employees working in the firm. According to Cohen (1992), a sample size recommended for PLS-SEM for statistical power of 80% is given in the Table 3 below. Thus, the sample size for minimum R^2 of 50% with 5% significance level is 45 and with minimum R^2 of 10% sample size is 147, therefore, our 205-sample size is suitable for PLS-SEM analysis. We have further assessed non-response bias using t-tests to compare the responding and non-responding organizations and found no significant differences ($p>0.05$). The appendix 1 presents the demographics of the respondents.

Table 3 – Sample size recommendation in a PLS-SEM for a statistical power of 80%

Maximum number of Arrows pointing at a construct	Significance Level	Minimum R^2 10%	Minimum R^2 25%	Minimum R^2 50%
5	1%	205	98	62
5	5%	147	70	45
5	10%	120	58	37

Source: Cohen (1992)

5.0 Data Analysis and Results

Structural equation modelling (SEM) is a second-generation multivariate data analysis technique, which overcomes the limitations of the first-generation techniques in terms of accounting for measurement error. We have used WarpPLS version 5.0, which relies on the Partial Least Squares (PLS), for analyzing the model as it exhibits several advantages in theory development and explanation of variance (Peng and Lai, 2012; Hazen et al. 2015). It has a higher level of statistical power in situations with complex model structures or smaller sample sizes (Hair et al., 2016). This technique relies on pre-specified networks of relationships between constructs as well as their measures (Mateos-Apricio, 2011). It works efficiently with complex relationships, makes practically no assumptions about underlying data. PLS-SEM's statistical properties provide very robust model estimations with data that have normal as well as non-normal distributional properties (Reinartz et al., 2009; Ringle et al., 2009; Hazen et al. 2015).

5.1 Measurement Model

Confirmatory factor analysis (CFA) was used to verify the convergent and discriminant validity of the first order measurement model. The study calculated all the item loadings which exceeded the cut-off values of 0.7 and were significant at $p<0.001$. The study calculated average variance extracted (AVE) and socio composite reliability (SCR) for all the constructs (Fornell and Larcker, 1981). AVE is found to be greater than 0.5 and socio composite reliability (SCR) is greater than 0.7 for all the constructs (Table 4 below). We can therefore conclude that data is supporting convergent validity. AVE measures the amount of variance that a construct captures from its indicators relative to measurement error, whereas SCR measures internal consistency (Chin, 2010). These two tests indicate extent of association between a construct and its indicators.

Discriminant validity is a comparison of values of squared correlation between latent variables with value of AVE of the construct. If the square root of AVE of the construct is larger than its squared correlation with other constructs, the discriminant validity is considered good (Hair et al., 2010). Discriminant validity of the reflective constructs was established using Fornell and Larcker (1981) criteria. The square root of AVEs of each latent variable was greater than its correlation with any other constructs. Examination of cross loadings yielded further support for discriminant validity (see Table 5). This test indicates that the constructs do not share the same type of items and they are conceptually distinct from each other (Chin, 2010). Thus, each construct and its measure are distinct from other constructs and corresponding measures. Overall, the measurement model is considered satisfactory as per evidence of convergent validity and discriminant validity as shown in Table 4 and Table 5.

Table 4: Convergent Validity Test

Item	Factor Loadings	Variance(λ^2)	Error	SCR	AVE
BR1	0.75	0.56	0.44	0.85	0.58
BR2	0.75	0.56	0.44		
D1	0.77	0.6	0.4		
D2	0.77	0.6	0.4		
T1	0.89	0.8	0.2	0.94	0.77
T2	0.94	0.89	0.11		
T3	0.91	0.83	0.17		
T4	0.9	0.81	0.19		
T5	0.74	0.54	0.46		
MS1	0.87	0.76	0.24	0.95	0.75
MS2	0.89	0.79	0.21		

Item	Factor Loadings	Variance(λ²)	Error	SCR	AVE
MS3	0.92	0.84	0.16		
MS4	0.9	0.81	0.19		
MS5	0.9	0.81	0.19		
MS6	0.7	0.49	0.51		
OL1	0.98	0.95	0.05	0.98	0.95
OL2	0.97	0.95	0.05		
OL3	0.97	0.95	0.05		
DD1	0.66	0.44	0.56	0.78	0.54
DD2	0.77	0.6	0.4		
DD3	0.77	0.59	0.41		
SP1	0.93	0.86	0.14	0.93	0.87
SP2	0.94	0.88	0.12		
EP1	0.92	0.84	0.16	0.96	0.85
EP2	0.95	0.91	0.09		
EP3	0.93	0.86	0.14		
EP4	0.89	0.79	0.21		
ECOP1	0.96	0.93	0.07	0.98	0.93
ECOP2	0.97	0.94	0.06		
ECOP3	0.97	0.93	0.07		
ECOP4	0.95	0.91	0.09		
SCBC1	0.8	0.63	0.37	0.9	0.6
SCBC2	0.77	0.6	0.4		
SCBC3	0.78	0.6	0.4		
SCBC4	0.67	0.45	0.55		
SCBC5	0.87	0.75	0.25		
SCBC6	0.77	0.59	0.41		

Table 5: Discriminant Validity Test

	TR	TS	MS	OL	DDC	SP	EP	ECOP	SCBC
TR	**0.88**								
TS	0.61	**0.87**							
MS	0.28	0.50	**0.97**						
OL	-0.02	0.03	0.23	**0.73**					

DDC	0.01	0.01	-0.04	-0.06	**0.93**				
SP	0.10	0.14	0.09	-0.07	-0.02	**0.92**			
EP	-0.22	-0.31	-0.36	-0.08	-0.03	0.08	**0.96**		
ECOP	-0.07	-0.09	-0.15	0.02	0.01	0.20	0.20	**0.96**	
SCBC	0.18	0.16	0.02	0.03	-0.05	0.17	-0.04	0.04	**0.77**

5.2 Common Method Bias (CMB) Test

As with all self-reported data, there is potential for CMB resulting from multiple sources such as consistency motif and social desirability (Podsakoff et al. 2003). Following Podsakoff and Organ (1986) arguments, we have conducted, single factor Harman's test. The results yielded that one factor could explain only 32.623% of the variance. Hence, we can argue that CMB may not be a major issue in our study. Although, Guide and Ketokivi (2015) argues that Harman's single factor test is not a robust approach to address the CMB. Hence, following Fawcett et al. (2014) we have requested the organization to respond after consulting their team members rather than responding based on their experiences. In this way, we have attempted to enforce procedural remedy which may have minimized the CMB effect on our data.

5.3 Hypothesis Testing

The PLS does not assume a multivariate normal distribution. Hence, traditional based parametric-based techniques for significance tests are inappropriate. PLS uses a bootstrapping procedure to estimate standard errors and significance of parameter estimates (Chin, 1998). We have reported the PLS path coefficients and p-values of the model (see Figure 2) in the Table 6.

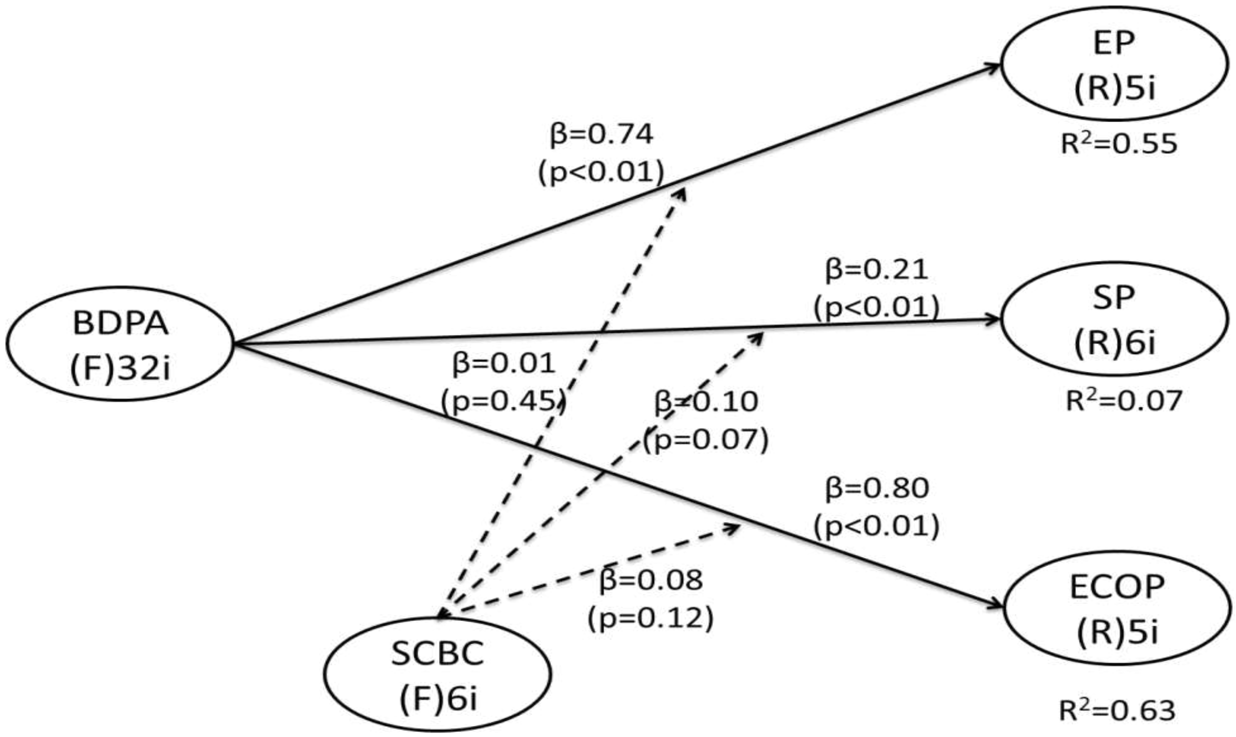

Figure 2: PLS-SEM Model

Table 6: Structural Estimates

Hypothesis	Effect of	on	β	p-value	Results
H1	BDPA	EP	0.74	<0.01	Supported
H2	BDPA	SP	0.21	<0.01	Supported
H3	BDPA	ECOP	0.80	<0.01	Supported
H4a	SBC	BDPA→EP	0.01	0.45	Not-supported
H4b	SBC	BDPA→SP	0.10	0.07	Not-supported
H4c	SBC	BDPA→ECOP	0.08	0.12	Not-supported

Addressing H1, first we observe support (Table 6) for the prediction that the BDPA is positively associated with EP (β=0.74; $p<0.01$), consistent with the previous studies (Dubey et al. 2016; Song et al. 2017; Xie et al. 2017; Zhao et al. 2017). Next, we found support for H2 (β=0.21; $p<0.01$), is consistent with the previous claim (see Song et al. 2017). Addressing the H3(β=0.80; $p<0.01$), found support is consistent with the previous findings (Akter et al. 2016; Gupta and George, 2016; Dubey et al. 2016). The hypotheses H4a-H4c, did not find support (see Table 6). H4a (β=0.01; p=0.45) did not find support. These results suggest that SBC is not significantly related to the path joining BDPA and the three dimensions of sustainability. The exact role of SBC in the role of BDPA and its influence on sustainable supply chain performance remains interesting questions for future research. Next, we have examined the R^2 value of the endogenous constructs to examine the explanatory power of the model. Using R^2 to assess the structural model is consistent with the objective of PLS to maximize the variance explained in the endogenous variables (Peng and Lai, 2012). The R^2 for environmental performance, social performance and economic performance are 0.55, 0.07 and 0.63, respectively, which are moderately strong except social performance construct (see Figure 2).

To evaluate the effect size of the predictor construct (BDPA), we used Cohen f^2 formula (see Cohen, 1988). The effect size of the BDPA on EP was 0.545, SP was 0.052 and ECOP was 0.660 are considered large in case of BDPA on EP and ECOP. However, in comparison to other two dimensions the effect size of the BDPA on SP is considerably small (see Cohen, 1988).

Next, to evaluate model's capability to predict, Stone-Geisser's Q^2 for endogenous constructs are 0.547, 0.075 and 0.691 for EP, SP and ECOP, respectively, which are all greater than zero, indicating acceptable predictive relevance (Peng and Lai, 2012).

6.0 Discussion

6.1 Theoretical Implications

The empirical results highlight that how BDPA as an organizational capability may help organization's initiative to improve environmental, social and economic performance of the organization. The data analyses suggest that BDPA and EP, SP and ECOP are positively related (H1-H3). Together, these results imply that BDPA as a higher order reflective construct which in combination with organization tangible and intangible resources may help organizations to achieve desired sustainability goal. Although, previous scholars have indicated the potential of BDPA in achieving sustainability in supply chains. What is less understood is how the BDPA affect process of sustainable business development. Two key aspects of this study signify our main contributions to the operations and supply chain management literature. First is the focus on the implementation of the BDPA. We have conceptualized our theoretical framework, grounded in RBV logic. In the current study, we have answered the most important question: What are the resources that are needed to build a BDPA capability?

From previous research, we can argue that organization achieve competitive advantage by building organizational capability which in turn created by combining and deploying several organization-level resources (Bharadwaj, 2000; Akter et al. 2016; Gupta and George, 2016). Following this stream of research, we have attempted to answer that what are the organization-level resources that may be required to build BDPA capability which may help organizations to achieve sustainable business development goal.

To answer second research question: How these resources and capability impact three dimensions of sustainability?

This study integrates the RBV logic and contingency theory into one model and reconciles what had previously been presumed to be independent in the literature. In this study, we show that how BDPA impact three dimensions of sustainability under moderating effect of SBC. This study extends the previous studies (Akter et al. 2016; Gupta and George, 2016) by including environmental and social performance measures along with economic performance measures. Hence, our study is one of the first studies which has empirically investigated the influence of BDPA on the supply chain sustainability. Hence, by doing so we have attempted to answer the previous research calls of (Waller and Fawcett, 2013; Song et al. 2017).

6.2 Managerial Implications

Our study yields some interesting results which may be useful for the practitioners and policy makers, engaged in sustainable business development programs. By highlighting the importance of technical skills and managerial skills, this study has offered numerous guidance to the big data managers, human resource managers and policy makers that how mastering these skills or focusing on cultivating these specific skills may provide sustainable competitive advantage to the organization. Secondly, our study further offers some interesting insights that by making investments, collecting hordes of data, and having access to world class technology are not sufficient for building successful BDPA capability. The organizational learning and an organizational culture have also significant influence on building BDPA capability. Finally, our study suggests that BDPA can help organizational initiatives towards sustainable business development. Hence, this may provide enough direction to the policy makers who are engaged in charting future path for sustainable business development.

6.3 Limitations and Future Research Directions

It is important to evaluate the study's results and contributions in the light of its limitations. Our study has the following limitations that can be addressed by future research. First, we have tested our research hypotheses using cross-sectional data. Guide and Ketokivi (2015) in their editorial note have outlined some specific guidelines for the empirical articles. The use of cross-sectional data for testing the model continues to be the common trend. However, the use of cross-sectional data using survey based instrument often leads to CMB. Although, we have tried to use multi-informants to minimize the effect of CMB in our study, but may not be sufficient to eliminate the CMB which may contaminate our results (Ketokivi and Schroeder, 2004). Hence, in the light of Guide and Ketokivi (2015) arguments, we believe that longitudinal data would further enrich our understanding by offering information about causal relationship between independent and dependent variables. It further allows us to investigate how SBC can influence the role of BDPA on the three performance measures of sustainable supply chains.

Second, this research focuses on a firm's perception on BDPA influence rather than actual impact. To ensure that the measures of BDPA capability can accurately predict the actual impact of BDPA on EP, SP and ECOP, we have conducted strict operationalization of item development to improve the validity and compatibility of the indicators. A stated impact of BDPA on three performance measures were used as proxy for the actual impact of BDPA may not represent a nomological net for the actual performance. Hence, it may be more interesting to examine the actual impact of BDPA for a model framed in the resource based view. Future research may focus on building more comprehensive scales for BDPA capability and its actual impact on sustainable supply chain performance measures.

Finally, the demographic of our research sample may limit the generalizability of our findings. To avoid noise caused by industry differences, we purposely chose to study auto components manufacturing industry. We acknowledge that generalizability is one of the major issues that trouble the survey based research because it is difficult to gather samples from large population base. However, we still believe that future research may explore data from more industries, countries and informants with diverse backgrounds to improve the generalizability.

Appendix 1: Sample Frame

Annual Sales Revenue	Number of Firms	Percentage
Under 10 Million USD	15	7.3%
10- 25 Million USD	15	7.3%
26- 50 Million USD	35	17.1%
76-100 Million USD	48	23.4%
101-250 Million USD	22	10.7%
251-500 Million USD	24	11.7%
Over 251 Million USD	46	22.4%
Number of Employees	Number of respondents	
0-50	16	7.8%
51-100	6	2.9%
101-200	13	6.3%
201-500	8	3.9%
501-1000	105	51.2%
1001+	57	27.8%

Appendix 2: Questionnaire

Questionnaire ID: __________

This study is being carried out to gain insight about impact of big data & predictive analytics (BDPA) on organizational performance. The information collected would be used for academic purposes only. Your cooperation would be a great help.

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, firm performance and supply base complexity that may be adopted in your firm. Using the scale provided, please indicate your preference by selecting relevant option.

(1)Strongly Disagree
(2)Disagree
(3) Neither Agree nor Disagree
(4 Agree
(5)Strongly Agree

Indicator	Survey Question	Rating				
BR1	We have allocated adequate funds for big data and predictive analytics project.	1	2	3	4	5
BR2	We have enough time to achieve desired results from big data and predictive analytics.	1	2	3	4	5
D1	We have access to very large, unstructured and fast moving data for analysis.	1	2	3	4	5
D2	We integrate data from multiple internal sources into a data warehouse.	1	2	3	4	5

Indicator	Survey Question	Rating				
D3	We integrate external data with internal to facilitate high-value analysis of our business environment	1	2	3	4	5
T1	We provide big data related training to our employees.	1	2	3	4	5
T2	We hire new employees that already have the big data & predictive analytics skill	1	2	3	4	5
T3	Our big data & predictive analytics staff has right skills to accomplish their jobs successfully.	1	2	3	4	5
T4	Our big data & predictive analytics staff has suitable education to fulfill their jobs.	1	2	3	4	5
T5	Our big data & predictive analytics staff is well trained.	1	2	3	4	5
TS1	We have explored or adopted parallel computing approaches (e.g. Hadoop) to big data processing	1	2	3	4	5
TS2	We have explored or adopted different data visualization tools	1	2	3	4	5
TS3	We have explored or adopted cloud based services for processing data and doing analytics	1	2	3	4	5
TS4	We have explored or adopted open-source software for big data and analytics	1	2	3	4	5
TS5	We have explored or adopted new forms of databases such as NoSQL (Not only SQL) for storing data	1	2	3	4	5
MS1	Our big data & predictive analytics managers understand and appreciate sustainable business development needs of other functional managers, suppliers and customers.	1	2	3	4	5
MS2	Our big data & predictive analytics managers can coordinate big data & predictive analytics related activities in ways to support other functional managers, suppliers and customers.	1	2	3	4	5
MS3	Our big data & predictive analytics managers can work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business.	1	2	3	4	5
MS4	Our big data & predictive analytics managers can anticipate the future business needs of the other functional managers, suppliers and customers.	1	2	3	4	5
MS5	Our big data & predictive analytics managers have good sense of where to use big data.	1	2	3	4	5
MS6	Our big data & predictive analytics managers can understand and evaluate the output generated from big data.	1	2	3	4	5
OL1	We can search for new and relevant knowledge.	1	2	3	4	5
OL2	We can acquire new and relevant knowledge.	1	2	3	4	5
OL3	We can assimilate new and relevant knowledge	1	2	3	4	5
DD1	We treat data as a tangible asset.	1	2	3	4	5
DD2	We base our decisions on data rather than instinct.	1	2	3	4	5
DD3	We are willing to override our own intuition when data contradict our view points.	1	2	3	4	5
SP1	Our firm believes in gender equality	1	2	3	4	5

Indicator	Survey Question	Rating				
SP2	Our firm pays significant attention to the mortality rate of the daily wage workers children	1	2	3	4	5
SP3	Our firm believes in poverty reduction	1	2	3	4	5
SP4	Our firm pays significant attention to the nutritional status of the meal served in the canteen	1	2	3	4	5
EP1	Our organization has adopted adequate measures for reduction of air emissions	1	2	3	4	5
EP2	Our organization has adopted adequate measures for re-cycling waste water	1	2	3	4	5
EP3	Our organization has adopted adequate measures to prevent discharge of solid waste	1	2	3	4	5
EP4	Our organization has adopted adequate measures to prevent consumption of hazardous harmful toxic materials	1	2	3	4	5
ECOP1	Decrease of cost for materials purchasing	1	2	3	4	5
ECOP2	Decrease of cost for energy consumption	1	2	3	4	5
ECOP3	Decrease of fee for waste treatment	1	2	3	4	5
ECOP4	Decrease of fee for waste discharge	1	2	3	4	5
SCBC1	The supply chain network involves a lot of players	1	2	3	4	5
SCBC2	The supply chain network is complex	1	2	3	4	5
SCBC3	Suppliers in this supply chain are of the same size	1	2	3	4	5
SCBC4	Suppliers in this supply chain have the same level of technical capability	1	2	3	4	5
SCBC5	We depend on on-time delivery from suppliers in this supply chain network	1	2	3	4	5
SCBC6	We can depend on short-lead times from suppliers in this supply chain	1	2	3	4	5

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