Risks associated with the implementation of big data analytics in sustainable supply chains

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Abstract

In the current era of unprecedented technological advancements, the effective use of big data analytics has become a fundamental requirement for organizations and provides opportunities for sustainable supply chains to increase competitiveness and enhance performance and productivity. However, implementing big data analysis entails risks so it is important that supply chain players develop deeper understanding of the risks in order to generate innovative strategies to overcome them. This paper therefore proposes a framework for the risks that may be encountered by organizations during the implementation of big data analytics within sustainable supply chains and further proposes overcoming strategies to control their occurrences. The best-worst method (BWM) is applied to assist in evaluating both the risks and overcoming strategies. The method is applied in the Indian automobile manufacturing industry which is the fifth largest in the world, contributing 8% to Indian GDP and a major source of environmental pollution. The results indicate that technological risks followed by human and organizational risks are the major risks related to big data analytics implementation in supply chains. Moreover, the ‘presence of commoditized hardware’ coupled with ‘skill development strategies’ are considered the most significant strategies for overcoming risks related to big data analytics implementation. This result of the study provides a better understanding and controlling of the nature of the inherent risks and pathways to achieve successful big data analytics implementation within supply chains.

Keywords: Big data analytics; Sustainable supply chain; Big data; Best-Worst Method

1 INTRODUCTION

One area of research that has gained popularity and received significant scholarly attention is sustainability (see, for example, Chen et al., 2017; Rajeev et al., 2017). There is a growing consensus that, if left unattended, environmental impacts may cause major changes to both the climate and the eco-systems (Zahiri et al., 2017). Organizations are unduly pressured to integrate sustainability along their supply chains to increase competitive and collaborative advantage since supply chains are crucial systems of organizations (Bubicz et al., 2019). The effective actualization of real sustainability performance in companies depends to a great extent on their network of suppliers to come up with a set of sustainability pre-requisites, and supply chain partners are required to collaborate to proactively address sustainability issues and meet laid-down standards (Silvestre et al., 2018). Different forms of firm-driven sustainability initiatives have been developed, such as the design of eco-friendly products, product life-cycle extensions, environmental life cycle inventory and assessment, and closed-loop supply chains (Gruner and Power, 2017). Moreover, companies are concentrating on designing their core business to (i) ensure competitiveness in supply chains, (ii) be on a par with their global objectives in the economic environment, and (iii) adhere to the goal of developing sustainable supply chains (Jamali and Rasti- Barzoki, 2019). Sustainable supply chains have become popular among governments, enterprises, and researchers/academics with an increasing focus on lack of resource and environmental sustainability (Wang et al., 2019).

In parallel, big data analytics has become widely regarded as an emerging disruptive technological development in business and attracted flourishing research attention in the academic world (Gupta et al., 2016; Horita et al., 2017; Sheng et al., 2017; Hindle et al., 2020). In the digital “Age of Data”, the significance of big- data-driven decision making in improving firm performance and increasing competitive advantage has garnered wide attention (Amankwah-Amoah and Adomako, 2019). This has resulted in companies seeking substantial investments in their pursuit to explore how they can best utilize their data to create value (Mikalef et al., 2019) and achieve a crucial competitive advantage over other firms in their sector (Cabrera-Sanchez and Villarejo-Ramos, 2020). The effective use of big data analytics relies on the premise that, by evaluating large volumes of unstructured data from numerous sources, insightful observations can be determined that can assist companies to change their business models (Mikalef et al, 2019; Hindle et al, 2020). More importantly, big data analytics can transform firms’ ability to apply sustainable practices in their supply chains more efficiently, and has a positive impact on firm performance, sustainable supply chains, and enhanced business values (Raut et al., 2019). Organizations utilize big data analytics to ensure transparency and collaboration among supply chain members to achieve sustainability goals and address environmental, social, and governance issues (Dubey et al., 2019).

While there are important benefits of big data analytics in supporting sustainable supply chains, there is not enough evidence of the potential risks that may arise during the implementation of big data analytics within sustainable supply chains, and the likely strategies to overcome the problems. There is obvious evidence that many firms have not succeeded in integrating big data analytics more effectively in their own decision-making processes (Tabesh et al., 2019). Although companies may encounter different risks during the effective utilization of big data analytics, existing literature has failed to account for the specific risks that relate to technological, organizational, environmental, and human aspects of the companies (Jamshidi et al., 2017). Additionally, there is a lack of understanding on the various innovative strategies to combat the risks to the effective implementation of big data analytics in sustainable supply chains (Niu and Zou, 2017). The scarcity of studies is rather surprising since sustainability and big data utilization in supply chains are critical to strategic decision making within many modern companies. Hence, this study exists to fill this gap by identifying the risks present during the implementation of big data analytics within sustainable supply chains and proposing strategies to overcome them.

This study proposes a framework of risks to implementing big data analytics within sustainable supply chains based on a combination of technological-organizational-environmental (TOE) theory and human-organizational-technological (HOT) theoretical foundations (Loh et al., 2020; Orji et al., 2020). This study further practically evaluates the relative importance of the identified risks, and then assesses and ranks the overcoming strategies aided by the Best-Worst Method (BWM) (Rezaei, 2015, 2016). The BWM is a multi-criteria decision-making (MCDM) method which helps determine the optimal weights of a set of criteria while depending on the preferential judgments of decision makers (Mohammadi and Rezaei, 2019). BWM achieves a greater performance in terms of consistency, minimum redundancy, total deviation, and conformity as compared to other MCDM techniques such as AHP/ANP (Su et al., 2015; Malek and Desai, 2019).

This paper offers several contributions to three streams of research – big data analytics, risks, and sustainable supply chains. First, previous studies have highlighted how big data analytics relates to sustainable supply chains (Hazen et al., 2016), without delving into the risks that are encountered when integrating big data analytics into sustainable supply chains operations. Additionally, although previous studies have made some progress in gaining insights on risks in implementing innovations in sustainable supply chains (Freise and Seuring, 2015; Giannakis and Papadopoulos, 2016; Kusi-Sarpong et al., 2019), risks to big data analytics implementation remains nascent in the published risks literature. Moreover, studies on the possible innovative strategies to overcome the risks that are encountered while integrating and implementing big data analytics within sustainable supply chains is currently non-existent. Drawing on the literature on supply chain sustainability (Silvestre et al., 2018) and big data analytics (Akter et al., 2018), we propose a framework of risks to implementing big data analytics within sustainable supply chains, as well as the respective strategies to overcome such risks. Furthermore, our study addresses the recent calls to examine the aspects that impact the process of organizational implementation of technological innovations (Cruz-Jesus et al., 2019; Oliveira et al., 2019) by classifying the risks to implementing big data analytics into various aspects that impact on the technological innovation adoption decisions. However, access to/ensuring sufficient resources with analytics capabilities remains the biggest risk to the implementation of the big data risk mitigation strategies and, as such, supply chains need to aspire to develop strong relationships between data experts and business functions (Tiwari et al., 2018). A vital way to ensure these risks are overcome would be to ensure cross-collaborative synergies among partnering firms in a supply chain.

This paper is organized as follows. In Section 2, the relevant literature on sustainable supply chains and big data analytics in supply chains is reviewed and discussed. The modeling framework based on BWM and the data collection process are presented in Section 3. In Section 4, the results and discussion are provided while the conclusion, academic and practical implications, and further studies are highlighted in Section 5.

2 LITERATURE REVIEW

2.1. Sustainable Supply Chains

Within the current dispensation and prevailing global environment, organizations operate in a market that is growing in complexity and dynamism. Thus, a sustainable supply chain that caters for the rapidly changing customer requirements is imperative (Manavalan and Jayakrishna, 2019). A sustainable supply chain involves a set of organization innovations and policies in terms of supply chain planning and management taking into account the economic, environmental, and social indicators (Luthra et al., 2016; Allaoui et al., 2019; Gupta et al., 2020) in a balanced way (Silvestre, 2015).

Sustainable supply chains can lead to increased efficiency and overall improvement in the organizational performance (Khan et al., 2018; Govindan et al., 2020). In essence, companies can increase their economic performance through emphasizing operations that provide environmental benefits and social responsibility (Kusi-Sarpong and Sarkis, 2019) leading to national prosperity (Mangla et al., 2018).

Currently, it is quite difficult to determine how firms can implement sustainable supply chains within the increasingly complex, modern and globalized supply chains as risks such as environmental pollution resulting from manufacturing activities or the utilization of child labor can result in huge liquidation effects and cause reputational damage (Wilhelm et al., 2016). Considering environmental and social concerns in managing sustainable supply chains, it becomes imperative that firms should be able to predict these issues through information technologies associated with big data analytics.

2.2. Big Data Analytics in Supply Chains

Big data analytics increases the competitiveness businesses and makes the supply chain resilient and sustainable (Kaur and Singh, 2018). Big data analytics can play a major role in changing and enhancing the supply chain functions (Arunachalam et al., 2018). In particular, big data analytics has resulted in intelligent supply chains, and it can help to enhance supply chain management (SCM) in multiple ways (Zhan and Hua, 2020). This is because there is enormous increase in data from a range of devices (e.g., computer systems, smart phones, embedded sensors, and computerized devices) that are connected at the borders of industrial enterprise supply chain (SC) networks. Different kinds of emerging technologies (such as sensors, barcodes, RFID, IoT, etc.) are increasingly used in SCM to integrate and organize every aspect of the chain; thus, not surprisingly, supply chains have been transformed by big data analytics (Wang et al., 2016; Nguyen et al., 2018). Big data analytics may enable supply chains to make informed decisions, identify and mitigate risks, enhance operational processes, design new products to the market, and engage in market analyses for particular products, and so on (Silvestre, 2015; Govindan et al., 2019; Moktadir et al., 2019; Chen et al., 2020; Duan et al., 2020; Jabbour et al., 2020 Zhan and Tan, 2020). Big data analytics is particularly important to the area of SCM as it supplies the techniques to support decision making in growing global, volatile, and dynamic value networks (RoBann et al., 2018). Empirical evidence recommends that firms that utilize big data analytics for decision making can observe critical advancements in both productivity and profitability (Nguyen et al., 2020), competitive advantage over rival firms and increased innovation (Duan et al., 2020), and ensure a competitive level of operational excellence (Tim et al., 2020). A variety of big data analytics techniques – namely, including business intelligence and data mining techniques – can be instrumental in companies acquiring information from various sources to be able to simultaneously improve supply chain visibility and determine the preferences and needs of customers (Zhan and Tan, 2020).

Past studies have shown the applications of big data analytics for improved competitiveness and performance in supply chains as set out in Table 1.

Table 1 Application of big data analytics in the supply chain domain

Authors	**Nature of contribution**
Tan et al. (2015)	Presented an analytic infrastructure to enable companies to utilize big data to enhance their supply chain innovation capabilities.
Addo-Tenkorang and Helo (2016)	Reviewed the use of big data in supply chain management.
Shukla and Kiridena (2016)	Applied big data analytics to predict supply chain configurations.
Mishra and Singh (2016)	Elaborated the characteristics of big data to mitigate the bullwhip effect in supply chain.
Zhong et al. (2016)	Analyzed current movements on big data analytics for supply chain management.
Kache and Seuring (2017)	Investigated the potential effects of big data analytics on using information in a supply chain context.
Papadopoulos et al. (2017)	Developed and tested a theoretical framework to discuss resilience in supply chain networks.
Gunasekaran et al. (2017)	Analyzed the positive effect of big data analytics on supply chain.
Hoffmann (2017)	Investigated the potential of big data analytics on the enhancement of the different supply chain procedures.

Some works have referred to the issues related to the implementation of big data analytics in supply chains. For example, Shukla and Mattar (2019) identified and ranked a comprehensive list of barriers to implementing big data analytics in the palm oil industry such as advanced immature technology, resolving the complex data management, lack of skilled labor, and legal and ethical challenges. Moktadir et al. (2019) identified and examined the critical barriers to big data analytics adoption in manufacturing supply chains in the Bangladesh context; these include complexity in reconfiguring production pattern, data insecurity, high investment, and lack of technological infrastructure. Earlier, Sivarajah et al. (2017) presented a holistic view of the challenges and methods of big data analytics in organizations to assist others to gain insights into the landscape with the goal of making robust investment decisions. These challenges are data challenges, process challenges and management challenges.

Although it is envisaged that big data analytics can enhance supply chain performance, only about 17% of enterprises have implemented big data analytics due to the lack of understanding of the risks involved (Nguyen et al., 2015; Papadopoulos et al., 2017; Brinch et al., 2018). One notable example is the Toyota Motor Corporation which has been particularly successful in adapting big data analytics by initiating a platform to collect big data for creating new and efficient business and services such as creating design service and feedback (Toyota Motor Corporation, 2016; Tiwari et al., 2018). However, there is a gap in research related to the identification and evaluation of the risks to implementing big data analytics in supply chains and outlining innovative strategies to overcome these risks.

2.3 MCDM Methods for aiding prioritization and ranking

Prioritization or ranking of factors/criteria that influence a system's performance becomes increasingly important particularly in situations where a large number of factors are involved and within a resource-constrained environment (Kusi-Sarpong et al., 2019; Orji et al., 2019, 2020). Such decisions may be considered highly relevant for guiding the implementation of the factors/criteria. This is a typical MCDM problem. Therefore, MCDM methods are suitable for aiding the modeling of these factors to help researchers and practitioners determine the most important factors among the multi-factors (Ishizaka et al., 2020). As argued by Peng et al. (2011) and Mulliner et al. (2016), MCDM methods are the most popular techniques utilized for supporting the assessment and selection decision-making process. MCDM methods have been applied to a variety of problems in various areas including corporate sustainability (Chowdhury and Paul, 2020), pipe material selection in the sugar industry (Anojkumar et al., 2014), critical factors of digital supply chain (Khan et al., 2021), and cross-border supply chain collaboration (Cui et al., 2020), among others. The prioritizing or ranking of the risks and solution strategies involved in this paper are also considered as MCDM problems, so they require the support of a suitable MCDM method. Such decisions, however, can only be completed via weight evaluation based MCDM methods (Malek and Desai, 2019). Numerous weight evaluation MCDM methods are described in the literature, such as Fuzzy Set Theory (FST), Grey Theory (GT), Shannon entropy, Analytics Network Process (ANP), Analytics Hierarchy Process (AHP), and the Best-worst method (BWM), among others. In as much as FST, SE and GT have seen some applications in the academic literature (see, for example, Kusi-Sarpong et al., 2015; Bai et al., 2017; Khan et al., 2019), however, they fall short in the decision-making process. One principal weakness of these methods is with the elicitation of the initial dataset. When eliciting the dataset for the decision making, these methods consider the decision criteria as independent of each other while, in practice, these criteria interact and are dependent on each other. The exclusion of these interactions results in some information loss, which eventually affects the final decision/outcome. The AHP/ANP methods on the other hand consider these interactions. However, the approaches taken by both methods when considering these interactions, particularly the ANP, complicate the decision-making process. These interactions (intra-and inter-relationships) among the criteria within ANP often result in huge numbers of pairwise comparisons. This amplification of pairwise comparisons makes it difficult for decision makers to handle, causing decision-maker fatigue due to the interactive nature of the information elicitation (Kusi-Sarpong et al., 2016). Even with AHP that only considers the hierarchy interactions (outer dependencies) among criteria, it fails to address the number of pairwise comparisons involved and still follows the bulky pairwise comparisons (see, for example, Büyüközkan and Guleryuz, 2016). The BWM is therefore introduced to address both limitations/weaknesses – considering the criteria interactions and significantly reducing the number of pairwise comparisons with the same number of criteria.

3. METHODOLOGY

This study proposes a research methodology composed of three phases as shown in Fig. 1 to identify and analyze risks associated with big data analytics implementation and overcoming strategies. These phases are explained as follows:

3.1 Phase 1: Identification of Risks and Overcoming Strategies

The risks (see Table 4) and overcoming strategies (see Table 5) were initially identified using a combination of an extensive literature review and the Modified-Delphi method. Generally, the Delphi method starts with an open question on what might be most important to the subject under consideration by the experts to create individual models and then combines, averages and analyzes these models to draw a final conclusion (Seuring and Müller, 2008). On the other hand, the Modified-Delphi method allows experts to work independently but on the same model until that model can be accepted without major additional modifications (Paul, 2008). As such, the Delphi method records multiple mental models and tries to draw conclusions from the results by analyzing statistical characteristics. On the other hand, the Modified-Delphi method proposes a single mental model that is then modified until a consensus is met, otherwise – as pointed out by Fernández-Viñé et al. (2010) –the discrepancies that might arise from such a venture are dealt with using geometric mean aggregation and selection of the most influential experts' answers using a threshold. In this study, a three-round Modified-Delphi method that uses the same set of experts within each round was employed to help refine, focus, and develop practical validation on the barriers (see Theißen and Spinler, 2014). Since consensus was not achieved during the second round of review, we decided to ask the experts to vote during the third round on each of the barriers indicating a "Yes/Acceptance" and "No/Rejection" and then collated the number of "Yes/Acceptance" and selected the most influential experts' answers using a threshold of 5 "Yes". This analysis resulted in a final set of barrier listing categorized into six main barriers and 33 sub-barriers presented in Table 4.

The risks were classified using the integrated TOE and HOT-fit theoretical frameworks. The TOE framework posits three aspects of the firm – namely, technological, organizational, and environmental aspects – that influence the process of organizational implementation of technological innovations (Abed, 2020; Cruz-Jesus et al, 2019). The HOT-fit framework overlaps with the TOE by considering the organizational and technological dimensions during firm decision to implement new innovations and uniquely considers the human dimension as well (Nilashi et al., 2016). Prior studies are available in extant literature that successfully utilize the TOE framework (Aboelmaged, 2018; Cruz-Jesus et al, 2019) and HOT- fit (Gao et al., 2019; Nilashi et al., 2019) in studies on innovation implementation. However, integrating the TOE and HOT- fit framework provides a broader view of the criteria that impact the innovation implementation process and presents significant improvement in study findings (Ahmadi et al., 2017; Orji et al., 2020). Hence, the TOE and HOT- fit theories has been integrated in the current study to provide a comprehensive classification of the risk to implementing big data analytics for sustainable supply chains in the current study. Given the multi-criteria nature of the risks and their potential overcoming strategies, their analysis is also considered a multi-criteria decision problem. Hence, a reliable modeling framework is crucial to enable the evaluation of the risks to the implementation of big data analytics within sustainable supply chains and the critical innovative strategies to overcome such risks.

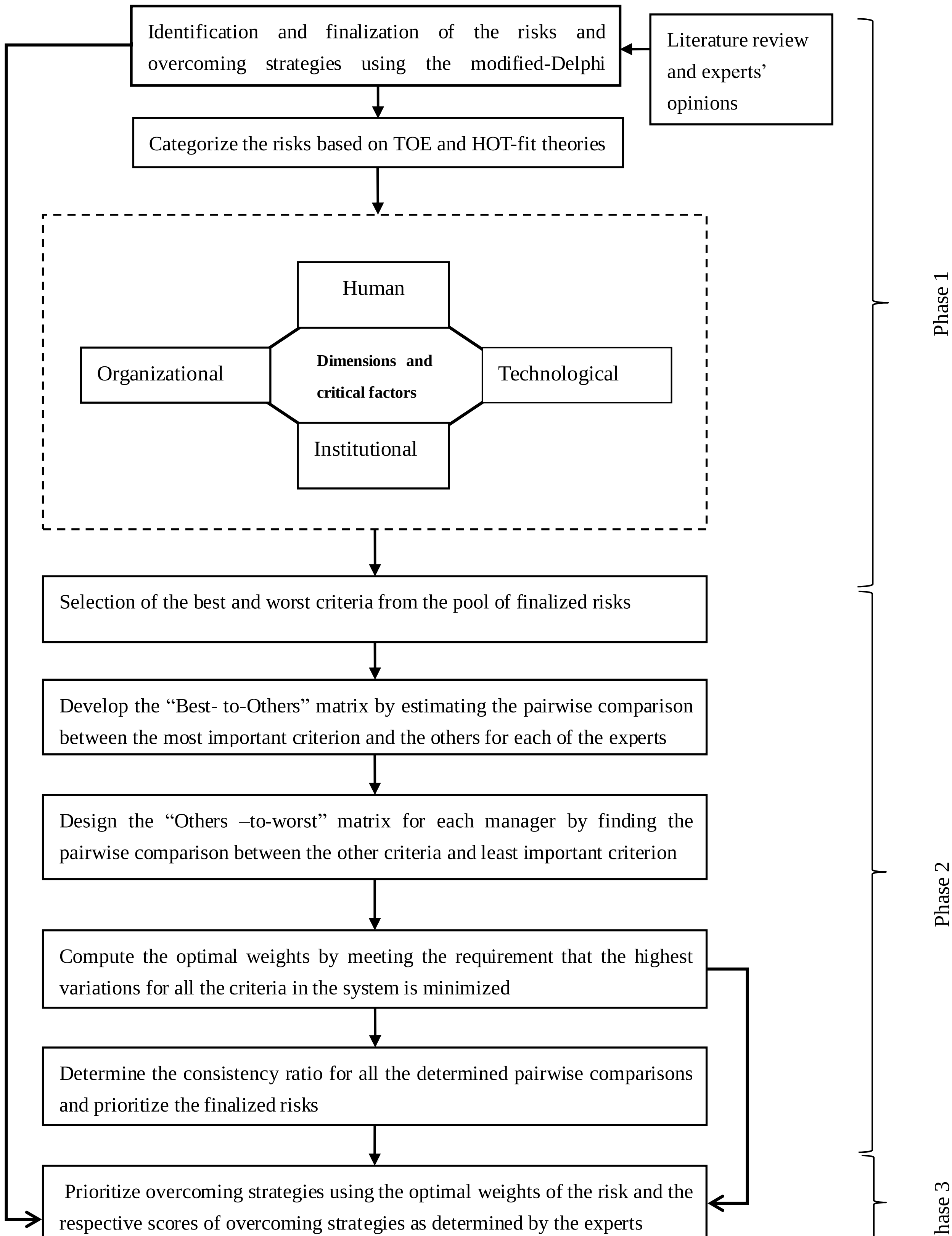

Fig. 1 Research methodology

3.2 Phase 2: Analysis and Ranking of Risks

The Best-Worst method is a popular and reliable mathematical method used to assist in evaluations (Orji et al., 2020). Therefore, the Best Worst Method (BWM) (Rezaei, 2015; 2016) was applied to evaluate and prioritize the risks that are considered in this study. These risks are ranked based on their weights derived from the BWM. Developed by Rezaei (2015, 2016), the BWM is one of the widely known and efficient multi-criteria decision-analysis (MCDA) techniques used for obtaining criteria weights. Specifically, we utilized the linear BWM in our study for two reasons: First, the non-linear version of BWM gives multiple optimal solutions for the problem due to inconsistency in the data provided by the experts. Additionally, the linear BWM was utilized due to its huge potential to give unique solutions to problems (Rezaei, 2015). Second, we applied the linear BWM due to its ease of computations unlike the non-linear BWM that is considered complicated. Generally, BWM has the advantage over other mostly commonly used MCDA techniques such as AHP (Loh et al., 2020). Among various MCDM techniques, AHP happens to be the most used according to the literature for computing weights of factors/criteria etc. In as much as the literature suggests the heavy presence and adoption of AHP in many studies, it does not guarantee its results (Orji et al., 2020). AHP is seriously marred with many inconsistencies inherent in the pairwise comparisons which compromise the final solutions. The complexity of handling the problem is further amplified when there are many criteria, leading to pairwise comparisons' inconsistencies (Kusi-Sarpong et al., 2016). To deal with these inconsistencies originating from the complexity of pairwise comparisons and provide consistent solutions, the Best-Worst Method (BWM) is deemed the most appropriate MCDM technique. BWM was compared with AHP statistically and Rezaei (2015) found that the results of BWM were more consistent over AHP (Mi et al., 2019). BWM is preferred over AHP in performance from four key aspects; these are minimum violation, consistency, conformity, and total deviation (Rezaei, 2015; Mi et al., 2019). BWM requires relatively smaller datasets and expert inputs which saves expert time and eases computation, thus enabling more consistent results (Kusi-Sarpong et al., 2019). Also, AHP uses a full matrix-based approach which requires decision maker to fill the full matrix, requiring considerable time and concentration. The BWM on the other hand uses the two vectors-based approach where two vectors are formed considering reference criteria; this reduces the time taken and efforts of the decision maker.

BWM has seen successful applications in risk-related problems associated with supply chains as shown in Table 2.

Table 2 Utilization of Best-Worst Method

Authors	**Nature of Contribution**
Tian et al. (2018)	Developing a risk factor weighting approach
Moktadir et al. (2018)	Assesses challenges for implementing industry 4.0
Wang et al. (2019)	Analyzing identified risk factors in energy performance contracting
Liu et al. (2019)	Optimization of risk measures for wind- hydro hybrid systems
Malek and Desai (2019)	Barriers to sustainable manufacturing
Kusi-Sarpong et al. (2019)	Evaluating supply chain sustainability innovation factors
van de Kaa et al. (2019)	Assess factors for technology success in residential grid storage market
Orji et al. (2019)	Challenges to implementing eco-innovations for freight logistics
Orji et al. (2020)	Critical factors for supply chain social sustainability

The computation steps of the BWM are presented below:

Step 1: Identify a relevant list of criteria.

Step 2: Choose best (B) and worst (W) criteria for main and sub-criteria.

Step 3: Using a scale of 1 to 9, ask each of the managers (experts) to elicit pairwise comparison between best criterion B over all the other criteria. This will result in vector $A_B = (a_{B1}, a_{B2}, \ldots a_{Bn})$.

Step 4: Similar to the above, each of the managers was asked to elicit pairwise comparison ratings of all the other criteria with worst criterion (W). This will also result in vector $A_w = (a_{1w}, a_{2w}, \ldots a_{nw})^T$.

Step 5: Next, obtain the optimized weights (w_1*, w_2*, …….,w_n*) for all the criteria. That is, we obtain the weights of criteria so that the highest absolute variations for all *j* can be minimized for $\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$. The following minimax model will be determined:

min max $\{|w_B - a_{Bj}w_j|,|w_j - a_{jW}w_W|\}$,

s.t.$\sum_j w_j = 1$,

$w_j \geq 0$, for each criterion. (1)

Model (1) is transformed to a linear model and is shown as:

minξ^L,

Subject to:

$|w_B - a_{Bj} w_j| \leq \xi^{L^*}$, for all j,

$|w_j - a_{jW} w_W| \leq \xi^{L^*}$, for all j,

$\sum_j w_j = 1$,

$w_j \geq 0$, for all j.

(2)

Model (2) can be solved to obtain optimal weights $(w_1^*, w_2^*, \ldots \ldots w_n^*)$ and optimal valueξ^{L^*}. Consistency (ξ^{L^*}) of attribute comparisons close to "0" is desired (Rezaei, 2016).

3.3 Phase 3: Analysis and Ranking of Overcoming Strategies

Once the global weights of each criterion are determined by multiplying the local weights of both main and sub-criteria, the next step is to compute the overall score of alternatives using Eq. (3):

$$V_i = \sum_{j=1}^{n} w_j u_{ij} \ , \tag{3}$$

where i is the index of any alternative, and u_{ij} is the normalized score of alternative i with respect to criterion j. The value of u_{ij} can be obtained using Eqs. (4) and (5), where expression (4) is used for positive criteria (for benefit criteria/whose criteria values we want to increase) and Eq. (5) is used for negative criteria (for cost criteria/whose criteria values we want to decrease).

$$u_{ij} = \frac{x_{ij}}{\sum_j x_{ij}} \qquad \text{for all j} \tag{4}$$

$$u_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_j \frac{1}{x_{ij}}} \qquad \text{for all } j \quad , \tag{5}$$

where, x_{ij} is the actual score of alternative i in criterion j.

4. CASE STUDY

4.1 Case Problem Description

This multi-case study focuses on the automobile industry of India. The Indian automobile industry and its organizations are chosen for the study because it is one of the largest automobile manufacturing countries in the world. It ranks fifth in terms of total global sales. The production growth rate is also exponential and the largest in the world (Furuta et al., 2019). With the current growth trend, India's automobile sector is expected to reach 280 billion dollars approximately in the next five to six years and is estimated to rank in the top three in the world (IBEF, 2020). India's automobile sector contributes approximately 8% of the country's GDP, which itself is a huge proportion considering the current decrease of the manufacturing sector contribution in India's GDP. With the continuous growth of the automobile sector, the environmental pollution caused by manufacturing activities related to automobile industry is also on the rise. In its recent green rating of India's industry project (2019) the Centre for Science and Environment (CSE) found that none of the 29 participating automobile manufacturing organizations was able to score desirable points; even the best-performing automobile company scored less than 50% of the score, and the automobile industry as a whole only scored 31% points, depicting the poor environmental condition of the automobile manufacturing industry (CSE, 2019). The automobile industry and its product generate heavy carbon footprints throughout the product life cycle. Sustainability measures is "the need of the hour" to make these automobile organizations environment friendly (Luthra et al., 2019). The impact of the automobile industry on environmental pollution is major and the entirety of the supply chains associated with the automobile industry is quite complex and difficult to manage. This therefore requires sharing of large amounts of data and information to keep the whole supply chains running while minimizing the environmental impact, making big data analytics an important tool with a significant impact on the sustainability of the automobile industry (Jeble et al., 2018). Although big data analytics and sustainable supply chains are highly critical for India's automobile organizational success, the implementation of big data poses some risks to the industry (Dubey et al., 2019); for example, due to a lack of understanding of the big data analytics tools, there is the likelihood of implementation failure (Loh et al., 2020). This is supported by the argument that big data analytics to is expected to enhance sustainable supply chain performance, but only a few (about 17%) enterprises have implemented big data analytics due to the lack of understanding and inherent risks (Nguyen et al., 2015; Papadopoulos et al., 2017; Brinch et al., 2018). Thus, it is important to identify and evaluate the inherent risks that are related to the implementation of big data analytics in sustainable supply chains of the Indian automobile industry and outline crucial innovative strategies to overcome the risks to achieve the desired value. This study therefore pursues this goal.

4.2 Case Application

The multi-case study analysis involved six industry experts selected from six different automobile manufacturing companies. The sample size of the experts is considered sufficient to provide statistically significant consensus on the investigated risks and overcoming strategies in the current study since the experts belong to a heterogenous group and not a homogenous group which requires a higher sample size (De Villiers et al., 2005; Jorm, 2015). Moreover, the method employed in Phase 1 of this study for identification of risks and overcoming strategies can provide reliable results with a small sample size due to the incorporated modifications we made to the Delphi method (Gupta et al., 2020). These experts were chosen purposively from the market leaders in the automobile manufacturing industry and have a minimum of 10 years of experience in the field. The details about these six industrial experts are set out in Table 3.

Table 3 Details about experts and case companies

Expert	Designation and Expertise	Experience (Years)	Educational Background
Expert 1	Manager - Procurement and Supply chain	11	B.Tech
Expert 2	Senior Manager – Supply Chain	14	MBA
Expert 3	Senior Manager – Supply Chain	15	B.Tech
Expert 4	Deputy Manager – Production Planning	11	B.Tech
Expert 5	Senior Manager Human Resource	14	Ph.D.
Expert 6	Manager – Production	11	B.Tech

4.2.1 Phase 1: Identification of Risks and Overcoming Strategies

This phase is composed of two steps. The initial step involves the identification of the risks, and the second step involves the identification of the overcoming strategies.

Step 1: Identification of Risks

In this step, following the Modified-Delphi approach (Gupta et al., 2020), we first conducted an extensive literature review, tabulated and presented the list to the industrial experts listed in Table 3 for their review, and categorized them using the four dimensions (Technology-Organizational-Technology-Human) based on the integrated TOE and HOT-fit theoretical framework in a group decision-making fashion facilitated by one of the authors via Zoom. After deliberations among the industrial experts and the removal of similar and overlapping risks, we arrived at 22 risks which are further put into four main categories. The final list and their categories after step 1 can be found in Table 4.

Table 4 Big data analytics implementation risks

Dimensions	**Risks**	**Brief description**	**References**
Technological (TH)	Complexity related to data and technology (TH1)	Technology and data are usually from different sources and difficult to integrate.	Brock and Khan (2017); Kwoon et al. (2014); Moktadir et al. (2019); Raguseo (2018); Sun et al. (2016); Verma et al. (2017); Yadegaridehkord et al. (2018); Yang et al. (2017)
	Poor quality and unorganized data (TH2)	Data sources and storage media may affect arrangement and quality of data.	
	Technical uncertainty (TH3)	Lack of effective technologies can deter firms from big data implementation.	
	Privacy and cyberattack risks/Security issues (TH4)	Cyberattack risks are highly significant as data must be secure for companies to compete favorably.	

	Scalability risks (TH5)	There is lack of large-scale infrastructure to effectively measure data.	
	Minimal technological resources and infrastructure support (TH6)	Available technologies do not meet infrastructural standards.	
Organizational (OG)	Huge cost of investment (OG1)	Investing in big data analytics requires huge funding for software and hardware development.	Ghasemaghaei (2018); Kwoon et al. (2014); Mikalef et al. (2019); ur Rehman et al. (2019); Surbakti et al. (2019); Sun et al. (2016); Verma et al. (2017)
	Shift of competencies (OG2)	Employees require extra skills set to effectively manage data.	
	Long and uncertain amortization (OG3)	The long and uncertain period required to pay off initial costs of investment can impede big data analytics.	
	Reassigning of employees trained on big data analytics solutions (OG4)	The delay in apportioning trained personnel to relevant tasks can impede big data analytics.	
	Resistance to change culture (OG5)	Employees are usually slow to adopt innovations.	
	Negative experience with previous information technologies (OG6)	Past experiences with failed information technologies may discourage adoption of big data analytics.	
Institutional (IN)	Uncertain government support and policies (IN1)	There is deficient government support and policies to facilitate big data analytics.	Byun et al. (2020); Katsoulacos and Ulph, (2017); Lang (2017); Sun et al. (2016); Verma et al. (2017)
	Absence of society pressure (IN2)	Pressure from the public with regards to data is minimal.	
	Legal uncertainties and intellectual property rights (IN3)	Lack of effective legal framework and property rights to protect data in companies.	
	Market- based risks (IN4)	The market environment is usually dynamic and demand for data is uncertain.	
	High inter- organizational competition (IN5)	Most firms are locked in intense competition and this can slow the big data analytics process.	
Human (HM)	Employees risk of job losses (HM1)	Employees are under constant fear of being laid off due to financial crisis.	Barcelo and Villanueva (2016); Gupta

Inadequate employees training and education (HM2)	Lack of adequate staff training can lead to data error and loss.	and Barua (2016); Kwoon et al. (2014);
Minimal employee's IT skill set (HM3)	Minimal IT skill set can confound data interpretation and analytics.	Lian et al. (2014); Nam
Absence of team commitment and involvement (HM4)	Firms lack effective teams to facilitate big data analytics.	(2019); Orji and Liu (2020); Raguseo (2018);
Reluctance of employees to adapt to change (HM5)	Providing good welfare and reward package to employees can aid their adaption to change.	Sun et al (2016)

Step 2: Identification Overcoming Strategies

Similarly, following the Modified-Delphi approach (Gupta et al., 2020) as in step 1, we conducted an extensive literature review, and tabulated and presented the list to the industrial experts listed in Table 3 for their review and refinement. After multiple rounds of discussions with the experts, again, in a group decision-making fashion, the innovative strategies for overcoming risks associated with big data analytics implementation were finalized and are presented in Table 5.

Table 5 Innovative strategies for overcoming risks

Strategies	**Description**
Provision/availability of big data tools for storage (ST1)	Big data service providers should provide specific big data tools such as Map Reduce to efficiently and reliably store complex data.
Presence of commodity hardware (ST2)	Commodity hardware should be used to enhance processing power and storage capacity.
Design strategic policies for Big data implementation (ST3)	Aligning strategic goals and providing clear policy for big data implementation.
Build financial capability and incentives-based strategy (ST4)	Provide access to financial incentives and increase firm's capital base.
Awareness and promotion-based strategy (ST5)	Creating awareness of big data implementation among external actors' such as NGOs, communities, and regulatory agencies.

	Establishing proper legal framework.
Government data security policy (ST6)	Enacting appropriate government policies to protect individuals from data misuse.
Collaborative strategy (ST7)	Effective collaboration between industry and academic institutions for big data skills transfer.
Internal employee's orientation and incentive strategy (ST8)	Organizing orientation programs to enlighten employees on the importance of big data. Developing teams and providing incentives to employees to encourage commitment and participation.
Data capturing and storing strategy (ST9)	Incorporating smart filters in the workspace to capture relevant and meaningful information and should be intuitive.
Data integration strategy (ST10)	Developing a strategy to integrate all the data that are collected from different stakeholders in a supply chain. These data can be in different formats.
Skill development strategy (ST11)	Developing analytical capabilities among employees through training programs or hiring data scientists for implementing and analyzing big data.
Change management program (ST12)	Involving all the stakeholders in the change required for big data implementation, catering to their training needs, and restructuring the organizational structure.

4.2.2 Phase 2: Analysis and Ranking of Risks

Within this phase, the risks associated with big data analytics implementation are ranked using BWM. The application of the BWM involves five key steps. However, since the first step of the BWM requires the identification of the decision criteria, and this has been determined during the first phase, we skipped the step.

In the second and third steps, all the experts were asked to preferentially judge the risks using a 1-9 linguistic scale, but this time on an individual basis. The experts were first requested to select the best risk and worst risk among the contexts as well as sub-criteria risks. After that they were asked to do pairwise comparison of best-to-others and others-to-worst for all the contexts as well as sub-criteria risks. The pairwise comparison of main category risks for all six experts is shown in Table 6.

Table 6 Pairwise comparison for main category big data analytics implementation risks

Best to Others for six respondents

Experts	Best Criterion	TH	OG	IN	HM
Expert 1	TH	1	3	9	6
Expert 2	TH	1	4	6	8
Expert 3	OG	6	1	9	3
Expert 4	HM	3	9	5	1
Expert 5	TH	1	3	7	9
Expert 6	HM	3	5	9	1

Others to Worst for six respondents

Experts	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Worst Criterion	IN	HM	IN	OG	HM	IN
TH	9	8	2	4	9	5
OG	4	3	9	1	4	2
IN	1	2	1	3	2	1
HM	2	1	4	9	1	9

The ratings for sub-criteria risks are shown in Supplementary Material.

The next step (step four) is to determine final ranking of both main criteria and sub-criteria risks. The weights of all the listed risks in Table 4 are obtained and these risks are prioritized with regards to these weights. The final weights and ranks of all the risks are presented in Table 7.

Table 7 Criteria weights and ranking of the big data analytics implementation risks

Main Criteria	Main Criteria Weight	Sub Criteria	Sub-Criteria Weights	Global Weights	Ranks
Technological (TH)	0.403	TH1	0.256	0.103	2
		TH2	0.066	0.027	13

		TH3	0.092	0.037	11
		TH4	0.073	0.030	12
		TH5	0.247	0.099	4
		TH6	0.267	0.107	1
Organizational (OG)	0.235	OG1	0.370	0.087	5
		OG2	0.094	0.022	15
		OG3	0.203	0.048	7
		OG4	0.065	0.015	21
		OG5	0.196	0.046	8
		OG6	0.072	0.017	19
Institutional (IN)	0.087	IN1	0.203	0.018	18
		IN2	0.190	0.017	20
		IN3	0.248	0.022	16
		IN4	0.119	0.010	22
		IN5	0.240	0.021	17
Human (HM)	0.275	HM1	0.091	0.025	14
		HM2	0.362	0.099	3
		HM3	0.167	0.046	9
		HM4	0.161	0.044	10
		HM5	0.219	0.060	6

4.2.3 Phase 3: Analysis and Ranking of Overcoming Strategies

This phase involves the evaluation of the strategies to aid in identifying the pathways to helping avoid and overcome the risks to big data analytics implementation. All the finalized (12) strategies were ranked with respect to each of the main as well as sub-category risks. Each of the six experts was first asked to rate each strategy with respect to the main category risks using the 1–9 linguistic scale, where 1 means very low importance and 9 means very high importance. The u_{ij} value in this case is obtained using Eq. 4, because we are considering strategies to be benefit criteria whose value we want to increase. The u_{ij} is obtained by taking the normalized score in this case, x_{ij} represents the average score of all the decision makers and, for each strategy, sum of these average scores is taken and x_{ij} values are now divided by the sum for each strategy to obtain normalized value u_{ij}. Further u_{ij} are multiplied by weights of risks obtained in second phase to obtain V_i. These V_i values represent the ranking of strategies for main criteria risks as depicted in Table 8. Similarly, the rankings of strategies for all the individual sub-category risks were done by following the above-mentioned steps. Combined values of V_i and corresponding ranks for each strategy with respect to main category and sub-category risks are presented in Table 8.

Table 8 Ranking of strategies

Strategies	Main Category Risks		Technological Risks		Organizational Risks		Institutional Risks		Human Risks	
	V_i	Rank	V_i	Rank	V_i	Rank	V_i	Rank	V_i	Rank
ST1	0.0882	4	0.0386	3	0.0183	7	0.0063	11	0.0220	7
ST2	0.0976	1	0.0401	1	0.0177	11	0.0067	7	0.0165	12
ST3	0.0746	10	0.0297	11	0.0213	4	0.0108	1	0.0174	11
ST4	0.0741	11	0.0396	2	0.0173	12	0.0066	8	0.0232	5
ST5	0.0762	9	0.0306	9	0.0231	2	0.0070	5	0.0200	10
ST6	0.0833	6	0.0269	12	0.0189	6	0.0094	2	0.0225	6
ST7	0.0961	3	0.0332	5	0.0180	9	0.0069	6	0.0247	4
ST8	0.0768	8	0.0329	6	0.0191	5	0.0064	10	0.0307	1
ST9	0.0724	12	0.0327	7	0.0182	8	0.0061	12	0.0216	9
ST10	0.0855	5	0.0303	10	0.0179	10	0.0071	4	0.0219	8
ST11	0.0974	2	0.0370	4	0.0220	3	0.0065	9	0.0281	2
ST12	0.0778	7	0.0309	8	0.0237	1	0.0075	3	0.0261	3

5. DISCUSSING THE RISKS AND STRATEGIES

5.1 Ranking Risks to Implement Big Data Analytics in Sustainable Supply Chains

When using the BWM for risks' ranking, the risk with the higher value is considered the critical risk that requires serious attention from the firm/industry. As such, “Technological” (TH) risks with a weight value of 0.403 are the most prominent among all the identified risks in Table 7 (column 2). This shows the significance for implementing big data analytics in the sustainable supply chain of the Indian automobile manufacturing sector. This is because implementing big data analytics requires extensive use of technology due to its inherent nature of handling a large amount of data in various formats. Organizations particularly in the developing countries lack sufficient infrastructure support to handle large amounts of data at a fast pace (Raguseo, 2018). The data are often complex, and it is not always possible to handle them with conventional tools and techniques. Also, sometimes, the quality of the data is not good, and the large amounts of data are unorganized. However, they can be organized and analyzed properly by using advanced tools (Brock and Khan, 2017; Moktadir et al., 2019). Second among the risks is the ‘Human risks (HM)’. Since big data analytics implementation requires adoption and application of latest technologies as discussed above, the employees are often reluctant to learn new things and change. They subsequently feel uncomfortable with the adoption of new technologies; hence they resist their adoptions. The reasons are that (i) they are not sufficiently equipped with the latest skills to process these tools due to lack of training and education in the related technologies and techniques and (ii) fear loss of their jobs due to new technologies and hence show minimal commitment (Lian et al., 2014; Raguseo, 2018; Nam., 2019; Orji and Liu., 2020). Third among the risks is the ‘Organizational risks (OG)’. Technological changes require substantial investment and organizations in developing countries often lack the financial resources to support this technological change which leads to delay or hindrances in implementing big data analytics. Further, since the initial investment is so huge there is always the fear and risk of uncertain amortization of these assets among the organizations. Furthermore, the organizations do not want to change their status quo in terms of use of technology and often resist adoption of new technology (Katsoulacos and Ulph, 2017; Lang, 2017).

Further analysis of sub-criteria risks (see Table 6 columns 5 and 6) indicates that ‘Minimal technological resources and infrastructure support (TH6)’ emerge as the most prominent risks to big data analytics implementation. Emerging markets like India face a challenge of lack of in-house technology and often rely on external support for the same; and also lack the necessary infrastructure for adoption and implementation of new technologies and tools (Yang et al., 2017; Yadegaridehkordi et al., 2018). Second among the sub-category risks is the ‘Complexity related to data and technology required for the big data analytics implementation (TH1)’. Big data analytics entails handling large amounts of data which are often in different forms and highly complex. Technological infrastructure required for the same is also very complex and is not readily available within most of the organizations. This poses a risk to many organizations in India when implementing big data analytics (Kwoon et al., 2014; Brock and Khan., 2017). Third among the sub-category risks is ‘Inadequate employees training and education (HM2)’. Implementation of big data analytics is a complicated process and is not a task to be handled by employees with regular skills. Employees require extensive training and education related to big data analytics tools in order to handle it, and so lack of employee training and skills in organizations of emerging nations poses a threat to big data analytics implementation (Barcelo and Villanueva, 2016). Next in the ranking is the 'Scalability risks (TH5)'. With the adoption of big data analytics, the amount of data processed increases exponentially and requires a large-scale infrastructure to handle the same. Lack of such infrastructure and technological capabilities can cause the system to collapse and fail if it is not taken care of in the advance (Sun et al., 2016; Verma et al., 2017; Yadegaridehkordi et al., 2018). All the support for big data analytics implementation, whether it is technological support, training and skill enhancement of employees, or capacity enhancement requires huge investment. These heavy costs of investment (OG1) pose another risk to organizations of emerging nations. Large investments in training programs, infrastructure building and for acquiring technology can substantially improve the big data analytics implementation overall (Ghasemaghaei, 2018; Mikalef et al., 2019; ur Rehman et al., 2019).

5.2 Strategies to Overcome Risks Associated with Implementing Big Data Analytics in Sustainable Supply Chains.

The next step in the analysis was to evaluate and rank the strategies to overcome the risks to big data analytics implementation. The ranking of the strategies was done by constructing an initial decision matrix that shows the impact of the solution strategies on the risks for main category and the four sub-categories (see Table 6) and then Eqs. (3), (4) and (5) were applied. As such, the solution strategy with the higher value is deemed to be very important for addressing the risks. This gives the firms flexibility in addressing these risks, particularly in situations where the firms cannot address all the risks simultaneously and instead need to adopt certain systematic approaches and pathways to deal with these risks. As it is evident that one strategy is not sufficient to overcome a particular risk, a mix of a few strategies can better help overcome the risks collectively. For overcoming the main category risks, "presence of commodity hardware (ST2)" emerged as the top strategy (refer to Table 7, column 2). Big data analytics involves dealing with voluminous data at high speed, which requires necessary data processing and storage capabilities to be in place. Technological risks being ranked the most severe for emerging economies can be tackled by building capabilities through ensuring necessary commodity hardware for high-speed data processing and storage. The second most important strategy for overcoming risks is "skill development strategy (ST11)". Big data analytics requires complex tools and techniques for its successful implementation. Employees doing their regular tasks are often not able to handle this complex system and require extensive training on the same. A skill development strategy can help the organizations to improve employees' analytical capabilities through specific training and by hiring data scientists for data analysis purposes. This will help organizations to address the technological risks, human risks, and uncertainties, and inculcate a positive culture within the organization for adopting new technologies.

For overcoming "technological risks (TH)", "presence of commodity hardware (ST2)" again emerges as the most important strategy with a weight value of 0.0976. As discussed above, the technological risks are the most prominent and require much attention in terms of sustainable and compatible technological support. The availability of commodity hardware can strongly enhance the capabilities of the organization in terms of handling, processing, and storing the voluminous data easily. The second most important strategy for technological risks is “financial capability development and incentives to employees (ST4)”. Technological capabilities can be enhanced through the procurement of latest tools and technologies and these require huge investment by the organizations. Thus, improving the organizations capital base and providing sufficient finance to procure the latest technology can certainly help overcome the technological risks related to big data analytics implementation.

For overcoming “organizational risks (OG)”, the “change management program (ST12)” emerges as the top strategy with weight value of 0.0237 and particularly in addressing the topmost ranked organizational sub-category barrier of “Long and uncertain amortization” (OG3). Organizations are often reluctant to make the change due to the huge costs involved as well as the uncertain future of the investment. Sometimes they are also unsure due to previous failure in implementing other technologies and fear of loss of their data. Change management through involvement of all stakeholders in the change process and providing them with the necessary training can help overcome the fears of the organizations and also build a new culture by reorganizing the organizational structure where people with analytical capabilities are involved in the organizational structure and decision making. Also, “government data security policy (ST6)” emerges as other important strategy for overcoming organizational risks. The fear of data loss and uncertain future can be addressed if governments devise an effective data security policy where organizations and their customers are assured about the security and privacy of their data, and also about the future of big data analytics implementation.

For overcoming “institutional risks (IN)”, “design strategic policies for big data implementation (ST3)” emerges as the top strategy. In emerging countries like India, the government support for technological advancement for tools like big data analytics is still very minimal and organizations that are already struggling to secure finance for implementation of these technologies fear the risk of loss or even collapse of their business. An effective and clear policy by government, mentioning its support and other technical help needs to be designed and implemented to overcome these risks. Also, legal help related to intellectual property regarding data storage and technologies can be provided by the government. Further, “government data security policy (ST6)” emerges as the second most important strategy, a policy by government assuring the security and legal validity of their data through supporting the organizations’ intellectual property. These strategies will help overcome market- and institutional-based risks that organizations often fear in big data analytics implementation.

For overcoming “human risks (HM)”, “internal employee’s orientation and incentive strategy (ST8)” emerges as the top strategy. Employees are often reluctant about the adoption of new technologies, primarily due to the fear of loss of their job and performance uncertainty due to lack of skills. Orientation of employees regarding the benefits of big data analytics can help overcome this fear; also, providing incentives for developing skills related to big data analytics and adopting techniques related to big data analytics will help enhance employee participation and motivation. Another important strategy is “skill development strategy (ST11): employees resist change because they lack the necessary skills for the implementation of these advanced technologies. By providing advanced and extensive training to employees regarding the tools and techniques related to big data analytics will help enhance their skills and thus employees will be more motivated and will not resist implementation of big data analytics in the organization.

5.3 Theoretical and Managerial/Practical Implications

Our study contributes to the successful implementation of information technologies for supply chain sustainability by providing insights into the risks and overcoming strategies to implementing big data analytics in sustainable supply chains. Particularly, by utilizing the BWM methodology, this study overcomes the limitation in elicitation of the initial dataset that is inherent in most accomplished MCDMs like AHP and ANP. As such, the BWM proffers reliable results by effectively reducing the number of pairwise comparisons and considering the interactions between the risks and overcoming strategies of implementing big data analytics in sustainable supply chains. This is highly significant since firms lack the practical insights to accurately predict environmental and social issues that may emerge when managing sustainable supply chains and necessarily require implementing big data analytics. Moreover, a gap still remains in knowledge of the risks that such firms might encounter during decisions to implement big data analytics in sustainable supply chains and, even more importantly, the strategies needed to overcome such risks for expected performance gains.

Thus, this works has implications for both theory and managers/practitioners from emerging economies, manufacturing and, more importantly, the Indian automotive manufacturing sector on big data analytics implementation for supply chain sustainability, that are presented in this section. This work has implications for both theory and managers/practitioners from emerging economies, for manufacturing and, more importantly, for the Indian automotive manufacturing sector on big data analytics implementation for supply chain sustainability. Theoretically, this study is in line with the TOE and HOT-fit theories which infer that risks that are connected to the technological, organizational, environmental, and human perspectives can hinder big data implementation for supply chain sustainability. These typological frameworks were validated and developed using some Indian automotive manufacturing industrial managers. The typological frameworks provided a wider scope of study and ensured significant improvement in the findings (Nilashi et al., 2019). Furthermore, by investigating the organizational risks as being highly critical in impeding big data analytics for sustainability objectives, our study corroborates the resource-based view (RBV) theory. This theory suggests that companies possessing resources (tangible and intangible) can achieve competitive advantage by using them to implement strategies (Yu et al., 2018). As such, resource-constrained organizations may struggle to implement innovative strategies that can improve their performance and competitiveness. Organizational risks like ‘huge cost of investment’ can be categorized as a tangible resource while ‘negative experience with information technologies’ can be classified as an intangible resource of the firm. Likewise, our study is in line with published studies that suggest that tangible firm resources play a significant role during implementing information technologies for sustainability goals (Raut et al., 2018; Wong et al., 2020; Yoon et al., 2020). This is because ‘huge cost of investment’ was ranked as the most important resource-related factor within the organizational category based on the BWM evaluations in this study. Furthermore, the high rank of ‘minimal technological resources and infrastructure support’ when compared to others considered in this study corroborates prior studies on its negative impact on adopting innovations (Yadegaridehkordi et al., 2018). Moreover, various scholars have pinpointed ‘complexity’ as a critical barrier that can hugely impede the implementing of organizational innovations (Yang et al., 2017; Ghasemaghaei, 2018; Moktardir et al., 2019). The current study supports other studies on the huge impact of scalability risks during organizational decisions for implementing new innovations (Yang et al., 2017; Yadegaridehkordi et al., 2018). In addition, Orji and Liu (2020) support this study by identifying employee training as a key factor to adopting innovations for actualizing sustainable supply chains. Furthermore, the huge cost of investment has been noted in extant literature as critical during implementing technological innovations for supply chain sustainability (Gupta and Barua, 2016; Moktadir et al., 2019; Orji et al., 2020). Even though, theoretically, the risks (categorized into technological, organizational, institutional, and human) and overcoming strategies seemed appropriate for the Indian automotive manufacturers as presented in this study, a wider theoretical examination is needed to extend this study to a wider scope of Indian manufacturing and non-manufacturing sectors as well. In addition, given that India is an emerging economy nation, theoretical application of these new typologies to bigger emerging economy populations is critical and necessitates theoretical and empirical consideration.

Managerially, the study has provided some information for managers and decision analysts in the Indian automotive manufacturing industry for evaluating and ranking big data analytics risks prior to implementation, and strategies for overcoming the risks. It is a very important business decision for managers to identify and understand the inherent risks that may confront them when attempting to implement big data analytics and to deal with these risks to pave the way for a smooth and successfully implementation. According to the results, industrial managers are made to understand that technological risks are the most severe risks that need to be given much more attention when organizations are seeking implementation of big data analytics. This means that, due to infrastructure challenges in emerging economies, the choice of technology must be given serious thought in order to ensure that the right choice of technology which is compatible with the existence infrastructure is selected. Therefore, this study and proposed frameworks afford managers in the automotive industries the relevant insights to make relevant decisions on big data analytics implementation. Practically, this study has demonstrated that additional efforts will be needed for enforcing the idea of big data analytics implementation in the Indian automotive manufacturing sector to achieve supply chain sustainability.

6 CONCLUSION

6.1 Summary

Sustainable supply chain management is a crucial vehicle for organizations to actualize sustainability. In support of this important transitional process, and for an effective sustainability adoption, organizations are required to make various kinds of decisions. One important decision is the implementation of analytical tools to aid management decision making, particularly in the case of big data analytics. However, unfortunately, big data analytics implementation is associated with a certain level of risk (Krasnow Waterman and Bruening, 2014). To pave the way for smooth implementation of big data analytics by organizations, particularly those from developing countries such as India, there is the need to identify these risks and introduce some strategies to overcome them.

This study has identified the inherent risks associated with big data implementation and introduces some strategies to overcome these risks within the Indian automotive manufacturing industry. The Best–Worst Method (BWM) was applied to help with the evaluation and ranking of these identified risks. The results are that Indian automotive manufacturing industrial managers viewed technological risks overall (from both the long and the short term perspectives) as the most severe risk they face or may be confronted with when seeking implementation of big data analytics to achieve sustainable supply chain management. In terms of overall strategies for overcoming these risks, ‘Presence of commodity hardware (ST2)' and 'Skill development strategy (ST11)' are ranked as first and second, and hence are considered as the top two ranked strategies that can aid Indian automotive manufacturers to deal with the inherent risks that they are confronted with and pave the way for a smooth and effective implementation. Given the technology state in emerging economies, this study serves as an important step for understanding and aiding big data analytics implementation for emerging economy organizations.

6.2 Limitations and Further Studies

The results of the study have some observed limitations and further study is suggested. These limitations present ample and futile grounds for future and important research on big data analytics implementation and sustainable analytics in general. For example, the fullness of the two new typological frameworks for the automotive manufacturing sector requires further and broader empirical investigation. Since only a few managers/experts (six experts/managers) participated and shared their views, a more profound scientific evaluation taking into consideration more experts and companies within the industry and region is required to help determine how many of these risks are confronted. For future studies that consider a larger number of experts in the automotive industry, we suggest the application of partial least squares and structural equation modeling (PLS-SEM) as the most appropriate tool for prediction and exploratory research with a minimum sample size of 50 respondents (Hazen et al., 2017; Yadlapalli et al., 2018; Delic and Eyers, 2020). An additional limitation might be that the findings are based on a single analytical method; therefore, the results are based on the assumptions of this tool for the case companies. More tools – e.g., AHP, ANP, etc. – can be employed to help with the evaluation and the comparison of results compared to make a more informed final decision.

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