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Effects of Big Data Analytics on Sustainable Manufacturing: A Comparative Study Analysis

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Application of big data analytics (BDA) is seen in various disciplines within an organization to predict trends, explore opportunities and monitor performance. Among all the industries, BDA presents immense value in sustainable manufacturing (SM) given that it is an industry that consumes a high amount of energy, emits high amounts of waste and carbon emissions and requires a large amount of manpower. This paper aims at illustrating the effects of BDA in supporting SM by studying the Indian manufacturing firms which have unfavorable labor laws compared to other developing countries. With an extensive literature review, this paper discusses the relationship between BDA and sustainability, the capabilities of BDA, the concept of SM, the BDA framework for SM, the relationship between Industry 4.0 and SM and the challenges of implementing BDA. Using qualitative meta-analysis research methodology, the paper examines the nine common critical success factors that enable SM through BDA implementation by comparing 15 primary studies. Finally, the paper concludes the research findings and outlines future research directions. The study provides theoretical and practical contributions to BDA implementation in achieving effective SM practices in emerging economies.

Keywords: Big data analytics; Indian manufacturing firms; developing economies; qualitative meta-analysis; sustainability.

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1. Introduction

Big data analytics (BDA) and sustainability are two topics that have gained imminent attention from industry and academia in recent years (Dubey *et al.*, 2019b). Data explosion has caused the growth of big data to expand exponentially and increased the need for

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companies to get their foot at the door of the area of big data. Big data is defined as information that possesses the characteristics of real-time, high volume, velocity and variety (Chen *et al.*, 2012; Gupta and George, 2016). In recent years, "veracity", "variability", "volatility" and "value" are added to the characteristics of big data (Gupta *et al.*, 2020). The ability to manage and process big data using a variety of applications including data science, predictive analytics, artificial intelligence and machine learning is termed as big data predictive analytics (Russom, 2011). Companies are forced to find ways to obtain data insights from large datasets that are created with high speed but with low accuracy and consistency. This gives rise to the transition from big data to BDA which underpins drawing patterns and insights from big data to formulate insightful data-driven actions (Gupta *et al.*, 2020). BDA can assist decision-making in customer intelligence, supply chain and performance management, quality management and improvement and risk management (Elgendy and Elragal, 2014).

Sustainability goals comprise mitigating ecological changes, creating a positive societal impact and strengthening economic growth. However, organizations nowadays do not place sufficient emphasis on the development of a viable natural environment and a nurturing community. The current rate of ecological changes resulting from the high consumption of energy resources ranging from greenhouse gas emissions, global warming and rising sea levels to climate changes has caused unprecedented catastrophes to human beings in recent years (Chevallier *et al.*, 2021; IPCC, 2021). Without proper practices on environmental sustainability from all organizations, the environment will go through more severe threats in the next few years causing significant risks to human lives. On the other hand, organizations often overlook the social aspect of sustainability including occupational health and safety management, societal commitment, human rights and training education. The prevalence of ignorance has hurt the community's well-being in the last 10 years (Ahmadi *et al.*, 2017). Above all, the commitment to maintaining good ecological and societal sustainability practices is often disrupted by the unstandardized guidelines for accessing sustainability holistically (Ness *et al.*, 2007).

Given that BDA provides real-time analytics of high volume and velocity of structured and unstructured data, organizations would be able to make intelligent decisions to transform ecological and social sustainability dimensions with proper BDA implementation. Among all the industries, there is a stronger call for the manufacturing industry to maintain sustainable development as it consumes a high amount of energy, emits high amounts of waste and carbon emissions and requires a large amount of manpower. BDA offers advantages in managing a green supply chain, sustainable manufacturing (SM) and procurement and also elevating the business values (Raut *et al.*, 2019). However, due to the wide range of sustainability measurements, there is inadequate research on the comprehensive framework available for sustainable manufacturing (Kumar *et al.*, 2007). Moreover, the available academic papers have not addressed the capabilities of BDA for sustainable manufacturing in real-life practical scenarios and have not incorporated managerial insights (Belhadi *et al.*, 2019). The paper is therefore centered on three main issues:

(1) Opportunities and challenges in implementing BDA in sustainable manufacturing.

(2) Assessing sustainability framework using big data analytics.
(3) Determining the outcomes of implementing BDA in sustainable manufacturing.

In developing countries, the manufacturing industry remains the key contributor to a country's gross domestic product (GDP). This paper will examine the Indian manufacturing companies as it has one of the highest GDP growth rates compared to other fast-emerging countries with close to 16% contribution by the manufacturing industry (Dubey *et al.*, 2019b). However, the sustainability issues in India are still inadequately managed. Thus, the paper aims to focus on the following research question: "How does BDA assist Indian manufacturing companies to improve the outcomes of environmental and social sustainability efforts?"

The paper is organized into sections as follows: Section 2 discusses the literature review. Section 3 focuses on research methodology. Section 4 presents the analysis and findings. Finally, Sec. 5 concludes the paper and outlines the future directions of the study.

2. Literature Review

2.1. *Big data analytics and sustainability*

Environmental issues have gained significant importance nowadays and driven increasingly more research in sustainability ground toward a green world. Mukred and Zheng (2017), Etzion and Aragon-Correa (2016) and Wu *et al.* (2016) presented that BDA enables real-time monitoring of the environment to reduce any disastrous damages. The capability for real-time monitoring allows environmental enforcers of a country to detect deforestation and monitor biodiversity. On the organizational front, BDA is used for real-time monitoring of the supply chain to maximize operational efficiency for better reservation of energy and natural resources (Etzion and Aragon-Correa, 2016).

Another key main theme mentioned in many journals is the prediction capability of BDA (Mukred and Zheng, 2017; Etzion and Aragon-Correa, 2016; Wu *et al.*, 2016; Ghalehkhondabi *et al.*, 2020). BDA allows predictions of weather, air pollution and damaging coastal wave condition for the local governments to prepare necessary mitigation action plans. The prediction capability of BDA permits organizations to proactively manage and optimize resources including energy, water and raw materials by balancing the demand and supply as well as reducing energy consumption that emits high carbon levels. Optimized resource consumption leads to lower financial costs and environmental damages which are part of the fulfillment of financial and environmental sustainability pillars.

Scholars also examined BDA usage in risk management where organizations can identify and control possible catastrophic events such as IT security threats, natural disasters, workplace accidents and financial liabilities (Huang *et al.*, 2019; Wu *et al.*, 2016). Strengthening the governance of risk management in manufacturing companies can (i) improve the safety management of production lines by providing a safe working environment which is crucial in the aspect of social sustainability; and (ii) increase stakeholders' trust with higher compliance to data security and privacy.

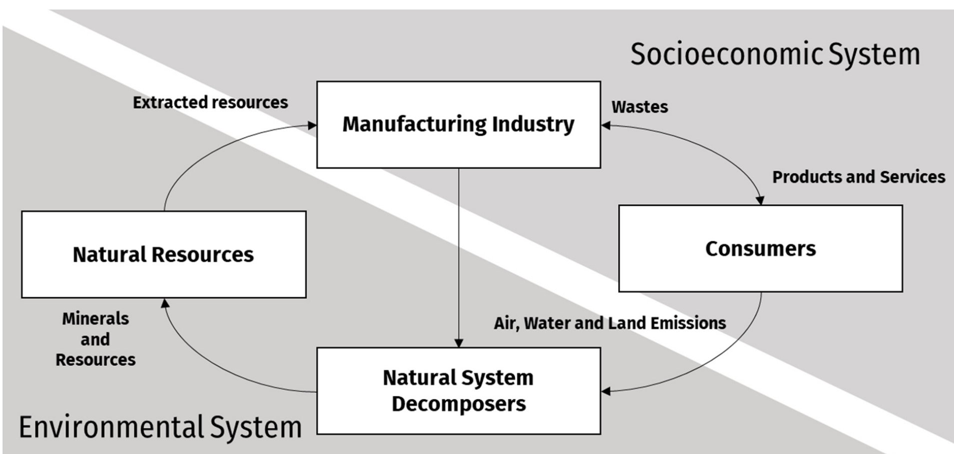
2.2. *Capabilities of BDA*

Scholars widely apply resource-based theory (RBT) to explain BDA capabilities (Gupta and George, 2016). BDA capabilities can be classified into tangible resources, human skills and intangible resources (Gupta and George, 2016). An organization requires an orchestration of these three pillars to form BDA capabilities. Tangible resources comprise data, technology (e.g. information systems) and basic resources (e.g. financial resources, equipment and facilities); BDA human skills consist of managerial and technical skills which encourage higher embracement of BDA to make better decisions (Belhadi *et al.*, 2020); and intangible resources encompass organizational learning and data-driven decision-making culture which is crucial in developing the most suitable IT infrastructure and technology solutions to draw insights from big data.

RBT encourages organizations to think beyond IT capability which is only one facet of what comprises true BDA capabilities. However, despite its wide adoption in academic work, the practical guideline on how to realize tangible resources, human skills and intangible resources has not been discussed. Conducting case studies in the practical implementation of all three dimensions of RBT will be useful for organizations to effectively implement BDA capabilities.

2.3. *Sustainable manufacturing*

Sustainable manufacturing is defined as the ability to create and distribute goods with optimal usage of resources to achieve the goals of the Triple Bottom Line (Garetti and Taisch, 2012). The concept of "Triple Bottom Line" was introduced to incorporate social, economic and environmental dimensions on top of mere profits (Elkington, 1994). Figure 1 depicts a closed system of manufacturing subsystems that coexist alongside natural, ecological and human subsystems which is also referred to as a circular economy



Source: Dechant and Altman (1994).

Fig. 1. The roles of manufacturing industries in sustainable manufacturing.

	Green manufacturing	Lean manufacturing	Mass manufacturing	Sustainable manufacturing
Economic		✓	✓	✓
Social	✓		✓	✓
Environmental	✓	✓		✓

Source: *Kaebernick* cited in Raut *et al.* (2019).

Fig. 2. Differences of “green manufacturing”, “lean manufacturing”, “mass manufacturing” and “sustainable manufacturing”.

system (Dechant and Altman, 1994). However, the phrase sustainable manufacturing is often used to describe measures related to reducing environmental impacts of manufacturing only (Paul *et al.*, 2014). Furthermore, there are confusions and misinterpretations regarding the concepts and applications of “green manufacturing”, “lean manufacturing” and “mass manufacturing” as “sustainable manufacturing”. Figure 2 shows the differences among the different terms of manufacturing practices related to sustainability. Despite the different sustainability aspects covered by each term, “green manufacturing”, “lean manufacturing” and “mass manufacturing” constituted the foundation of SM to implement cleaner production responsibly. Due to the complexity and ambiguity to measure environmental and social performances as well as the high variation of SM context in each country, SM practices often faced challenges (Paul *et al.*, 2014). Scholars agreed that technologies on product, process and practices are one of the key enablers for the success of SM (Garetti and Taisch, 2012; Pusavec *et al.*, 2010; Rosen and Kishawy, 2012). Hence, more in-depth studies about the use of technology for SM should be conducted.

2.4. *BDA framework for sustainable manufacturing*

In terms of manufacturing, BDA plays an important role in research and development, manufacturing, customer service, maintenance/repair and overhaul technical support, recycling and remanufacturing (Zhang *et al.*, 2017). There are several conceptual structures related to BDA framework for sustainable manufacturing presented in recent years.

Zhang *et al.* (2018) proposed a BDA framework for energy-intensive manufacturing industries using the application of statistics and mathematics to analyze manufacturing energy consumption to improve energy efficiency, optimize manufacturing process and reduce emissions. Ren *et al.* (2019) suggested a Smart Sustainable Manufacturing (SSM) framework using BDA throughout the entire manufacturing lifecycle that focuses on data and service-driven mode to improve economic and environmental aspects and enhance the intelligence in decision-making. The SSM model is aimed at reducing resource wastage, increasing digitization level and achieving global intellectualization in manufacturing. The proposed SSM framework consists of intelligent design, intelligent production, intelligent maintenance and service and intelligent recovery. Dubey *et al.* (2016) proposed a world-class sustainable manufacturing system that is composed of leadership, regulatory pressures, supplier relationship management, employee involvement, customer relationship, quality management, productive maintenance and lean manufacturing system.

Most of the academic works discuss the BDA framework for manufacturing as an entity, without a specific scope in sustainability area. In addition, the existing academic works focus on conceptual framework and not specific BDA solutions and case studies that companies can easily adopt. While the advanced production paradigms are effective in environmental performance, there is still a strong need for manufacturing industries to further improve their sustainability practices, especially in the social aspect that is inadequately discussed in the academic journals.

2.5. *Industry 4.0 and sustainable manufacturing*

To manage the challenge of the growing worldwide demand for capital and consumer goods while maintaining the sustainability goals of social, environmental and economic dimensions, the development toward the fourth stage of industrialization, termed Industry 4.0, was launched to realize sustainable manufacturing (Stock and Seliger, 2016). The macro- and micro-perspectives of Industry 4.0 provide cross-linkage of stakeholders, products and equipment along the product life cycle to create sustainable industrial value. In Industry 4.0 framework, technology is the main accelerator for the success of SM, wherein BDA allows smart data collection, storage and analysis alongside Internet of Things and Cloud Computing (Kamble *et al.*, 2020; Chalmeta and Santos-deLeón, 2020).

2.6. *Challenges of implementing BDA*

While BDA provides many benefits in the sustainability area as well as in the manufacturing system, it poses challenges as well. Due to the nature of big data which comprises high amount of data, high costs of infrastructure and technology framework in the likes of Hadoop are usually incurred (Mukred and Zheng, 2017; Raut *et al.*, 2019; Jeble *et al.*, 2016). To manage and assess data using BDA, experienced data scientists, data analysts and IT professionals are mandated to operate the entire process (Ghasemaghaei, 2020; Mukred and Zheng, 2017; Jeble *et al.*, 2016). Not only specialists in the domains of statistics, ERP integration, mathematics, network and cybersecurity are required, but a wide set of knowledge-involving businesses and project management are also needed to launch and maintain the entire system.

Notwithstanding that BDA offers data advantages, it also presents data-related challenges. Big data that deals with high variety of data results in spurious correlation yielding inconsistent variable in the model outcome (Jeble *et al.*, 2016). Such variable will distort the accuracy of the model outcome. Consequently, high processing cost is required to derive the algorithm to mitigate data consistency issue (Fan *et al.*, 2014). In addition, highly sensitive data stored by organizations on-premises for BDA implementation presents significant data security risk (Ghasemaghaei, 2020). The fear of exposing organizations to high data security risk is usually the main reason why many organizations choose not to implement BDA.

Organizational behavior is another challenge that hinders the implementation of BDA. The first and foremost challenge is the data culture of an organization. The lack of data culture of the entire firm results in low management buy-in of BDA projects especially due to that BDA implementation is resource-intensive and has uncertain return on investment (Raut *et al.*, 2019).

One of the key challenges that is missing in many journals is the lack of governmental support particularly in developing countries. Governmental support of tangible resources such as monetary support, infrastructure as well as intangible resources such as regulations, training and awareness campaigns assist organizations to embrace BDA in all areas much swiftly and more effectively.

2.7. *Research gaps*

Through the literature review, we found that BDA and sustainability practices are two emerging topics but have varying adoption issues in developing countries. Organizations in developing countries often do not appreciate the strategic value of BDA due to the presence of hygiene factors leading to organizational and technological difficulties (Verma and Bhattacharyya, 2017). The main organizational inhibitors of BDA adoption in developing countries are the high perceived costs and unclear perceived values to implement BDA (Kuan and Chau, 2001). The non-adopters in developing countries reported that the existing technologies were adequate to support their current business needs and they do not see a need to venture into BDA for any other business objectives (Verma and Bhattacharyya, 2017). In terms of technological challenges, firms in developing countries often quote that they are not having the required skilled professions for BDA adoption, and the required storage infrastructure and computing capacity to implement BDA projects (Luna *et al.*, 2014). The current problems in developing countries are evident for presenting the lack of discussion about the roles and responsibilities of each player in applying BDA in the sustainability field. Without a clear understanding of each stakeholder's roles, newcomers who wish to adopt BDA for sustainable manufacturing will not be able to operationalize the entire process smoothly and may impede the achievement of circular economic values. With this paper, we aim to discover stakeholders' roles to reinforce BDA's benefits in sustainability management.

3. Methodology

This paper seeks to appraise primary evidence using qualitative synthesis method to accommodate both quantitative and qualitative evidence. There is a variety of qualitative synthesis methods; the common ones include thematic analysis, grounded theory, meta-ethnography, meta-study, Miles–Huberman data analysis techniques, content analysis, case survey, qualitative comparative analysis and Bayesian meta-analysis (Dixon-Woods *et al.*, 2005). The common methods are summarized by techniques, advantages and disadvantages in Table 1. This paper aims to establish a comprehensive theoretical framework in an integrative manner to summarize both qualitative and quantitative

Table 1. Common methods of qualitative syntheses.

No.	Types of qualitative synthesis	Techniques	Advantages	Disadvantages
1	Thematic analysis	– Identifies common and prominent themes under thematic categories	– Organized and structured – Integrates qualitative and quantitative evidence	– Lack of transparency – Lack of clarity
2	Grounded theory	– Groups concepts into new categories and conducts axial coding – Synthesizes study in the form of data using constant comparative method	– Maintains the interpretive properties and encourages reflexivity	– Lack of transparency
3	Meta-ethnography	– Employs three strategies: (i) Reciprocal translational analysis to identify key themes (ii) Refutational synthesis to identify and contrast key themes (iii) Lines of argument synthesis to develop a general interpretation	– Preserves the interpretive properties of the primary data and can deal with quantitative data	– Does not provide appraisal on sampling – Time-consuming
4	Qualitative meta-analysis	– Establishes a comprehensive framework with the summary of theory, method and data	– Encompasses a holistic framework – Flexible method for synthesis	– Involves thorough synthesis methods; the process is time-consuming
5	Miles–Huberman data analysis techniques	– Summarizes data using content analysis, case-ordered display or time-ordered display	– Focuses on quantitative data display and well-structured procedures	– Lack of guidelines in appraising the primary papers
6	Content analysis	– Systematically categorizes data in quantitative form to deduce the concepts of validity	– Easy to employ within quantitative frameworks	– May lose the interpretive characteristics of qualitative evidence due to over-simplifying nature – May not consider the significance of evidence with frequency-counting
7	Case survey	– Uses well-organized questions to extract data from case studies and code qualitative cases for quantitative analysis	– Able to synthesize both qualitative and quantitative evidence	– Requires a larger number of cases to conduct quality quantitative analysis – May eliminate the interpretive properties of qualitative data

Table 1. (*Continued*)

No.	Types of qualitative synthesis	Techniques	Advantages	Disadvantages
8	Qualitative comparative analysis	– Analyzes complex causal relationship with Boolean logic to draw outcomes	– Does not require as many cases as the case survey method – Encourages integrative knowledge curation as it can be conducted with previous studies and new studies – Enables integration of qualitative and quantitative evidence in an organized manner – May explore complicated causal relationship	– Appropriate for causal pathway only and may not be suitable for most qualitative research
9	Bayesian meta-analysis	– Synthesizes qualitative data using quantitative statistical methods	– Integrates qualitative and quantitative forms of evidence – Ensures meta-analyses considers various primary evidence by considering crucial examples from primary research	– Difficult to implement and has methodological challenges

Source: Dixon-Woods *et al.* (2005).

evidence with flexible methods. Considering all advantages and disadvantages, the most viable method is qualitative meta-analysis synthesis. Qualitative meta-analysis is an approach in which the findings of primary qualitative data from case studies are synthesized into a theoretical model (Major and Savin-Baden, 2011). The generation of a new theory through the recognition of recurring patterns is made possible through qualitative meta-analysis (Hoon, 2013). The reasons to employ such approach are as follows:

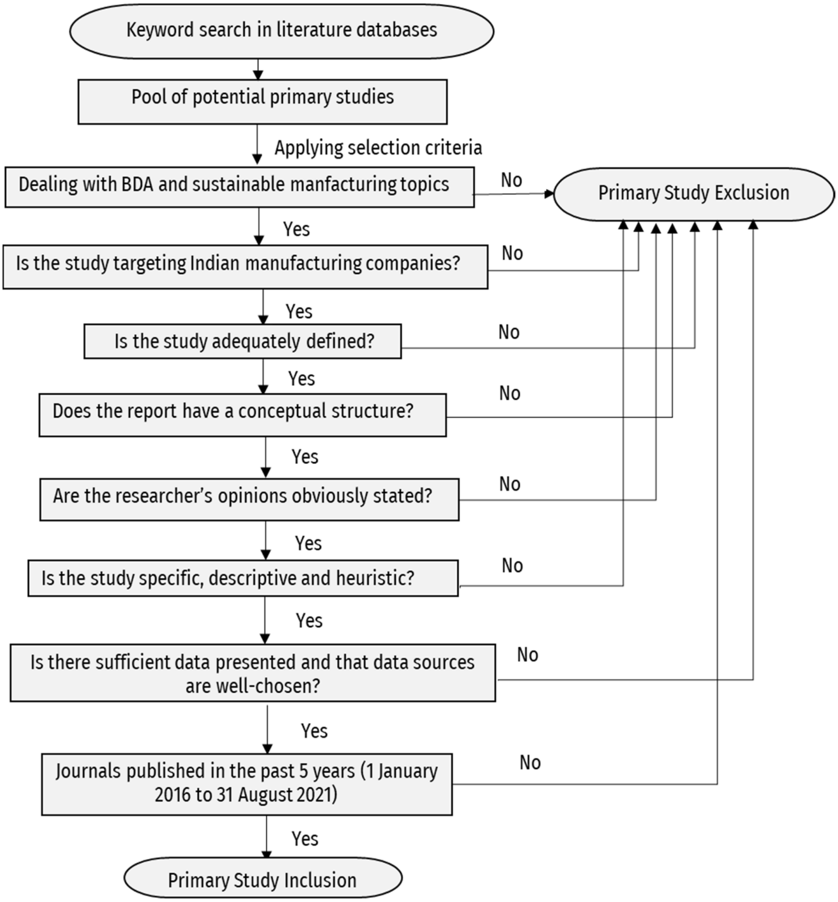
– There is a need to conceptualize a model by integrating the existing frameworks of BDA and sustainable manufacturing with a holistic approach.
– A review synthesizing existing academic works add values to the topic of *sustainability* which garners a lot of attention in recent years.
– Qualitative meta-analysis summarizes past empirical and theoretical works in the literature and includes both experimental and non-experimental studies to effectively conduct the research (Whittemore and Knafl, 2005).
– Qualitative meta-analysis compares and contrasts findings of all qualitative and quantitative studies to reveal new interpretations and to conceptualize new model or generalize patterns from the existing information (Paterson *et al.*, 2001).

Although qualitative meta-analysis may not provide sample-to-population results and may involve a time-consuming process, it adequately compares cases as there is high transferability from case to case to identify factors for BDA and sustainable manufacturing (Punch, 2013). Furthermore, qualitative meta-analysis is a good approach to examine the common factors of each conceptual framework that employs different statistical analysis methods.

3.1. *Selection and appraisal of primary studies*

The selection flow is listed in Fig. 3. Computer databases (EBSCO, ProQuest and Google Scholar) were searched to identify relevant research works on the BDA and sustainable manufacturing fields. The search terms used were sustainability, big data analytics and sustainable manufacturing. Items matching the keywords were included to a potential pool of case studies and checked against the selection criteria listed in Fig. 3. According to Stake (1995), a rigorous assessment criteria list assists in selecting highly relevant studies to the research question. The selection criteria are: (1) the item has to deal with BDA and sustainable manufacturing topics; (2) the study has to target Indian manufacturing companies; (3) the study is adequately defined; (4) the study has a conceptual structure; (5) the researcher's opinions are obviously stated; (6) the study is specific, descriptive and heuristic; (7) there is sufficient data presented and the data sources are well chosen; and (8) the journal articles are published in the past five years (from January 1, 2016 to August 31, 2021). If all criteria were met, the study was included in the meta-analysis.

Out of the pool of 67 potential studies, 15 articles were included to form the basis of this work. Most qualitative meta-analyses were conducted using an average of 12 studies with a minimum of two studies (Paterson *et al.*, 2001). Hence, a total of 15 studies is a considerable amount to conduct a qualitative meta-analysis.



Source: Paterson *et al.* (2001).

Fig. 3. Criteria for the selection of primary studies.

3.2. *Data analysis*

The paper followed a few steps to synthesize the frameworks presented in the selected articles. Relevant meta-analytic data such as the approach adopted, statistical model used, path analysis, sample type and size, theoretical framework and hypothesis testing were extracted from the original study. Once the meta-analytic data were gathered, the discussions of the original studies were inspected for the fundamental framework that depicts a clear organization of the data. After the identification of the framework, the hypothesis testing and path analysis of each dimension/factor were inspected to determine the causal relationships. Then, the results and discussion sections of the original studies were examined to understand the insights that were presented as paradigmatic and categorical examples.

Next, the dimensions/factors articulated in the studies were extracted. When two articles discuss about the same factor, it will be categorized as a common factor. The factors were presorted based on the path analysis of correlation between one factor and another. The causal relationships were clearly sorted. Then, the factor descriptions provided in the articles were reviewed and concepts were reported. If a concept contained subdimensions, they will be sorted into various categories. Last, the hypotheses that were supported were grouped and those that were rejected were sorted in another table column.

It was observed that the original publications presented the effects of BDA on manufacturing performance, the factors influencing BDA adoption and BDA frameworks. Furthermore, the original publications, in general, adopted a coherent approach to present findings in a clear sequential order inherent in the findings. Thus, two domains, *Effects of BDA on Manufacturing* and *Factors influencing BDA Adoption* were included in Sec. 4.

4. Discussion

4.1. *Effects of BDA on manufacturing*

Table 2 summarizes different types of discussion of the articles about BDA. The path analysis of the relationship of BDA with other dimensions using partial least squares (PLS)–structural equation modeling (SEM) or artificial neural network (ANN) model was presented in 60% of the articles (nine articles); conceptual frameworks using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), variations of fuzzy logic or regression analysis were presented in 13% of the articles (two articles); frameworks using mathematical models were presented in 13% of the articles (two articles); and the explanation of BDA impact using literature review and case study was seen in 13% of the articles (two articles).

All 15 articles proposed BDA-related frameworks for sustainable manufacturing or sustainable supply chain based on the conceptual models. In addition, all articles proved that BDA positively influences SM directly or indirectly.

BDA is tested to have a direct positive impact on both social and environmental performances in 28% of the articles (four articles). Dubey *et al.* (2019b), Jeble *et al.* (2018) and Raut *et al.* (2019, 2021) used hypothesis testing of conceptual models to prove the statistical significance of BDA against social and economic performances. Furthermore, these articles used PLS–SEM to test the cause–effect relationships between BDA and social and environmental performances.

BDA is presented to have a positive impact on SM management in 72% of the articles (11 articles) through various aspects. Arya *et al.* (2017) proved that BDA has a positive impact on supply chain performance. Gunasekaran *et al.* (2017) and Mangla *et al.* (2020) demonstrated that BDA adoption positively influences organizational performance. Dubey *et al.* (2018) tested that BDA adoption has a positive impact on collaborative performance. Dubey *et al.* (2019a, 2021) tested that BDA positively influences supply chain resilience and competitive advantage. Mani *et al.* (2017) analyzed that BDA could reduce social risks. Dev *et al.* (2019) proposed a BDA architecture for supply chain key performance indicators. Kumar *et al.* (2018) and Lamba *et al.* (2019) conceptualized BDA frameworks for condition-based maintenance and supplier selection, respectively. Dubey *et al.* (2016) identified the building blocks of SM by visiting the characteristics of BDA.

Table 2. Summary of discussion for selected articles about the effects of BDA on sustainable manufacturing.

No.	Source	Approach/type of model	Path analysis	Sample type and size	Key findings
1	Arya *et al.* (2017)	Conceptual model using literature review	No path analysis used	Not applicable	– BDA has positive impacts on planning, maintenance, distribution and collaboration of a supply chain
2	Dev *et al.* (2019)	– TOPSIS to assess efficient ranking – Integration of fuzzy logic and conventional analytical network process (ANP) to evaluate big data influences in a real-time supply chain setting	No path analysis used	Three suppliers, one manufacturer, two distributors and four retailers	– Proposed a BDA architecture conceptual framework to manage supply chain key performance indicators (KPIs) in an RFID-enabled and cloud ERP system – Compared the KPIs of average fill rate, average inventory levels, average inventory time and average cycle time to find significant KPIs across the entire supply chain in a systematic real-time manner
3	Dubey *et al.* (2016)	Conceptual model, CFA, PLS–SEM	No path analysis used	Indian manufacturing firms ($n = 280$)	– Identified leadership, regulatory pressure, supplier relationship management, employee involvement, customer relationship management, total quality management (TQM), total productive maintenance and lean manufacturing as the building blocks of sustainable manufacturing by visiting the roles of BDA
4	Dubey *et al.* (2018)	Conceptual model, PLS–SEM	Path analysis using causal model	Indian manufacturing firms ($n = 190$)	– BDA positively influences collaborative performance – Organizational compatibility and resource complementarity have positive moderating effects on the path connecting BDA and collaborative performance – The control variables' temporal orientation and interdependency do not have significant effects on the model

(*Continued*)

Table 2. (*Continued*)

No.	Source	Approach/type of model	Path analysis	Sample type and size	Key findings
5	Dubey *et al.* (2019a)	Conceptual model, PLS–SEM	Path analysis using causal model	Manufacturer of auto components ($n = 173$)	– BDA capabilities positively influence supply chain agility (SCA) and competitive advantage (CA) – SCA positively influences CA – Organizational flexibility positively facilitates the relationship between BDA and SCA and between BDA and CA – Control variable of industry dynamism has significant effects on the model, whereas organizational size and organizational age do not have significant effects
6	Dubey *et al.* (2019b)	Conceptual model, PLS–SEM	Path analysis using PLS results	Indian manufacturing firms ($n = 205$)	– BDA is one of the organizational capabilities to improve social performance (SP) and environmental performance (EP) – Organizational culture (i.e. flexibility orientation and control orientation) does not have significant influence on the paths connecting BDA and SP/EP – The organizational size included in the model as a control variable, is not significantly related to SP and EP
7	Dubey *et al.* (2021)	Conceptual model, empirical analysis, PLS–SEM	Path analysis using PLS–SEM analysis	Manufacturing organizations ($n = 213$)	– BDA capabilities positively influence supply chain resilience and CA – The control variables industry dynamism, competitive intensity and organizational size do not have significant effect on the model

Table 2. (*Continued*)

No.	Source	Approach/type of model	Path analysis	Sample type and size	Key findings
8	Gunasekaran *et al.* (2017)	Regression analysis	No path analysis used	Manufacturing organizations ($n = 205$)	– Connectivity has a positive impact on information sharing – Connectivity and information sharing with top management commitment positively influence BDA acceptance – BDA acceptance with BDA routinization positively influences BDA adoption – BDA adoption positively influences organizational performance
9	Jeble *et al.* (2018)	Conceptual model, PLS–SEM	Path analysis using PLS–SEM analysis	Auto manufacturing firms ($n = 215$)	– BDA positively influences environmental, economic and social performances – Control variable of supply base complexity does not have significant effects on the path connecting BDA and environmental, economic and social performances
10	Kumar *et al.* (2018)	Mathematical model of two-phase prediction-based BDA framework using feature engineering and fuzzy logic	No path analysis used	Not applicable	– Proposed a condition-based maintenance (CBM) BDA framework for SM via significant analysis and parameters, cost estimation and risk optimization
11	Lamba *et al.* (2019)	Mathematical formulation of mixed integer nonlinear program	No path analysis used	Not applicable	– Proposed a BDA framework of supplier selection by considering the factors of dynamic demand, supplier capacity, product cost, variety of products/suppliers in different periods, number of products and number of suppliers

(*Continued*)

Table 2. (*Continued*)

No.	Source	Approach/type of model	Path analysis	Sample type and size	Key findings
12	Mangla *et al.* (2020)	Conceptual model, EFA, CFA, SEM	Path analysis using CFA and SEM analysis	Manufacturing SMEs ($n = 106$)	– Project knowledge management, green purchasing influences and project operational capabilities influence BDA adoption positively – BDA adoption positively impacts SME performance – Hypotheses of top management, environmental influence, social responsibility, project complexity and explorative learning influencing BDA adoption are not supported
13	Mani *et al.* (2017)	Case study	No path analysis used	Supply chain managers in India ($n = 54$)	– Integrating big data analytics into the supply chain can mitigate social risks
14	Raut *et al.* (2019)	Conceptual model, PLS–SEM, ANN model	Path analysis using ANN model	Large-scale manufacturing firms in India ($n = 316$)	– Green lean practices and quality management negatively impact BDA – System integration, internal business process, state and central government policies and BDA positively influence sustainable business performance
15	Raut *et al.* (2021)	Conceptual model, EFA, CFA, PLS–SEM	Path analysis using SEM model	Indian manufacturing firms ($n = 297$)	– Total quality management, environmental practices, organizational practices, lean management practices (LMP), supply chain management practices, social practices and financial practices positively influence BDA adoption – BDA positively influences sustainable supply chain business performance

Source: Made by the authors.

4.2. *Common factors of implementing BDA for a successful sustainability framework in the manufacturing industry*

In the synthesis, a total of nine common factors were found in the papers for SM. These nine factors were sorted and condensed based on the logical relationships presented in the original studies. "Lean manufacturing", "lean management practices", "green lean practices" and "lean practices" were merged as these terms reflect the same series of solutions to reduce waste, eliminate non-value-added operations and improve the value-added (Dora *et al.*, 2014; Wee and Wu, 2009). Similarly, "organizational culture", "organizational practices", "organizational flexibility" and "organizational compatibility" were merged as they fundamentally addressed the same issue of the shared assumptions, values and beliefs that assist the employees to understand the functions and goals of the organization (White *et al.*, 2003; Liu *et al.*, 2010). Furthermore, "state and central government policies" and "regulatory pressure" were combined as both explain the role of legislation in sustainable manufacturing. The synthesis led to nine common factors to form the basis of most studies. These factors are (1) organizational practices; (2) management and leadership style; (3) total quality management; (4) lean manufacturing practices; (5) customer relationship management; (6) supplier relationship management; (7) government policy; (8) environmental practices and (9) social practices. The summary of the common factors discussed is shown in Table 3.

Five articles discussed organizational practices. Dubey *et al.* (2018, 2019a, 2021) and Raut *et al.* (2021) proved that organizational practices influence BDA adoption leading to sustainable manufacturing. Organizational practices encompass a few different subfactors including organizational compatibility, organizational flexibility and organizational culture. Organizational compatibility means the alignment of organizational goals and vision to build synergy within the strategic resources of the organization to gain competitive advantages (Holcomb and Hitt, 2007; Das and Teng, 1998). Organizational flexibility is defined as the range of managerial capabilities and the activation speed to manage the

Table 3. Common factors influencing BDA adoption.

No.	Common factors influencing BDA adoption	Positively influences BDA adoption	Negatively influences BDA adoption
1	Organizational practices	Dubey *et al.* (2018, 2019a, 2021), Raut *et al.* (2021)	Dubey *et al.* (2019b)
2	Management and leadership style	Raut *et al.* (2019), Dubey *et al.* (2016), Gunasekaran *et al.* (2017)	Mangla *et al.* (2020)
3	Lean management practices	Raut *et al.* (2021), Dubey *et al.* (2016)	Raut *et al.* (2019)
4	Total quality management	Raut *et al.* (2021), Dubey *et al.* (2016)	Raut *et al.* (2019)
5	Customer relationship management	Raut *et al.* (2019), Dubey *et al.* (2016)	
6	Supplier relationship management	Raut *et al.* (2019), Dubey *et al.* (2016)	
7	Government policy	Raut *et al.* (2019), Dubey *et al.* (2016)	
8	Environmental practices	Raut *et al.* (2021)	Mangla *et al.* (2020)
9	Social practices	Raut *et al.* (2021)	Mangla *et al.* (2020)

Source: Made by the authors.

organization against all headwinds (Braunscheidel and Suresh, 2009; Volberda, 1996). Organizational flexibility allows agility of decision-making to respond to unexpected changes in the market (Sethi and Sethi, 1990). Good organizational practices improve operational excellence in optimizing inventory and smoothening decision-making (Raut *et al.*, 2021). Training and development among all employees of the organizations in the fields of BDA and SM are essential to accentuate BDA in manufacturing (Raut *et al.*, 2021). All the organizational practices emphasized that dynamic environments encourage organizations to achieve competitive advantage by having strategic flexibility in managing resources. Contrary to the rest of the articles, Dubey *et al.*'s (2019b) work does not support organizational practice as a factor influencing BDA adoption and it argued that the motivation to adopt BDA is mainly driven by economic factors and not social and economic factors, thus the organizational practices do not support BDA adoption to achieve SM.

Four articles discussed management and leadership style. Raut *et al.* (2019), Dubey *et al.* (2016) and Gunasekaran *et al.* (2017) reviewed that management and leadership style influences BDA adoption. Management's commitment to sustainability is paramount as BDA requires investment costs to kick-start (Raut *et al.*, 2019; Dubey *et al.*, 2016). The management must first embrace the mindset of green practice and formulate strategies for sustainable practices (Dubey *et al.*, 2016; Gunasekaran *et al.*, 2017). Leaders play the role of implementing training for employees to achieve sustainable project performance and encourage employees to participate in providing ideas vis-à-vis clean and sustainable operations (Raut *et al.*, 2019; Dubey *et al.*, 2016; Mangla *et al.*, 2020). However, Mangla *et al.* (2020) demonstrated that management and leadership styles do not influence BDA adoption.

Three articles discussed LMP and TQM. These two factors will be analyzed concurrently as they are interrelated. TQM is a method that originated from lean manufacturing to manage the quality of goods and services through continuous improvement of all processes, from planning and designing to self-inspection (Anvari *et al.*, 2011). On the other hand, LMP is about managing the resources according to customers' needs with the aim to reduce waste. TQM and LMP are similar wherein the two principles use analytical tools to improve processes. There are some distinct differences between TQM and LMP. First, LMP focuses on improving the entire value stream whereas TQM focuses on individual operations. Second, LMP focuses on reducing waste while TQM focuses on improving productivity. Organizations that adopt LMP effectively with the use of BDA which accounts for precise decision-making would reduce energy consumption and risks to the environment and costs (Raut *et al.*, 2019). Through just-in-time (JIT) tools, a pull system and the optimized use of mixed model assembly and mass customization, organizations can effectively reduce waste, minimize material movement and standardize operations (Raut *et al.*, 2021; Dubey *et al.*, 2016). Studies carried out by Raut *et al.* (2021) and Dubey *et al.* (2016) show that LMP supports BDA adoption while the study by Raut *et al.* (2019) shows that it negatively impacted BDA adoption.

Two articles discussed about customer relationship management, supplier relationship management and government policy. Focusing on customer satisfaction encourages BDA implementation for SM through satisfying environmental performance objectives such as reduction in carbon footprints and waste emissions (Raut *et al.*, 2019; Dubey *et al.*, 2016). Supplier relationship management enforces better green practices in multiple aspects (Raut *et al.*, 2019; Dubey *et al.*, 2016). Good supplier selection with robust environmental criteria alongside environmental collaboration with suppliers provides added values in implementing BDA for SM. With BDA capabilities, the mutual information sharing with suppliers ensures their commitment toward sustainable practices, *inter alia* training suppliers in implementing ISO 14001 and conducting an environmental audit for suppliers periodically (Dubey *et al.*, 2016). Government policy provides a "top–down" pressure for manufacturing companies to implement sustainable practices. Regulatory pressure usually comes in the form of carrot-and-stick approach. Government policies pressure firms to adopt sustainable practices through periodic scrutiny of the pollution level of firms and penalty fee enforcement for non-adhering firms (Dubey *et al.*, 2016). With governments' strict control and clear guidelines, firms are more inclined to integrate sustainable practices. On the other hand, governments can introduce incentives and subsidies for companies to implement sustainable practices (Raut *et al.*, 2019). In countries like India, the government launched campaigns like Digital India, Skill India and Make-in-India to enhance sustainable development in the manufacturing industry which is a good starting point for regulatory pressure involvement (MEITY, 2017).

Two articles discussed environmental practices. Environmental practices encompass the measures of waste management, energy reduction, environmental monitoring and the implementation of environmental technology. The Holy Grail of environmental practices is to have visible and comprehensive practices that cover the full range of environmental impacts that are transparent to internal and external stakeholders (Vilchez *et al.*, 2017). Raut *et al.* (2021) found that environmental practices positively influence BDA adoption in the success of SM with lower environmental impacts and higher economic value gain. In contrast, Mangla *et al.* (2020) found that environmental practices, in particular the environmental technologies, negatively influence BDA adoption. The research by Mangla *et al.* (2020) has similar findings as a previous notable study about environmental technologies by Klassen and Whybark (1999) whereby environmental technologies significantly reduced environmental pollutants but worsened the overall manufacturing performance including cost, speed and quality and deteriorated the flexibility performance.

Two articles discussed social practices. Social practices incorporate internal and external participations of stakeholders, macro-social performance and legislative standards such as ISO 14001, ISO/CD 45001 and OHSAS 18001:2007 (Mangla *et al.*, 2020). Raut *et al.* (2021) demonstrated that social practices positively influence BDA adoption, whereas Mangla *et al.* (2020) indicated that social practices negatively influence BDA adoption.

4.3. *Theoretical and managerial contributions*

Qualitative meta-analysis has enabled a broad analysis of BDA adoption and SM. Our qualitative meta-analysis has complemented primary statistical analysis results and mathematical frameworks by providing a comprehensive picture of similarities and differences using secondary interpretations. Thus, the aggregation of findings from this study offers a different perspective in a wider context than analyzing a single primary study alone.

This paper that focuses on the case of Indian manufacturing firms contributes to realizing the role of BDA in sustainable manufacturing firms in developing countries. It provides insights to top management and executives about their roles to implement BDA adoption for sustainability. The list of factors of the primary studies assists management to understand the implications of BDA. Management can refer to the findings of the study to maximize the capabilities of BDA for better sustainability performance.

5. Conclusion

Past research works examine the implications of BDA on sustainability and factors influencing BDA for SM separately; this paper combines both topics to gain better insights. It is imperative to address the effects of BDA on the sustainability performance of manufacturing firms and understand the key drivers in a developing economy. This study explores the implication of BDA for SM in India to address this issue based on 15 primary selected studies. All primary studies proved that BDA adoption has positive effects on sustainable manufacturing. This study will guide top management to understand the critical success factors enabling BDA for SM through the comparison of conceptual BDA frameworks developed in the primary studies. The findings will help the executives to implement BDA for SM effectively. The common factors listed in this study would help researchers to develop experiential research in the aspects of BDA and SM. Legislators can also shape relevant regulations and guidelines to accelerate the implementation of BDA in manufacturing firms.

There are certain limitations to the study. First, the data collection is based on primary studies which adopted different statistical methods to assess the factors influencing BDA adoption. Second, the study did not explore in detail the roles of all stakeholders involved in applying BDA for sustainability purposes. Third, most of the primary studies of this study employed questionnaire-based surveys focusing on managers' perceptions as opposed to the actual performances which may skew the hypothesis testing results. Fourth, this study only provides a foundation to understand the effects of BDA in SM and the factors influencing BDA adoption.

Hence, future research should specify the categories of common factors influencing BDA adoption vis-à-vis the research methods adopted. Future studies should also be devoted to developing roles and responsibilities of every stakeholder including the legislators, management of a company and employees in applying BDA in sustainability field. In addition, future work should examine BDA's effects and factors influencing BDA adoption using the actual impact of BDA on sustainable performance. Moreover, future work should explore diagnostic solutions to better enhance sustainability performance catering to the existing manufacturing systems that already adopted advanced process improvement models such as lean six sigma manufacturing, green manufacturing, agile manufacturing and sustainable manufacturing.

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References

Ahmadi, Hadi Badri, Simonov Kusi-Sarpong, and Jafar Rezaei. 2017. "Assessing the Social Sustainability of Supply Chains using Best Worst Method." *Resources, Conservation and Recycling*, 126: 99–106.

Anvari, Alireza, Yusof Ismail, and Seyed Mohammad Hossein Hojjati. 2011. "A Study on Total Quality Management and Lean Manufacturing: Through Lean Thinking Approach." *World Applied Sciences Journal*, 12(9): 1585–1596.

Arya, Vedpal, Pankaj Sharma, Ashwani Singh, and PTM. De Silva. 2017. "An Exploratory Study on Supply Chain Analytics Applied to Spare Parts Supply Chain." *Benchmarking: An International Journal*, 24(6): 1571–1580.

Belhadi, Amine, Karim Zkik, Anass Cherrafi, Sha'ri M. Yusof, and Said Elfezazi. 2019. "Understanding Big Data Analytics for Manufacturing Processes: Insights from Literature Review and Multiple Case Studies." *Computers & Industrial Engineering*, 137: 106099.

Belhadi, Amine, Sachin S. Kamble, Karim Zkik, Anass Cherrafi, and Fatima Ezahra Touriki. 2020. "The Integrated Effect of Big Data Analytics, Lean Six Sigma and Green Manufacturing on the Environmental Performance of Manufacturing Companies: The Case of North Africa." *Journal of Cleaner Production*, 252: 119903.

Braunscheidel, Michael J., and Nallan C. Suresh. 2009. "The Organizational Antecedents of a Firm's Supply Chain Agility for Risk Mitigation and Response." *Journal of Operations Management*, 27(2): 119–140.

Chalmeta, Ricardo, and Nestor J. Santos-deLeón. 2020. "Sustainable Supply Chain in the Era of Industry 4.0 and Big Data: A Systematic Analysis of Literature and Research." *Sustainability*, 12(10): 4108.

Chen, Hsinchun, Roger HL. Chiang, and Veda C. Storey. 2012. "Business Intelligence and Analytics: From Big Data to Big Impact." *MIS Quarterly*, 36(4): 1165–1188.

Chevallier, Julien, Stéphane Goutte, Qiang Ji, and Khaled Guesmi. 2021. "Green Finance and the Restructuring of the Oil-Gas-Coal Business Model under Carbon Asset Stranding Constraints." *Energy Policy*, 149: 112055.

Das, Tapas K., and Bing-Sheng Teng. 1998. "Resource and Risk Management in the Strategic Alliance Making Process." *Journal of Management*, 24(1): 21–42.

Dechant, Kathleen, and Barbara Altman. 1994. "Environmental Leadership: From Compliance to Competitive Advantage." *Academy of Management Perspectives*, 8(3): 7–20.

Dev, Navin K., Ravi Shankar, Rachita Gupta, and Jingxin Dong. 2019. "Multi-Criteria Evaluation of Real-Time Key Performance Indicators of Supply Chain with Consideration of Big Data Architecture." *Computers & Industrial Engineering*, 128: 1076–1087.

Dixon-Woods, Mary, Shona Agarwal, David Jones, Bridget Young, and Alex Sutton. 2005. "Synthesising Qualitative and Quantitative Evidence: A Review of Possible Methods." *Journal of Health Services Research & Policy*, 10(1): 45–53.

Dora, Manoj, Dirk Van Goubergen, Maneesh Kumar, Adrienn Molnar, and Xavier Gellynck. 2014. "Application of Lean Practices in Small and Medium-Sized Food Enterprises." *British Food Journal*, 116(1): 125–141.

Dubey, Rameshwar, Angappa Gunasekaran, Stephen J. Childe, Samuel Fosso Wamba, and Thanos Papadopoulos. 2016. "The Impact of Big Data on World-Class Sustainable

Manufacturing.” *The International Journal of Advanced Manufacturing Technology*, 84(1–4): 631–645.

Dubey, Rameshwar, Angappa Gunasekaran, Stephen J. Childe, Zongwei Luo, Samuel Fosso Wamba, David Roubaud, and Cyril Foropon. 2018. “Examining the Role of Big Data and Predictive Analytics on Collaborative Performance in Context to Sustainable Consumption and Production Behaviour.” *Journal of Cleaner Production*, 196: 1508–1521.

Dubey, Rameshwar, Angappa Gunasekaran, and Stephen J. Childe. 2019a. “Big Data Analytics Capability in Supply Chain Agility: The Moderating Effect of Organizational Flexibility.” *Management Decision*, 57(8): 2092–2112.

Dubey, Rameshwar, Angappa Gunasekaran, Stephen J. Childe, Thanos Papadopoulos, Zongwei Luo, Samuel Fosso Wamba, and David Roubaud. 2019b. “Can Big Data and Predictive Analytics Improve Social and Environmental Sustainability?” *Technological Forecasting and Social Change*, 144: 534–545.

Dubey, Rameshwar, Angappa Gunasekaran, Stephen J. Childe, Samuel Fosso Wamba, David Roubaud, and Cyril Foropon. 2021. “Empirical Investigation of Data Analytics Capability and Organizational Flexibility as Complements to Supply Chain Resilience.” *International Journal of Production Research*, 59(1): 110–128.

Elgendy, Nada, and Ahmed Elragal. 2014. “Big Data Analytics: A Literature Review Paper.” In *ICDM 2014: Advances in Data Mining: Applications and Theoretical Aspects*, Lecture Notes in Computer Science, Vol. 8557, pp. 214–27. Cham: Springer.

Elkington, John. 1994. “Towards the Sustainable Corporation: Win-Win-Win Business Strategies for Sustainable Development.” *California Management Review*, 36(2): 90–100.

Etzion, Dror, and J. Alberto Aragon-Correa. 2016. “Big Data, Management, and Sustainability: Strategic Opportunities Ahead.” *Organization & Environment*, 29(2): 147–155.

Fan, Jianqing, Fang Han, and Han Liu. 2014. “Challenges of Big Data Analysis.” *National Science Review*, 1(2): 293–314.

Garetti, Marco, and Marco Taisch. 2012. “Sustainable Manufacturing: Trends and Research Challenges.” *Production Planning & Control*, 23(2–3): 83–104.

Ghalehkhondabi, Iman, Ehsan Ahmadi, and Reza Maihami. 2020. “An Overview of Big Data Analytics Application in Supply Chain Management Published in 2010–2019.” *Production*, 30: e20190140.

Ghasemaghaei, Maryam. 2020. “The Role of Positive and Negative Valence Factors on the Impact of Bigness of Data on Big Data Analytics Usage.” *International Journal of Information Management*, 50: 395–404.

Gunasekaran, Angappa, Thanos Papadopoulos, Rameshwar Dubey, Samuel Fosso Wamba, Stephen J. Childe, Benjamin Hazen, and Shahriar Akter. 2017. “Big Data and Predictive Analytics for Supply Chain and Organizational Performance.” *Journal of Business Research*, 70: 308–317.

Gupta, Manjul, and Joey F. George. 2016. “Toward the Development of a Big Data Analytics Capability.” *Information & Management*, 53(8): 1049–1064.

Gupta, Shivam, Sachin Modgil, and Angappa Gunasekaran. 2020. “Big Data in Lean Six Sigma: A Review and Further Research Directions.” *International Journal of Production Research*, 58(3): 947–969.

Holcomb, Tim R., and Michael A. Hitt. 2007. “Toward a Model of Strategic Outsourcing.” *Journal of Operations Management*, 25(2): 464–481.

Hoon, Christina. 2013. “Meta-Synthesis of Qualitative Case Studies: An Approach to Theory Building.” *Organizational Research Methods*, 16(4): 522–556.

Huang, Lang, Chao Wu, and Bing Wang. 2019. “Challenges, Opportunities and Paradigm of Applying Big Data to Production Safety Management: From a Theoretical Perspective.” *Journal of Cleaner Production*, 231: 592–599.

IPCC. 2021. "Climate Change Widespread, Rapid, and Intensifying — IPCC." August 9. https://www.ipcc.ch/2021/08/09/ar6-wg1-20210809-pr/ (accessed November 1, 2021).

Jeble, Shirish, Rameshwar Dubey, Stephen J. Childe, Thanos Papadopoulos, David Roubaud, and Anand Prakash. 2018. "Impact of Big Data and Predictive Analytics Capability on Supply Chain Sustainability." *The International Journal of Logistics Management*, 29(2): 513–538.

Jeble, Shirish, Sneha Kumari, and Yogesh Patil. 2016. "Role of Big Data and Predictive Analytics." *International Journal of Automation and Logistics*, 2(4): 307–331.

Kamble, Sachin, Angappa Gunasekaran, and Neelkanth C. Dhone. 2020. "Industry 4.0 and Lean Manufacturing Practices for Sustainable Organisational Performance in Indian Manufacturing Companies." *International Journal of Production Research*, 58(5): 1319–1337.

Klassen, Robert D., and D. Clay Whybark. 1999. "The Impact of Environmental Technologies on Manufacturing Performance." *Academy of Management Journal*, 42(6): 599–615.

Kuan, Kevin KY., and Patrick YK. Chau. 2001. "A Perception-based Model for EDI Adoption in Small Businesses Using a Technology–Organization–Environment Framework." *Information & Management*, 38(8): 507–521.

Kumar, Ajay, Ravi Shankar, and Lakshman S. Thakur. 2018. "A Big Data Driven Sustainable Manufacturing Framework for Condition-based Maintenance Prediction." *Journal of Computational Science*, 27: 428–439.

Kumar, Rajiv, Amitendu Palit, and Karan Singh. 2007. "Sustainability of Economic Growth in India." CIGI Working Paper No. 25, https://ssrn.com/abstract=990082 or http://dx.doi.org/10.2139/ssrn.990082. (accessed December 18, 2022).

Lamba, Kuldeep, Surya Prakash Singh, and Nishikant Mishra. 2019. "Integrated Decisions for Supplier Selection and Lot-Sizing Considering Different Carbon Emission Regulations in Big Data Environment." *Computers & Industrial Engineering*, 128: 1052–1062.

Liu, Hefu, Weiling Ke, Kwok Kee Wei, Jibao Gu, and Huaping Chen. 2010. "The Role of Institutional Pressures and Organizational Culture in the Firm's Intention to Adopt Internet-enabled Supply Chain Management Systems." *Journal of Operations Management*, 28(5): 372–384.

Luna, DR., JC. Mayan, MJ. García, AA. Almerares, and M. Househ. 2014. "Challenges and Potential Solutions for Big Data Implementations in Developing Countries." *Yearbook of Medical Informatics*, 9(1): 36–41.

Major, Claire Howell, and Maggi Savin-Baden. 2011. "Integration of Qualitative Evidence: Towards Construction of Academic Knowledge in Social Science and Professional Fields." *Qualitative Research*, 11(6): 645–663.

Mangla, Sachin K., Rakesh Raut, Vaibhav S. Narwane, Zuopeng (Justin) Zhang, and Pragati Priyadarshinee. 2020. "Mediating Effect of Big Data Analytics on Project Performance of Small and Medium Enterprises." *Journal of Enterprise Information Management*, 34(1): 168–198.

Mani, Venkatesh, Catarina Delgado, Benjamin T. Hazen, and Purvishkumar Patel. 2017. "Mitigating Supply Chain Risk via Sustainability using Big Data Analytics: Evidence from the Manufacturing Supply Chain." *Sustainability*, 9(4): 608.

MEITY. 2017. "ICTE Manufacturing." Ministry of Electronics and Information Technology, Government of India. http://meity.gov.in/writereaddata/files/ICTE Manufacturing Presentation_to_the_PM_vFinal.pdf (accessed November 10, 2022).

Mukred, Maged Adel Abdo, and Jianguo Zheng. 2017. "Use of Big Data to Improve Environmental Sustainability in Developing Countries." *International Journal of Business and Management*, 12(11): 249–256.

Ness, Barry, Evelin Urbel-Piirsalu, Stefan Anderberg, and Lennart Olsson. 2007. "Categorising Tools for Sustainability Assessment." *Ecological Economics*, 60(3): 498–508.

Paterson, Barbara L., Sally E. Thorne, Connie Canam, and Carol Jillings. 2001. *Meta-Study of Qualitative Health Research: A Practical Guide to Meta-Analysis and Meta-Synthesis*. Vol. 3. New York: SAGE Publications, Inc.

Paul, I. D., G. P. Bhole, and J. R. Chaudhari. 2014. "A Review on Green Manufacturing: It's Important, Methodology and Its Application." *Procedia Materials Science*, 2014(6): 1644–1649.

Punch, Keith F. 2013. *Introduction to Social Research: Quantitative and Qualitative Approaches*. 3rd edn. London: SAGE Publications Ltd.

Pusavec, Franci, Peter Krajnik, and Janez Kopac. 2010. "Transitioning to Sustainable Production — Part I: Application on Machining Technologies." *Journal of Cleaner Production*, 18(2): 174–184.

Raut, Rakesh D., Sachin Kumar Mangla, Vaibhav S. Narwane, Bhaskar B. Gardas, Pragati Priyadarshinee, and Balkrishna E. Narkhede. 2019. "Linking Big Data Analytics and Operational Sustainability Practices for Sustainable Business Management." *Journal of Cleaner Production*, 224: 10–24.

Raut, Rakesh D., Sachin Kumar Mangla, Vaibhav S. Narwane, Manoj Dora, and Mengqi Liu. 2021. "Big Data Analytics as a Mediator in Lean, Agile, Resilient, and Green (LARG) Practices Effects on Sustainable Supply Chains." *Transportation Research Part E: Logistics and Transportation Review*, 145: 102170.

Ren, Shan, Yingfeng Zhang, Yang Liu, Tomohiko Sakao, Donald Huisingh, and Cecilia MVB. Almeida. 2019. "A Comprehensive Review of Big Data Analytics throughout Product Lifecycle to Support Sustainable Smart Manufacturing: A Framework, Challenges and Future Research Directions." *Journal of Cleaner Production*, 210: 1343–1365.

Rosen, Marc A., and Hossam A. Kishawy. 2012. "Sustainable Manufacturing and Design: Concepts, Practices and Needs." *Sustainability*, 4(2): 154–174.

Russom, Philip. 2011. "Big Data Analytics." *TDWI Best Practices Report*, 19(4): 1–34.

Sethi, Andrea Krasa, and Suresh Pal Sethi. 1990. "Flexibility in Manufacturing: A Survey." *International Journal of Flexible Manufacturing Systems*, 2(4): 289–328.

Stake, Robert E. 1995. *The Art of Case Study Research*. Thousand Oaks: SAGE Publications. https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,sso&db=edshlc&AN=edshlc.005388201.6&site=eds-live (accessed January 3, 2022).

Stock, Tim, and Günther Seliger. 2016. "Opportunities of Sustainable Manufacturing in Industry 4.0." *Procedia CIRP*, 40: 536–541.

Verma, Surabhi, and Som Sekhar Bhattacharyya. 2017. "Perceived Strategic Value-based Adoption of Big Data Analytics in Emerging Economy: A Qualitative Approach for Indian Firms." *Journal of Enterprise Information Management*, 30(3): 354–382.

Vilchez, Vera Ferrón, Nicole Darnall, and Juan Alberto Aragón Correa. 2017. "Stakeholder Influences on the Design of Firms' Environmental Practices." *Journal of Cleaner Production*, 142: 3370–3381.

Volberda, Henk W. 1996. "Toward the Flexible Form: How to Remain Vital in Hypercompetitive Environments." *Organization Science*, 7(4): 359–374.

Wee, HM., and Simon Wu. 2009. "Lean Supply Chain and Its Effect on Product Cost and Quality: A Case Study on Ford Motor Company." *Supply Chain Management: An International Journal*, 14(5): 335–341.

White, J. Chris, P. Rajan Varadarajan, and Peter A. Dacin. 2003. "Market Situation Interpretation and Response: The Role of Cognitive Style, Organizational Culture, and Information Use." *Journal of Marketing*, 67(3): 63–79.

Whittemore, Robin, and Kathleen Knafl. 2005. "The Integrative Review: Updated Methodology." **Journal of Advanced Nursing**, 52(5): 546–553.

Wu, Jinsong, Song Guo, Jie Li, and Deze Zeng. 2016. "Big Data Meet Green Challenges: Big Data toward Green Applications." *IEEE Systems Journal*, 10(3): 888–900.

Zhang, Yingfeng, Shan Ren, Yang Liu, and Shubin Si. 2017. "A Big Data Analytics Architecture for Cleaner Manufacturing and Maintenance Processes of Complex Products." *Journal of Cleaner Production*, 142(2): 626–641.

Zhang, Yingfeng, Shuaiyin Ma, Haidong Yang, Jingxiang Lv, and Yang Liu. 2018. "A Big Data Driven Analytical Framework for Energy-intensive Manufacturing Industries." *Journal of Cleaner Production*, 197(1): 57–72.