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Big data analytics in mitigating challenges of sustainable manufacturing supply chain

Rohit Raj[1] · **Vimal Kumar**[1] · **Pratima Verma**[2]

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Abstract

Manufacturing Supply Chain (MSC) becomes more complex not only from the business viewpoint but also for environmental care and sustainability. Despite the current progress in realizing how Big Data Analytics (BDA) can considerably enhance the Sustainable Manufacturing Supply Chain (SMSC), there is a major research gap in the storyline relating to factors of Big Data-based operations in managing several forms of SMSC operations. This study attempts to fill this major research gap by studying the key challenges of using Big Data in SMSC operations obtained from IoT devices, group behavior parameters, social networks, and ecosystem frameworks. Big Data Analytics (BDA) is receiving more attention in management, yet there is relatively little empirical research available on the topic. The authors use the multi-criteria strategy employing analytic hierarchy process (AHP) and grey relational analysis (GRA) methodology due to the dearth of comparable information at the junction of BDA and MSC. The presented multi-criteria strategy findings add to the body of understanding by identifying eleven critical criteria and five associated challenges (Financial, Quality, Operation, Technical, and Logistics) related to the emergence of Big Data Analytics from a corporate and supply chain perspective. The findings reveal that product safety barriers (C4) and lack of information sharing (C8) are the critical factor immensely surge and affect the MSC in attaining sustainability. As no empirical study has yet been presented, it is important to examine the challenges at the organizational and MSC levels with a focus on the effects of BDA implementation to achieve sustainability with enhanced customer trust and improved SMSC performance.

Keywords Sustainability · Supply chain · Big data · Resilience · Prospects · Barrier model

1 Introduction

Today, firms in the global manufacturing supply chain view the productive and effective usage of big data analytics (BDA) by manufacturing industries as a critical success factor. Big data (BD) has evolved into a valuable resource for businesses as a result of the rapid and comprehensive advancement of information and communication technologies (ICT) (Truong et al. 2018). In order to comprehend trends and get valuable conclusions from big data with the goal of enhancing business performance, analytics are required in today's business climate. Due to the constantly growing global data, data privacy, data complexity, etc., manufacturing organizations are having difficulty managing big data (BD). Additionally, the amount of global data has grown quickly as a result of advancements like Web 2.0 as well as the Internet of Things (IoT).

The likelihood of achieving sustainability is decreasing as the manufacturing supply chain (MSC) becomes more complex. In order to integrate and coordinate each chain link and ensure sustainability throughout the supply chain, the manufacturing supply chain (MSC) has been widely utilizing a range of new technologies, including tracking devices, barcodes, wireless tags, IoT, etc. (Prajapati et al. 2022; Kumar Dadsena and Pant 2023). Therefore, it should come as no surprise that BDA has revolutionized supply chains (SCs),

✉ Vimal Kumar
vimaljss91@gmail.com

Rohit Raj
rohitraj2034@gmail.com

Pratima Verma
way2pratima@gmail.com; pratima@iimk.ac.in

[1] Department of Information Management, Chaoyang University of Technology, Taichung-413310, Taiwan

[2] Department of Strategic Management, Indian Institute of Management, Kozhikode 673570, India

and its deployment in SMSC has been described in several specific problems (Prajapati et al. 2022; Wamba et al. 2017). Using radio-frequency identification (RFID), sensory data, tracking devices, etc. SMSC collects a ton of data (Zhong et al. 2017). Utilizing these data alongside information technology (IT), such as business intelligence perspectives, analytics, and other tools, could help to enhance current procurement procedures, lower costs, and enable better inventory control (Raman et al. 2018). Following the post-covid, BDA's reliance on the global manufacturing supply chain has grown, which has allowed it to gather vast amounts of data from numerous processes, such as the usage of sensors, RFID, and tracking devices, which serve as a breeding ground for data generation. By offering an integrative approach for performance monitoring and customer contact through relevant analysis of data and pressing decision-making situations, the idea of BD reduces challenges and SC instability and breakdowns (Raman et al. 2018). BDA originated from internet giants like Google and Yahoo, thus it is not entirely new. These businesses use analysis of end-user activity data for making decisions (Gandomi and Haider 2015). BDA employs sophisticated analytics techniques to extract pertinent information from vast amounts of data, permitting data-driven decision-making (Tsai et al. 2015).

There is a huge growing interest in defining a specific set of capabilities for SC data analysts as a result of the numerous advantages of BDA-based operations in SMSC, including decreased operation costs, greater SC resilience, and increased sharp growth in satisfaction with customers (Ramanathan et al. 2017). In today's technologically evolved world, it is vital to consider BDA challenges in the manufacturing supply chain. A thorough analysis of the challenges to BDA can help big manufacturing enterprises to develop successful strategies. A lot of manufacturers seek to deploy BDA to boost the working efficiency of their large network of SC. However, they might not succeed because of a lack of knowledge about BDA, an absence of BD investment, or other supply chain-related problems (Moktadir et al. 2019). Studies on the challenges to BDA in SMSC are scarce. This study presented a qualitative examination of the challenges to the use of BDA. However, a thorough examination of the challenges to implementing BDA for the manufacturing supply chain is still lacking (Alharthi et al. 2017). Data security concerns, limited acceptability, centralization and absorption of BDA in manufacturing organizations and their SC partners, and a lack of understanding of how it may be applied are the key causes of low uptake (Fawcett and Waller 2014; Dubey et al. 2016). This inspires us to examine the available research and BDA's uses in SMSC.

Nevertheless, industry managers can be advised in its implementation, to quantitatively evaluate the challenges to implementing BDA in SMSC in the setting. A multi-criteria decision-making and evaluation method is presented in this study. To define the weights of the challenges and criteria and prioritize them, the AHP and GRA are utilized to systematically integrate different assessments from decision-makers. The study suggests a cutting-edge method that combines AHP and GRA to improve decision-making. The primary challenges and weights of the criteria might be determined using AHP, and the criteria's closeness would be assessed using GRA. Another noteworthy benefit of the AHP-GRA is the flexibility with which major difficulties can be weighted, allowing for constant adjustment of the criteria's order to meet changing industrial needs. With the use of this integrated method, managers may also easily communicate the evaluation of criteria using natural language terms, leading to a set of values for the grey-weighted correlation coefficient that BDA implementers can use. They will be able to develop plans for BDA challenges mitigation with the help of a statistical analysis of BDA impediments. As a result, the following research questions are the main emphasis of this study:

RQ1: What challenges prevent BDA from being implemented in SMSC?
RQ2: How can industry managers do a quantitative analysis of particular challenges?
RQ3: Can the findings aid in the development of BDA implementation methods by industry managers?

The following goals of this research are intended to address the aforementioned research questions: (i) To pinpoint challenges that prevent BDA from being used in SMSC. (ii) To use AHP and GRA to quantitatively analyze the impediments. (iii) To offer some management considerations for the application of BDA in sustainable supply chains for manufacturing.

The remainder of the study is structured as follows: The pertinent literature is discussed in Sect. 2. AHP and GRA methods are given in Sect. 3 before data analysis and findings are shown in Sect. 4. Section 5 discusses the study's analysis and findings, including its theoretical and managerial implications. The study is ended in Sect. 6 with a discussion of its limitations and the range of future potential.

2 Literature review

Several research papers were read while the study was being developed in order to accomplish the study's goal. All research paper has been carefully read, evaluated, and summarized before being presented in the review of literature portion of the study. Significant keywords like "Big data analytics," "manufacturing supply chain," and "sustainable manufacturing supply chain" were used with attention when choosing the literature for the study. The previous works were culled from well-known international journals, particularly those in the production and supply chain management fields. In addition, recent studies were gathered for the investigation. We conducted a thorough analysis of the relevant studies for the current investigation in order to provide a meaningful study. The literature on identifying associated challenges and uncertainties in the deployment of BDA in SMSC. The following subsections provide explanations for each of these.

2.1 BDA and the SMSC

One of the forces that could eventually create future SC is BDA (Fawcett and Waller 2014). According to Nguyen et al. (2018), SC's marketing strategy, logistics, procurement, and production functions may benefit from BDA capabilities. Information systems are yet another important use of BDA research (Grover et al. 2020; Zhang et al. 2017). According to Jarrahi (2018), BDA and artificial intelligence (AI) work effectively together to handle complicated decision-making. Furthermore, big data could be used to automate non-routine cognitive tasks (Frey and Osborne 2017). Roberts and Hazen (2016) emphasized the SC redesign by fusing aspects of big data technology, process, and people. A paradigm for SC with BDA characteristics in terms of data creation, visualization, analytics, management, and integration was put forth (Arunachalam et al. 2018). The initiation stage, the acceptance stage with unstructured data and rich analysis, the adaptation with enriched data and bad analytics, and the routinization were the four stages that were taken into consideration. It was meant for a proposed framework to include the main categories of absorptive competency, sustainability outputs, and SC proactivity for the firm (Rodriguez and Da Cunha 2018). BDA's capacity to attain sustainability and the ability of manufacturing firms to gain a competitive edge in a fast-moving world. With an emphasis on data structure, availability of data, fundamental analytics, and advanced analytics (Kumar Dadsena and Pant 2023), Sanders (2016) developed a four-stage maturity map. Leading SC organizations are driven by big data, but the bulk of organizations haven't adopted it because top management doesn't comprehend it. Additionally, there are several challenges for BDA implementations in SC in terms of ethics, operations, privacy, and security (Ogbuke et al. 2022). A model based on theory and corporate process theory was put out in which SC practitioners are required to comprehend the worth of BD and to conceptualize implementation strategies (Brinch 2018). Additionally, Grover et al. (2018) suggested a methodology for study on BDA's potential to add strategic commercial value. The framework showed how different constructs related to BDA's value creation and associated challenges. Future BDA research issues were also covered in the framework for the study.

2.2 Affecting challenges in SMSC performance

A significant challenge to Big Data technology's mainstream is its adoption. In order to prevent it manufacturing firms have to raise funds or financial assistance from multiple sources in terms of resources, infrastructure, and BD technology which will result in reducing the production cost leading to enhanced supply chain performance (Araújo et al. 2021). Although BDA has shown to be helpful for firms, SC managers must compare the advantages of using new technology with the expenses of doing so (Chanchaichujit et al. 2020). A producer can decide to sell his produced goods to the closest warehouse in order to save on transportation costs. But taking into consideration environmental conditions such as temperature and moisture may lead to a higher contamination rate in warehouses or conventional storage, resulting in a greater amount of contaminated items being wasted (Gautam et al. 2017). Management is more difficult because the products have a limited shelf life and are sensitive to temperature and humidity. This calls for the use of appropriately chilled storage as well as better environment-friendly facilities for storage and transit (Tagarakis et al. 2021).

Proper item monitoring and tracing made possible by big data help retailers combat product fraud and the spread of counterfeit goods. Companies must be perceptive enough to identify and evaluate their items if they hope to satisfy customers (Chanchaichujit et al. 2020). Employee opposition is usually noted after a complete lack of awareness, less technical knowledge, and expertise about BDA and its implementation (van Hoek 2019; Kumar et al. 2021). Due to proper training facilities for staff with non-specialized backgrounds are one of the main challenges preventing SMSC from adopting new technology (Narwane et al. 2022). A lack of information interchange in the SC may be the root of the bullwhip effect, or the phenomenon wherein few changes in demand at the retailer stage result in increased fluctuation at the retailer, supplier, manufacturer, and production cost supplier levels (Chanchaichujit et al. 2020). Due to a longer delivery time lag caused by poor coordination between SMSC bodies and information, there is an increase in the distribution of goods and associated costs to maintain their safety and dependability (Yadav et al. 2020). An integrated Big Data approach to logistics accelerates the deployment of resources, wastage reduction, improved traceability, and sustainability (Kumar Dadsena and Pant 2023). As a result, logistic times can be cut down and effectiveness can be increased (Paul et al. 2022; Tsang et al. 2017; Zhang et al. 2017).

Manufacturing firms have begun using BDA products to help and support companies globally. Nevertheless, firms face challenges while implementing BD. These challenges should be thoroughly examined before using BD tools to reduce associated challenges, increase production, improve quality, etc. According to the related literature review, it has been determined that no studies have been conducted on the ranking and relationships between challenges to the operation based on BDA in SMSC from the viewpoint of the industry; however, such studies have been carried out in a variety of fields, including Lean Management. An investigation of the challenges to BDA-based functioning is what is lacking from the managerial and professional perspective. It's important to identify and prioritize the challenges (Moktadir et al. 2019). In this paper, an attempt was put forth in this research to address these flaws by creating a framework using a thorough literature review. The main challenges to the BDA-based operations in SMSC were identified through literature research and addressed. For further investigation, eleven challenges were divided into four aspects based on their responses. Table 1 presents the different aspects of challenges and their criteria.

3 Research gaps

The literature research identifies several BDA-related problems. First off, despite the fact that certain studies have demonstrated BDA acceptance, very few have combined FC and QC criteria into a single SMSC to address BDA problems. In addition, only a small number of studies (Bag et al. 2021; Gangwar et al. 2023) have developed BDA problem mitigation in the setting of SMSC. The majority of studies focus on investigating novel selection techniques such as Fuzzy AHP and PROMETHEE (Preference Ranking Organization METHOD for Enrichment of Evaluations) (Verma et al. 2023) technique has been used to measure the data quality dimensions considering criteria whereas Kashyap et al. 2022 used interpretive structural modeling (ISM) and MICMAC (Matrice d'impacts croisés multiplication appliquée á un classment) for the validation of the model in MSC. The effectiveness, transparency, and resilience of supply chain management have been improved by certain research; nevertheless, many studies have not addressed the challenges in adopting BDA to support sustainably in MSC (Kumar Dadsena and Pant 2023; Tsang et al. 2017). One of the crucial elements in implementing and upholding sustainability industrial principles in the combative economic environment of today is the use of BDA technologies. The manufacturing companies are working extremely hard to achieve sustainability in the MSC (Moktadir et al. 2019). It is crucial to realize whether the measures implemented to reduce difficulties throughout the MSC are financially beneficial or merely increase financial costs. The insightful data that BD analyzes and the benefits that the manufacturing business derives from it are crucial to the SMSC's success. Finding and addressing related issues is essential to enhancing SMSC performance and profit margins while addressing production issues related to achieving sustainability.

Numerous studies based on BDA applications and using various methodologies have been published. These investigations lack mathematical modeling and rely primarily on the Delphi technique, prioritized theories of decisions (Lamba and Singh 2017; Dubey et al. 2018; Moktadir et al. 2019). The small number of studies that have been done and the significant gap between them make our study innovative in the context of the present investigation. By integrating AHP and GRA multi-criteria decision-making (MCDM) techniques in the context of the SMSC, this study aims to fill a gap in the existing research that inadequately addresses the BDA challenges criteria. Therefore, the purpose of this research is to reduce the challenges that prohibit BDA from being applied in SMSC, by suggesting an integrated AHP and GRA approach for reducing those obstacles. The findings of this study may offer a practical strategy for SMSC businesses looking to embrace BDA by reducing the challenges involved. Our research study addresses these constraints using the right modeling techniques, which were left over from earlier investigations.

4 Research methodology

A numerical modeling technique has been used to help the current research problem find relevant solutions. The study applies the Delphi approach AHP method to state the rank of associated challenges as per their criticalness and used the GRA method to rank the criteria as per their criticalness to understand which criteria are needed to mitigate sooner. Numerous academics have considered the Delphi approach-based AHP to be relevant due to its practical application and problem-solving methodology in the study of reducing problems in SMSC (Kumar et al. 2022; Moktadir et al. 2019). The analysis is based on mitigating challenges that MSC must overcome in order to achieve sustainability in a variety of scenarios. To comprehend the step-by-step approaches used in the study, the methodology's outline is shown in Fig. 1.

The study obtained all its data from the city of Taichung, Taiwan-based ABC Pvt. Ltd company. The information was gathered using a questionnaire that was distributed to specialists working in various SMSC branches. The secrecy of

Table 1 Explanation of different aspects of challenges and their criteria

Aspects of challenges		Criteria		Description	References
1	Financial challenges(FC)	C1	uncertainty about financial assistance	The hope of receiving assistance from multiple sources in terms of resources, infrastructure, and technology is crucial for enhancing supply chain performance	Mangla et al. 2018; Raut et al. 2021
		C2	Lack of funds	The biggest barrier to widespread technology use is cost. In order to avoid having an impact on the ultimate price, it should be maintained as low as feasible. A high price would not be suitable since it would cause consumers' purchasing habits to change	Bibi et al. 2017; Khan et al. 2021; Raut et al. 2021
2	Quality challenges(QC)	C3	counterfeit products	BDA enables real-time tracking and identification of things to lessen product theft and the proliferation of counterfeit goods. If businesses want to keep their customers happy, they must be able to recognize and monitor their products	Chanchaichujit et al. 2020; Misra et al. 2020
		C4	Product safety barrier	Maximizing safety across the entire supply network is crucial and a significant obstacle to the establishment of trustworthy SMSC	Tagarakis et al. 2021; Talari et al. 2021
3	Operational challenges(OC)	C5	lack of managerial commitment	Supply chain managers must compromise between the costs of using new technology and its advantages. Implementation costs were substantial during the early stages of technology introduction, but as the technology has advanced, they have become less expensive	Chanchaichujit et al. 2020; Raman et al. 2018
		C6	lack of knowledge and skillful workforce	key challenges impacting the high technology adoption is the lack of training facilities for educating working personnel with unspecialized backgrounds	van Hoek 2019; Kamble and Gunasekaran 2020
		C7	lack of proper inventory management	By transmitting radio signals and receiving signals from the tag, RFID tags can be used to track and identify supply problems and provide information on the overall efficiency of the supply chain	Tagarakis et al. 2021; Raman et al. 2018
4	Technical challenges(TC)	C8	lack of information sharing	Demand changes at the retail stage start modest and get bigger and bigger as they go up to the trader, importer, distributor, and input materials supplier levels	Chanchaichujit et al. 2020; Yadav et al. 2020; Kamble and Gunasekaran 2020
		C9	Technology Adaptability barrier	There aren't enough technical experts in the workforce to operate and comprehend complex systems	Kumar et al. 2021, Yadav et al. 2020, Sharma et al. 2020

Table 1 (continued)

	Aspects of challenges	Criteria		Description	References
5	Logistics challenges (LC)	C10	proper modern infrastructure dependency,	Additional maintenance is required for products in order to supply high-quality products to clients. This suggests the necessity for storage facilities with changing atmospheres, as well as transit methods, and enough cooling for the storage	Tagarakis et al. 2021, Yadav et al. 2020; Zhang et al. 2017
		C11	poor traceability	primarily because of a deficient SMSC entity and information coordination system, increased logistics expenses, and increased product monitoring costs due to longer lead times	Yadav et al. 2020; Agrawal et al. 2018

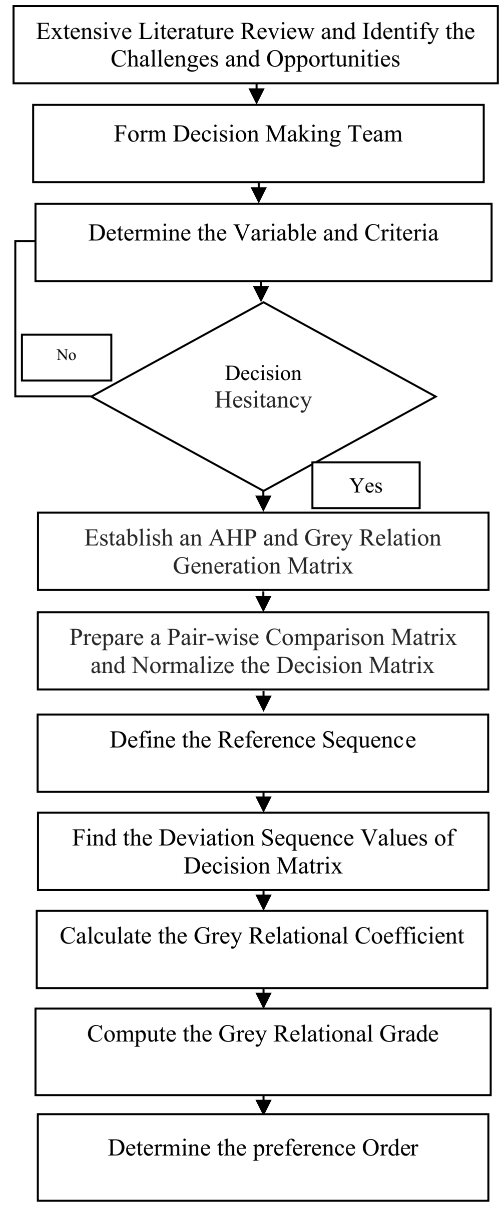

Fig. 1 Flowchart for the research study

the factory's data exchange is taken into consideration by team leaders and managers. The experts on the factory's production line provided the data and figures. The business produces optical lens modules and optoelectronic parts, which are mostly utilized in optical mice, rear-projection TVs, scanners, cameras, digital cameras, multi-function products, LCD (Liquid–crystal display) projectors, and phone lenses. This company is regarded as the world's largest provider of smartphone camera lenses.

Out using, a multi-criteria decision-making process has been applied to both explore and prioritize them. The SMSC uses observational methods and focuses on both quantitative and qualitative techniques based on questionnaires. In

Table 2 Respondents' demographic details

Profile	*Classification*	*Count*
Gender	Female	7
	Male	8
Age	20–30	5
	31–40	9
	41–50	1
	Above 50	0
Designation	Supervisor	5
	Manager	5
	Senior manager	3
	Executive	2
Qualification background	Diploma	2
	Bachelors	7
	Post Graduate	6
Current work Position	Technical	5
	Managerial	10
Current firm Tenure	1–5 years	6
	6–10 years	6
	11–15 years	3
	above 16 years	0
Work Areas	Warehouse	5
	Logistics	2
	Audit	2
	Accounting	1
	Human Resource	1
	Business Division	4

order to collect the viewpoints of different levels of target respondents from the company's top management, we first defined several issues and criteria. Then, we developed a set of questions. Among those who actively contributed were the 15 experts from the many departments including logistics, auditing, accounting, human resource, and business division. These responders have a wealth of experience and are industry leaders. Table 2 provides a summary of respondents' demographic information. The questionnaire and methodology of data collection are laid out in Appendix A.

4.1 Analytic hierarchy process method

To determine the most vital characteristics, this study uses AHP, which combines qualitative and quantitative methodologies. It is hoped that using AHP as a framework for comparison would help to effectively improve how building projects are managed in India. This method is employed as a general judging strategy as well as a qualitative technique in dealing with difficult and unstructured issues (Saaty 1988). It helps to break down a complex issue into several intermediate levels of the hierarchy (Crowe et al. 1998; Saaty 1980). The rankings of all the contributing elements are established with the aid of experts' and scholars' opinions. Pair-wise evaluation findings based on professional judgment and expert panel have been related to sets of identical criteria (Saaty 1980). The AHP method is frequently employed in numerous contexts and for a variety of objectives. The following are the several steps that make up the AHP technique.

Step-1: Define the objective of the study.
Step-2: Creating an AHP hierarchical framework Step two.
Step 3: Gather empirical data using the collective expertise of experts.
Step 4: Create pair-wise comparisons using Saaty's 1–9 point scale (to assess the priority weights of components).
Step-5: Divide each entry by the total number of entries in the column to normalize the column of numbers.

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}$$

For each factor, the approximate priority weight (Z1, Z2,…….Zj) is calculated as:

$$Z_j = \frac{1}{n} \times \sum_{i=1}^{n} a_{ij}$$

In this case, a is the cell value assigned in a pairwise matrix, and n is the number of components.

Step-6: Verify that the resultant pair of norms is consistent.

$$CI = \frac{\lambda_{max} - n}{(n-1)}$$

Here, CI is the consistency index; λ_{max} the maximum value of eigenvalues and n is the number of components;

Step-7: Calculate the Consistency Ratio (CR) (RCI scores are given in Table 3).

$$CR = \frac{CI}{RCI}$$

Table 3 Random Consistency Index (RCI) (adopted from Saaty 1985)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RCI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Where n: number of components

Note: (Dyer and Forman 1992; Madaan and Mangla 2015)

	Generally, if	CR =	< 10% (0.1)	Consistent & Acceptable
			> 10% (0.1)	Inconsistent & Revised
Generally, if	CR	=	< 10% (0.1)	Consistent & Acceptable
			> 10% (0.1)	Inconsistent & Revised

4.2 Grey relational analysis (GRA) method

According to the grey system theory, "grey" denotes primitive data that have weak, incomplete, and unclear information, and the "grey relation" is the relationship between these data that have inadequate information (Chatterjee and Chakraborty 2014). The GRA methodology is useful for finding grey relational grades and solving problems requiring complex interrelationships among numerous elements and variables (Kuo et al. 2008; Tosun 2006). (Chan and Tong 2007; Zeng et al. 2007). A grey relational generation is the creation of grey relational coefficients to address unclear systematic challenges with only partially available knowledge, according to Hamzaçebi and Pekkaya (2011). Instead of relying on expert judgment, the GRA technique is often used, deployed, and evaluated to select and rank performance alternatives. In recent works, Yi et al. (2021) used GRA to evaluate the sustainable environment of 15 Chinese sub-provincial regions in order to encourage sustainable growth, while Niu et al. (2021) employed GRA in a Taguchi-adopted method to minimize air-jet supply. In order to assess their quality as well as address various associated challenges for this decision-based model, the majority of Multiple criteria decision-making (MCDM) approaches generate multiple dimensions of specific criteria to one region of space of alternatives and consider multiple facets of criteria with multiple dimensions of alternatives. Additionally, it evaluates the effectiveness of a comparable sequence known as a grey relational generation. On this based sequence, a reference sequence (or ideal target sequence) is built, and the grey relational coefficients among the reference sequence and all other comparability sequences are then calculated. Afterward, these coefficients are used to calculate the grey relational grade. The best alternative is the one with the highest grey relational grade in between the reference sequence and itself in a comparative sequence transformed from an alternative; the worst alternative has the lowest. The following is a list of the steps in the GRA technique (Chatterjee and Chakraborty 2014; Lotfi 1995).

5 Step 1: Grey relation generation (normalization)

Normalizing sometimes referred to as grey relational generation as well as analysis, is required to transform all of the performance scores for each option into a comparable sequence when the units of numerous selection criteria vary. A decision-making problem with m alternatives and n criteria can be represented as $Yi = (yi1, yi2, \ldots, y_{ij}, \ldots, y_{in})$, where y_{ij} is the score of criterion performance j of alternative i. The word Yi can be transformed into the appropriate comparison sequence, $Xi = (xi1, xi2, \ldots, x_{ij}, \ldots, x_{in})$, using Eq. (1) or Eq. (2). (2). Equation (1) can be used to normalize the decision matrix if the criterion is useful, i.e., a higher value is preferred. To normalize the non-beneficial criterion, apply Eq. (2).

$$x_{i,j} = \frac{\left[\left(y_{ij}\right) - \min\left(y_{ij}, i = 1, 2, \ldots, m\right)\right]}{\left[\max\left(y_{ij}, i = 1, 2, \ldots, m\right) - \min\left(y_{ij}, i = 1, 2, \ldots, m\right)\right]} \quad (1)$$

$$x_{i,j} = \frac{\left[\max\left(y_{ij}, i = 1, 2, \ldots, m\right) - \left(y_{ij}\right)\right]}{\left[\max\left(y_{ij}, i = 1, 2, \ldots, m\right) - \min\left(y_{ij}, i = 1, 2, \ldots, m\right)\right]} \quad (2)$$

6 Step 2: Define the reference sequence

Once the grey relation generating operation is complete, the performance figures will range from 0 to 1. The alternative performance of I is the finest for that criterion j if the value x_{ij}, which is standardized utilizing the grey relation generating approach, is equal to or close to 1 then the values of the other option. As a result, the optimal choice will be made if all performance of an alternative's measures is near to or equal to 1. The alternative reference, which is specified as $X0 = (\times 01, \times 02, \ldots, x0j, \ldots, x0n) = (1, 1, \ldots, 1, \ldots, \ldots, 1)$, aims to identify the alternative that has the reference sequence's most comparable comparability sequence.

Table 4 Pair-wise comparison scale

Preference degree	Challenges Effect
1	Equal importance
3	Moderate importance of one over another
5	Essential or strong importance
7	Very strong importance
9	Extreme/absolute importance
2,4,6,8	Intermediate values between two adjacent judgments

Table 5 Compare pair-wise matrix for the challenges

S.N	challenges	TC	LC	FC	QC	OC
1	TC	1	3	3	1/2	1/2
2	LC	1/3	1	2	1/8	1/2
3	FC	1/3	1/2	1	1/5	1/2
4	QC	2	8	5	1	2
5	OC	2	2	2	1/2	1
	SUM	5.67	14.5	13	2.32	4.50

7 Step 3: Calculate the grey relational coefficient (Ψ)

The grey relational coefficient is used to determine how close x_{ij} is to x_{0j}. Equation (3) can be used to compute the grey relationship coefficient. The greater the value Ψ, the closer x_{ij} and x_{0i} are to each other.

$$\Psi(x_{0,i}, x_{i,j}) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{i,j} + \zeta \Delta_{\max}} \; (for\; i = 1, 2, \ldots, m \; and \; j = 1, 2, \ldots n) \tag{3}$$

where $\Psi(x_{0,i}, x_{i,j})$ is the grey relational coefficient between $x_{i,j} and x_{0,i}$, $\Delta_{i,j} = \left| x_{0j} - x_{ij} \right|$

$$\Delta_{min} = min\left\{\Delta_{i,j}, 1, 2, \ldots., m; j = 1, 2, \ldots, n\right\}$$

$$\Delta_{max} = max\left\{\Delta_{i,j}, 1, 2, \ldots., m; j = 1, 2, \ldots, n\right\}$$

and ζ is the distinctive coefficient ($\zeta \in [0, 1]$), generally taken as 0.5.

The distinctive coefficient's function is to either widen or narrow the grey relational coefficient's range.

8 Results and discussion

On a scale from "1" to "9," comparable pair-wise key obstacles were given preference in AHP (Saaty 1988). as stated in Table 4, where "1" denotes equal importance and "9" denotes great or ultimate importance.

As per the unified judgment of experts, a pairwise comparison matrix for the challenges is developed. The pairwise comparison matrix for challenges is presented in Table 5.

Table 6 reveals the priority weights of associated challenges and also shows quality challenge (QC) is the most affecting challenge with a priority weight of '0.433' followed by (OC) with a priority weight of '0.216', (TC) with a priority weight of '0.188', (LC) with a priority weight of '0.089', (FC) with a priority weight of '0.073'.

Further, relative weights (^{TM}), are computed by using the formula: A × W_j=^{TM},

1	3	3	1/2	1/2		0.188		1.001
1/3	1	2	1/8	1/2		0.089	=	0.461
1/3	1/2	1	1/5	1/2		0.073		0.376
2	8	5	1	2	X	0.433		2.323
2	2	2	1/2	1		0.216		1.134

A = Pair-wise comparison matrix; where j = 1, 2,…n

The Eigen vector '⌊':

$$\lfloor = \frac{ith\ entery\ in\ relative\ weight\ ()}{ith\ entry\ in\ priority\ weight}$$

Eigenvalue maximum, $\lfloor_{max}$ = 5.369, CI (consistency index) = 0.092, and CR (Consistency Ratio) = 0.082.

In GRA, there is a total of 15 decision-makers (DMs), who are members of the top management of ABC Pvt. Ltd. With their best practices for the research questions presented in this article. Each of the DMs (DM1 to DM15) has a positive experience. To determine the criticalness of the major SMSC strategies in the context of the manufacturing industry, an MCDM method GRA analysis of the supply chain strategies has been conducted. For each of these significant supply chain difficulties, scores have been compiled based on the experience of DMs (DM1 to DM15). The choice

Table 6 Normalized and priority weights for improper planning (IP) classified challenges

S.N	challenges	TC	LC	FC	QC	OC	SUM	Priority weights
1	TC	0.176	0.207	0.231	0.215	0.111	0.940	0.188
2	LC	0.059	0.069	0.154	0.054	0.111	0.447	0.089
3	FC	0.059	0.034	0.077	0.086	0.111	0.367	0.073
4	QC	0.353	0.552	0.385	0.430	0.444	2.164	0.433
5	OC	0.353	0.138	0.154	0.215	0.222	1.082	0.216

Table 7 The decision matrix scores (for challenges)

S N	challenges	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	DM9	DM10	DM11	DM12	DM13	DM14	DM15
1	C1	2	2	4	4	2	4	3	2	2	5	4	3	3	5	3
2	C2	3	1	5	4	2	3	3	5	1	1	5	4	5	1	1
3	C3	3	1	4	4	5	5	1	3	4	1	3	3	5	3	5
4	C4	4	2	3	3	5	5	5	4	4	5	3	4	4	4	4
5	C5	4	3	5	3	5	3	4	4	3	1	4	3	4	3	5
6	C6	2	2	2	3	4	3	4	4	4	1	4	3	4	3	2
7	C7	5	2	4	4	2	4	3	4	2	1	4	3	4	5	2
8	C8	5	2	5	4	1	4	3	5	4	1	5	3	3	5	1
9	C9	2	3	5	3	5	3	2	3	3	1	5	3	3	1	2
10	C10	3	2	5	4	5	2	4	3	3	1	3	3	3	3	3
11	C11	4	3	5	3	1	4	3	4	3	1	4	3	5	4	3
Min		2	1	2	3	1	2	1	2	1	1	3	3	3	1	1
Max		5	3	5	4	5	5	5	5	4	5	5	4	5	5	5

matrix scores for each of the major challenges are shown in Table 7.

Using step 1, which integrates the scores of all the major difficulties into a comparable normalized sequence, the primary GRA methodology procedure gets started. Table 8 contains the choice matrix's normalized values. Sequences of references are identified and shown in given (Appendix B) relying on this normalized pattern by applying Step 2. The grey relationship coefficients between each comparable sequence and the sequence of reference are calculated using Step 3 and shown in (Appendix C) for viewing. The grey relationship grade between each comparability sequence and the reference sequence is now generated using Step 4 and shown in Table 9. The optimal option will always be the one with the highest score, hence Fig. 2 displays the ranking of these major supply chain management difficulties based on the computed grey relational grade.

The final rank of key SMSC challenges are C4 > C8 > C5 > C3 > C10 > C7 > C11 > C9 > C2 > C1 > C6. Table 9 shows "Product safety barrier" (C4), "lack of information sharing" (C8), "lack of managerial commitment" (C5) while "Lack of funds" (C2), "uncertainty about financial assistance" (C1), "lack of knowledge and skillful workforce" (C6) have been ranked as the top three and bottom three major associated challenges, respectively. The placements of further difficulties are then gauged between two ends. Additionally, it facilitates better planning and supply chain distribution levels to meet difficulties with informed choices.

9 Discussion and findings

The challenges are clearly stated in this paper, along with management strategies for utilizing BDA operation-based opportunities to address the associated challenges through

Table 8 Normalized values of decision matrix (for challenges)

SN	Challenges	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	DM9	DM10	DM11	DM12	DM13	DM14	DM15
1	C1	0	0.5	0.66	1	0.25	0.66	0.5	0	0.33	1	0.5	0	0	1	0.5
2	C2	0.33	0	1	1	0.25	0.33	0.5	1	0	0	1	1	1	0	0
3	C3	0.33	0	0.66	1	1	1	0	0.33	1	0	0	0	1	0.5	1
4	C4	0.66	0.5	0.33	0	1	1	1	0.66	1	1	0	1	0.5	0.75	0.75
5	C5	0.66	1	1	0	1	0.33	0.75	0.66	0.66	0	0.5	0	0.5	0.5	1
6	C6	0	0.5	0	0	0.75	0.33	0.75	0.66	1	0	0.5	0	0.5	0.5	0.25
7	C7	1	0.5	0.66	1	0.25	0.66	0.5	0.66	0.33	0	0.5	0	0.5	1	0.25
8	C8	1	0.5	1	1	0	0.66	0.5	1	1	0	1	0	0	1	0
9	C9	0	1	1	0	1	0.33	0.25	0.33	0.66	0	1	0	0	0	0.25
10	C10	0.33	0.5	1	1	1	0	0.75	0.33	0.66	0	0	0	0	0.5	0.5
11	C11	0.66	1	1	0	0	0.66	0.5	0.66	0.67	0	0.5	0	1	0.75	0.5
Min		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Max		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 9 The Summary of Grey Relation Grades (GRG) and Ranking (for challenges)

SN	Challenges	GRG	Rank
1	C1	0.518	10
2	C2	0.523	9
3	C3	0.587	4
4	C4	0.678	1
5	C5	0.597	3
6	C6	0.472	11
7	C7	0.542	6
8	C8	0.661	2
9	C9	0.532	8
10	C10	0.572	5
11	C11	0.536	7

uncertainty management, on-time information sharing, and SMSC agility. Research results reveal that product safety barriers (C4) and lack of information sharing (C8) immensely surge and affect the MSC in attaining sustainability. There are 11 criteria for managing opportunities and 5 challenges. Because current events, geographic conditions, infrastructure, and secondary data from the firm profile highlight a specific business setting in a certain industry, the factors employed in the study were taken from the body of relevant literature. Five-point Likert scales are used to ask participants their opinions on these factors. The data is then analyzed using the AHP and GRA techniques, and the rankings of the most and least important elements for the challenges and criteria are the result.

The implementation of BDA in SMSC is hampered by 11 significant issues, which have been outlined in this paper. The impact of the product safety barrier (C4) is seen as the most important issue the SMSC is currently dealing with. The product safety barrier (C4) raises the level of uncertainty in all aspects of supply chain operations, including inventory management, shipping, and receiving. Reduced product safety barriers throughout the whole supply chain are crucial and significant obstacles to the establishment of dependable SMSC. Sometimes security collapse leads to tampering with products due to which customer trust decreases as well as a decline the product demand. The bullwhip effect, which is the phenomenon of few variations in demand at the retailer causing significantly greater fluctuations at the suppliers, manufacturer, and input materials supplier levels, is caused by a lack of information sharing (C8), which is ranked second in this study. The shortage of raw resources is brought up suddenly by increased demand, which disrupts SMSC. Lack of managerial commitment (C5) third most crucial factor that causes delays in investment and fundraising for the modern technologies-based operation process a critical problem for SMSC firms. Furthermore, another strict factor is the lack of knowledge and skillful workforce (C6) for the use of the BDA is rated as the least crucial factor chased by uncertainty about financial assistantship(C1) and Lack of funds (C2) for the investment in new technologies are identified as a second and third least important factor. Therefore, this research study affirms a few of the belonging factors to on-time information sharing which significantly affect sustainability in MSC.

In the global SMSC, important action to reduce risks and obstacles throughout the supply chain is managing the opportunities. After investigating 5 challenges, Quality Challenges (QC) are listed as the most critical challenge. Product safety issues, counterfeit products, tampering with

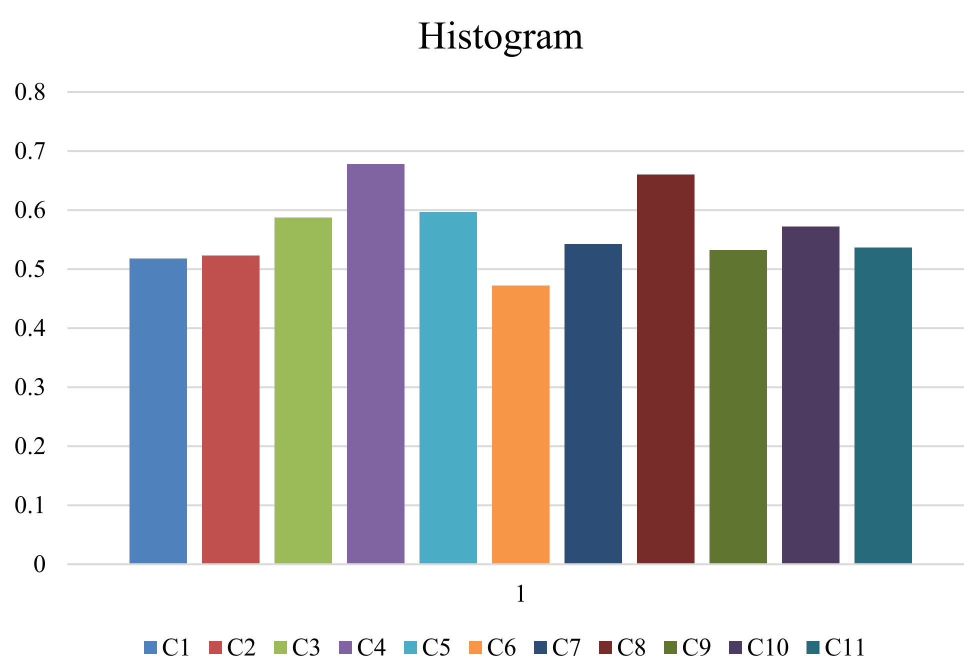

Fig. 2 Ranking of the key SMSC challenges

product quality due to security lapses, and other critical factors cause significant impacts on the quality of the product. Operational challenges (OC) second most crucial challenge and also have negative effects on inventory management which are almost connected with a lack of managerial commitment towards firms. The third most important factor in overcoming it is technological challenges (TC), which are crucial for operating at low cost with automation and enhancing SMSC performance through the use of BDA. Reducing quality damages in logistical challenges (LC) is the fourth most crucial component of operation management because the cost has become a factor. Financial problems (FC), which are always crucial in regular situations, are surprisingly the least significant aspect of SMSC. It shows that BDA adoption is significantly important in managing opportunities and mitigating associated challenges in MSC to attain sustainability.

10 Implications

10.1 Theoretical implications

The research study finds the highest critical level of mitigating the associated challenges in SMSC and reducing the magnitude of a barrier for managing the opportunities based on the digital supply chain while the most challenging concerns appeared as the product safety barrier, lack of information sharing, and lack of managerial commitment. Relevant literature reveals that product quality should be managed properly to maintain customer trust (Tagarakis et al. 2021). Since the SC has several nodes throughout the chain, process delay is a usual bottleneck, due to proper information sharing and it should be managed by all stakeholders (Yadav et al. 2020). One of the critical factors affecting process hesitation in an adaptation of a new technology system choice is of great importance to global SMSC. The choice of investment in technologies like BDA also impacts automation, and inventory management (Govindan et al. 2014). At last, a factor product safety barrier is the best contribution of this research study by placing it at the highest challenging level.

10.2 Managerial implications

From a managerial viewpoint, this study has various ramifications. Product safety barrier (C4), the most difficult component, is frequently connected to underdeveloped nations. Business executives and managers need to be aware that it has a vital impact on MSC's potential to achieve sustainability. Product tampering as a result of a security breach is another factor. With the development of the new world in the global SMSC, we have all come to believe that the market today is extremely competitive. However, it does not appear to be operating properly without causing disruptions in the supply chain or to be making it more difficult to embrace it. Business managers must consider potential interruptions because there are numerous stakeholders in the SC in order to satisfy customers. Additionally, the decision about whether to invest in new technologies or modify existing ones has gotten appropriate attention, and it continues to be the most crucial factor in managing the chances to lessen related difficulties. Business executives and future researchers must be aware of additional factors that the MCDM method used in this study ranked in the medium range of importance level, including dependence on contemporary infrastructure, inventory management, traceability performance concerns, and uncertainty in financial assistance.

11 Conclusions, limitations, and future scope

In order to regulate the process in SMSC, the study attempts to identify the main issues and minimize them by adapting BDA opportunities. Being a leader in the field makes it difficult to manage things well, thus the corporation recognizes its various obstacles and works to reduce and manage them. They have also been prioritized using the AHP and GRA methodologies as many connected issues and opportunities. Five difficulties and eleven criteria are in total identified, emphasized, and measured from the prior literature. We identified the obstacles and elements that need to be managed initially in the MSC process to achieve sustainability using the AHP and GRA approach and grey relational grade calculation. To ensure that the MSC process runs well and creates the potential for the firm to fulfill its business objectives, it is important that its focuses on these issues. By implementing BDA in each supply chain segment, these opportunities and problems are managed in the SMSC through three categories: uncertainty, real-time information, and agility.

As only the organization's highest management level provided a judgment or opinion, the current study has several limitations. The corporation is having a very difficult time maintaining its performance level in the global SMSC supply in response to the demands of the customer. Another drawback is that the present research was only conducted from the viewpoint of manufacturing firms; however, future studies may conduct comparable research in other types of enterprises and other developing countries. The following points provide an explanation of the directions for further research. In addition to checking the statistical validity of the relationship model and preference ranking methodology, there is a great opportunity to establish a structural relationship model between these important challenges and opportunities. Various methods, including the interpretive structural method (ISM), the analytical network process (ANP), and the method for order of preference by similarity to the ideal solution (TOPSIS), should be taken into consideration. Future research may take into account this study for multi-sectorial organizations and concentrate on a comparative analysis using different Delphi methodologies. Uncertainty, on-time information sharing, and agile factors are taken into account for future study; we may classify them into main groups and then afterward their subclasses factors and prioritize them through particular and group decision-makers settings taking TOPSIS and ANP into consideration. From earlier research and actual world experience, many more relevant criteria can be found to improve SMSC distribution performance. The model can validate and the effectiveness of relative performance measures can be increased in the future with the help of hybrid MCDM methods such as TOPSIS and VIekriterijumsko KOmpromisno Rangiranje. To enhance the SMSC procedure, a similar study might be done in other developing nations. The performance of the supply chain can be compared. In order to establish a positive relationship between the identified components on a continuous marking scale and assess the associated effect on performance, the modeling of structural equations can also be taken into consideration. In the manufacturing and distribution process, some additional modeling techniques, including Bayesian belief networks, might be used, which could considerably improve the quality of output with different operations, productivity, and efficiency in the future research of this study. There is still a huge scope after this research that can be satisfied, thus the readers of the research study can expand it. Finally, to conclude the BDA has vast potential to efficiently plan MSC for sustainable operations and critical bottlenecks need to be assimilation in data collection, treatment, and analysis.

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