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A PDCA based approach to evaluate green supply chain management performance under fuzzy environment

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ABSTRACT

This paper proposes a novel plan-do-check-act (PDCA) based group decision making model to evaluate the GSCM performance of manufacturing organizations. This research employs an integrated fuzzy multi-criteria decision-making (MCDM) approach in which the fuzzy-analytical hierarchy process (FAHP) method determines criteria weights and the fuzzy-technique for order preference by similarity to the ideal solution (FTOPSIS) method ranks the organizations. Five qualitative criteria are selected from the extant literature, which encompass both environmental, operational, and economic aspects of sustainability. Data is collected by developing a questionnaire, establishing a decision-makers' committee, and carrying out a survey. To illustrate the industrial application of the proposed model, this study considers a real-world case study in the Indian manufacturing sector, in which three organizations (Organization A, Organization B, and Organization C) are selected from three distinct industrial segments, namely the leather industry, the pharmaceutical industry, and the steel industry, respectively. The result reveals that the *environmental impact of harmful substances released from production* is the most influential parameter. The result also reveals that Organization C is the benchmark organization and its strategies can guide other organizations for GSCM performance improvement. Moreover, the proposed model is capable of handling vagueness and ambiguity in decisions.

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KEYWORDS
Green supply chain management; Performance Evaluation; MCDM; Fuzzy set theory; PDCA cycle

1. INTRODUCTION

During the last few decades, the environmentally-conscious supply chain practises of business organizations across the globe have received increasing interest from both researchers and practitioners (Ghosh, Mandal, & Ray, 2021b). In order to minimize the detrimental impact on the environment, it is suggested to incorporate various GSCM practises into an organization's supply chain policies (Pan, Pan, Song, & Guo, 2019). GSCM implies the integration of environmentally-friendly thinking into each phase of the supply chain, including raw material procurement, product design and development, manufacturing processes, and ultimately delivery of finished goods to customers, as well as end-of-life management of the product after disposal (Sumrit et al., 2020). Nowadays, organizations in both developing and developed nations are involved in various GSCM activities in order to survive in the highly competitive market, attain customer reliance, improve brand value, and minimize ecological footprints (Kaur et al., 2018). Various GSCM activities include green procurement, green design, green manufacturing, green packaging, green logistics, green marketing and distribution, and reverse logistics (Ramanathan et al., 2020). With an emphasis on GSCM practises in supply chain operations, organizations have become more reliant on suppliers, making it relevant to assess supplier performance and select what best fits the organization's objectives (Gupta, Soni, & Kumar, 2019). On the other hand, green supplier selection (GSS) is considered a critical aspect, ensuring that procurement of raw materials has minimal adverse impact on the environment (Dubey, Gunasekaran, & Papadopoulos, 2017). By evaluating appropriate suppliers, firms can acquire leverage sources to diminish the adverse environmental impacts of various supply chain activities (Yu, Zhang, & Huo, 2020). While business organizations in developed countries have already gained competitive advantages by adopting GSCM practices, GCSM implementation is still in its early stages in developing countries. This is mainly due to barriers like: lack of investment and financial support, inadequacy of infrastructure, lack of government legislation, reluctance of top management, lack of technical competence, scarcity of resources, and so on (Rahman, Ali, Moktadir, & Kusi-Sarpong, 2019). Subsequent research suggests that the development of a proper GSCM performance evaluation (GSCMPE)framework is very necessary as it enables organizations to understand their relative stance in the market as compared to their peers and what strategies they should follow in order to enhance their performance.

The performance evaluation process is quite a complicated task since it involves several conflicting criteria and a vast number of alternatives available for a single item. MCDM techniques are recommended to overcome such types of problems. Various MCDM approaches have been widely used by authors in diverse fields, such as supplier selection (Hamdan et al., 2017), strategic sourcing (Ghosh, Mandal, & Ray, 2021c), order allocation (Mohammed, Harris, & Kannan, 2019), risk assessment (Chatterjee, Zavadskas, Tamošaitienė, Adhikary, & Kar, 2018), project management (Erdogan, Šaparauskas, & Turskis, 2019), performance measurement (Beheshtinia et al., 2017), optimal design (Emovon et al., 2020) and criteria weight determination (Zavadskas et al., 2016). Khan, Chaabane, and Dweiri (2018) presented a review of various MCDM methodologies reported in supply chain applications. MCDM can handle both qualitative

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(subjective) and quantitative (objective) data. Subjective evaluation of criteria makes it more complex due to the presence of ambiguity and vagueness in the decision-making process. Under certain circumstances, crisp data does not fit well with projected real-world situations. As human perception and judgments are often vague and subjective preferences cannot be represented with an exact numerical figure, a more realistic approach may use linguistic terms instead of numerical values (Sumrit, 2020). Fuzzy set theory is often combined with classical MCDM approaches to make feasible decisions under complex and uncertain conditions (Li, Wang, Fan, Li, & Chen, 2020). Again, the distribution of research articles in the literature indicated that FAHP and FTOPSIS have been utilised by 21% and 17% of researchers respectively (Stojčić, Zavadskas, Pamučar, Stević, & Mardani, 2019). It can be seen from the above analysis that fuzzy-based MCDM approaches have been widely used to measure the performance of various kinds of organizations.

Most of the previous studies considered only environmental or economic aspects of GSCMPE, but there is hardly any research on GSCMPE that simultaneously considers all dimensions of sustainability. However, there is a rich literature on GSCMPE in the context of developed countries. In the context of developing countries, there is a notable lack of GSCMPE frameworks for manufacturing organizations. Subsequently, this research aims to address the following research questions:

RQ1 *What is the degree of GSCM implementation in manufacturing organizations in the context of a developing country?*

RQ2 *Which organization is ahead of other organizations in terms of GSCM performance and what are the strategies of that organization?*

RQ3 *What strategies should be followed by organizations in order to enhance their GSCM performance?*

RQ4 *What is the most influential parameter that should be taken into consideration for GSCMPE?*

RQ5 *How to handle vagueness in the decision-making process that involves qualitative data and human judgment?*

In order to address the afore-mentioned research questions, the following research objectives are ascertained:

(i) To construct a valid framework for GSCMPE in a fuzzy environment by taking into consideration all dimensions of sustainability.
(ii) To measure the GSCM performance of manufacturing organizations in the context of a developing country and rank them accordingly.
(iii) To identify significant criteria for GSCMPE and the most influential criteria.
(iv) To identify the benchmark organization and explore its strategy.

This research proposes an integrated fuzzy-MCDM approach (FAHP & FTOPSIS) to evaluate the GSCM performance of India-based manufacturing organizations. The dynamic and complex characteristics of GSCMPE in an uncertain environment make the combined FAHP-FTOPSIS methodology a suitable tool for this study. This research makes a notable contribution to the body of literature. This study corroborates and improves the fundamental postulates of previous works. By identifying the benchmark organization and exploring its strategies, this research provides empirical evidence for the statement that there exists a positive association between the implementation of GSCM practices and GSCM performance. Next, this research facilitates the implementation of GSCM practices by providing evidence that GSCM performance can be enhanced by assessing the environmental impact of harmful substances and emissions that emerge during production processes and utilizing renewable energy for savings in energy. Hence findings of this study are in line with prior studies that underlined the influence of green and sustainability-oriented practices on successful GSCM implementation (Narimissa, Kangarani-Farahani, & Molla-Alizadeh-Zavardehi, 2019; Ramanathan et al., 2020; Sahu, Narang, Rajput, Sahu, & Sahu, 2018). However, this research evaluates the GSCM performance of manufacturing organizations with distinct supply chain characteristics in the context of a developing country, which has not been investigated in previous studies. In light of the context present above, the contributions of this paper are summarized as follows:

(i) An integrated FAHP and FTOPSIS methodology has been deployed in this research, which is capable of handling vagueness and ambiguity in decisions.
(ii) A PDCA-based group decision-making approach is proposed, which involves stakeholders from both the strategic, tactical, and operational levels of the case organizations. Therefore, the outcome of this research is in line with the group opinion.
(iii) PDCA is a management tool for continuous improvement in business. Using this technique, policymakers can identify system constraints and formulate strategies to improve GSCM performance in the context of manufacturing industries.
(iv) The efficacy of the proposed model is founded on concrete evidence from real-world case studies. Three distinct types of manufacturing organizations (leather, pharmaceutical, and steel) are considered for GSCMPE. Like prior studies, this research is not specific to a focal organization. Therefore, the findings of this study have broader implications.
(v) The benchmark organization is identified and its strategies are explored, which can guide other organizations to improve their performance.
(vi) Both environmental, operational, and economic aspects of sustainability have been taken into consideration for GSCMPE. Hence, the strategies of the benchmark organization have a direct impact on sustainability.

2. RESEARCH BACKGROUND

Regarding the scope of this research, this section comprises three sub-sections: green supply chain management, green supply chain management performance measurement, and fuzzy-MCDM methods.

2.1 Green supply chain management

Growing negative impacts of industrial activities and harmful environmental consequences, such as global warming, climate change, greenhouse gas effect, ozone layer deterioration, and rapid depletion of natural resources, have motivated business organisations to think more environmentally friendly and find the best possible solution to environmental sustainability (Kaur, Sidhu, Awasthi, & Srivastava, 2018). The term 'green supply chain' refers to the idea of incorporating environmentally-friendly practises into the traditional supply chain (Ghosh, Mandal, & Ray, 2021a). Famiyeh, Kwarteng, Asante-Darko, and Dadzie (2018) defined GSCM as the direct participation of suppliers and customers in planning to reduce the ecological impact of products, processes, and services of firms. GSCM aims to reduce environmental burdens through the adoption of green practises in supply chain activities. Although the basic objective of GSCM is to mitigate environmental degradation and curtail production costs (Isaloo et al., 2019), it can also spur economic growth (Nourmohamadi Shalke, Paydar, & Hajiaghaei-Keshteli, 2017) and create competitive advantages in terms of greater consumer satisfaction and improved brand image (Abdallah et al., 2019). Younis, Sundarakani, and Vel (2016) found that adoption of GSCM practises improved corporate performance in various ways. According to Wong, Wong, and Boon-itt (2020), green purchasing and environmental cooperation have a positive impact on operational performance, while green purchasing plays a vital role in enhancing economic performance, and reverse logistics practises were found to have a significant impact on social performance. Sahu et al. (2018) stated that GSCM can significantly improve the environmental and operational performance of supply chains.

2.2 Green supply chain management performance measurement

The widespread recognition of GSCM introduces a new horizon for reengineering the existing supply chain. Once the GSCM is implemented, a standard performance measurement system is required to check its effectiveness (2021). Supply chain performance measurement is a tedious task and requires decisive steps for effective supply chain management (Puška, Kozarević, & Okičić, 2019). Babaeinesami, Tohidi, and Seyedaliakbar (2020) stated that performance measurement stabilises the GSCM process and suggests further improvement in the system. Many organizations are adopting performance measurement systems, but not all of them are flexible enough to adapt easily to any system (Arabsheybani et al., 2021). Therefore, supply chain performance measurement models should be designed in a manner that reduces their complexity and makes them more robust and flexible (Khan et al., 2018). Empirical evidence shows that most of the previous research considers intra-organizational issues and focuses mainly on the operational aspect of sustainability. Dey et al. (2012) applied the analytical hierarchy process (AHP) method for measuring the environmental performance of UK-based manufacturing firms. Wang (2013) conducted a survey over 160 manufacturing units in China and developed a performance measurement system for GSCM. Ahi and Searcy (2015) identified the key constructs from the existing literature on green supply chain performance measurement. Azfar, Khan, and Gabriel (2014) highlighted the precedents of traditional supply chain processes and developed a conceptual framework which industries could adopt to measure supply chain performance. Bhattacharya et al. (2013) developed a green supply performance measurement model using a fuzzy-analytic network process-based green-balanced scorecard. The author validated the proposed method with a UK-based carpet-manufacturing firm.

2.3 Fuzzy-MCDM Methods

As a major research topic in the domain of decision analysis, MCDM has wide applications in real-life decision making. It is basically a methodological and modelling tool for dealing with complicated engineering problems. MCDM mainly deals with structuring and solving managerial problems that involve multiple conflicting criteria to support DMs. However, traditional MCDM approaches cannot solve many MCDM problems with incomplete and unstructured information. In such cases, fuzzy extensions of classical MCDM methods (Sufiyan, Haleem, Khan, & Khan, 2019) are used to evaluate alternatives versus selected criteria through a committee of DMs, where the priority weights of the criteria can be evaluated in linguistic variables represented by fuzzy numbers (Das, Ghosh, & Mandal, 2020). Shen, Olfat, Govindan, Khodaverdi, and Diabat (2013) developed a fuzzy multi-criteria approach for evaluating green suppliers' performance in a green supply chain with linguistic preferences. Chatterjee and Bose (2013) applied the fuzzy-MCDM approach to evaluate criteria weights for selecting and ranking vendors. Chang, Yeh, and Chang (2013) developed a new method selection approach for fuzzy-multi-criteria group decision making (fuzzy-MCGDM) that gives the most preferred group ranking outcome. Moreover, several authors employed fuzzy-based MCDM approaches in various fields of decision making, such as supply chain risk identification and assessment (Khalilzadeh, Shakeri, & Zohrehvandi, 2021), resilient supplier selection (Haldar, Ray, Banerjee, & Ghosh, 2014), facility location selection (Çebi et al., 2014), sustainable supplier selection (Pandey, Shah, & Gajjar, 2017), and so on. Kaya, Çolak, and Terzi (2019) presented a comprehensive review of fuzzy-MCDM methodologies for energy policy making. Among various fuzzy-MCDM approaches, FAHP (Secundo, Magarielli, Esposito, & Passiante, 2017) and FTOPSIS (Jahangiri et al., 2020) are two of the most commonly used methods. Conversely, blending of both FAHP and FTOPSIS methods has been used by several authors in the literature (Kannan, Khodaverdi, Olfat, Jafarian, & Diabat, 2013; Lima Junior, Osiro, & Carpinetti, 2014). Apart from this, various fuzzy-MCDM approaches have been used by researchers in the literature, such as fuzzy-COPRAS (Shaikh, Singh, Ghose, & Shabbiruddin, 2020), fuzzy-DEMATEL (Nasrollahi, Fathi, Sobhani, Khosravi, A, & Noorbakhsh, 2021), fuzzy-VIKOR (Falak, Kunjan, Nagaraju, & Narayanan, 2020), fuzzy-MULTIMOORA (Lin, Huang, & Xu, 2019), fuzzy-GRA (Zakeri et al., 2015), fuzzy-PROMETHEE (Senvar, Tuzkaya, & Kahraman, 2014), and so on.

The remainder of this research paper is organized as follows: Section 3 delineate the fundamentals of various methods used in this research. Section 4 narrates the research design. Section 5 demonstrates the validation of the proposed framework through an empirical case study. Section 6 discusses the results and highlights the research implications. Finally, Section 7 concludes by depicting future research direction in Section 8.

3. METHODS

This section highlights the stepwise procedure of the proposed methods in this research, i.e. the FAHP method and the FTOPSIS method.

3.1 The FAHP Method

Classical AHP ignores the randomness and biasness of human judgments, which can be eliminated by the FAHP method (Falak et al., 2020). In FAHP, linguistic variables in the pairwise comparisons are represented by triangular fuzzy numbers, or TFNs (Sahu et al., 2018). In this research, Buckley's method has been used for determining the relative weights of criteria (Buckley, 1985). The stepwise procedure of FAHP is shown below.

Initially, criteria are compared with each other in accordance with the linguistic scale as shown in Table 1.

If a DM strongly prefers a criterion over another or if the DM states that criterion 'a' is strongly important than criterion 'b', then the TFN number will be (6,7,8) and the TFN for the vice versa will be $\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$ or $(0.125, 0.143, 0.167)$ $\left({}^{1}\!/_{8}= 0.125,{}^{1}\!/_{7}= 0.143,{}^{1}\!/_{6}= 0.167\right)$. The fuzzy-pairwise comparison matrix ($\tilde{D}$) is expressed in the following format.

$$Đ = \begin{bmatrix} 1 & \widetilde{a^{k}_{12}} & \dots & \widetilde{a^{k}_{1n}} \\ \widetilde{a^{k}_{21}} & 1 & \dots & \widetilde{a^{k}_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{a^{k}_{n1}} & \widetilde{a^{k}_{n2}} & \dots & 1 \end{bmatrix}$$

Here, $\widetilde{d^{k}_{ij}}$ denotes k^{th} DM's preference for i^{th} criterion over j^{th} criterion in terms of TFNs, for all $i, j\{1, 2, \dots, n\}$. For example, $\widetilde{d^{1}_{12}}$ denotes the first DM's preference regarding the first criterion over the second one. All $\widetilde{d^{k}_{ij}}$ are TFNs and are represented as $\widetilde{d^{k}_{ij}} = \left(l_{ij}, m_{ij}, u_{ij}\right)$, where l_{ij} is the lower limit, u_{ij} is the upper limit, and m_{ij} is the medium point where the membership function, $\mu_A(x)$ becomes unity.

If several DMs (say n) evaluate their judgment, then an averaged preference for fuzzy-pairwise comparison matrix is updated as follows (Dang, Dang, & Dang, 2019):

Table 1. The linguistic scale and corresponding fuzzy extensions.

Linguistic	Crisp Numbers	Triangular fuzzy numbers
Equally important	1	(1,1,1)
Weakly important	3	(2,3,4)
Moderately important	5	(4,5,6)
Strongly important	7	(6,7,8)
Extremely important	9	(9,9,9)
	2	(1,2,3)
The Intermittent Values	4	(3,4,5)
	6	(5,6,7)
	8	(7,8,9)

$$\tilde{D} = \begin{bmatrix} 1 & \widetilde{d_{12}} & \dots & \widetilde{d_{1n}} \\ \widetilde{d_{21}} & 1 & \dots & \widetilde{d_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{d_{m1}} & \widetilde{d_{m2}} & \dots & 1 \end{bmatrix}$$

where,

$$\widetilde{d_{ij}} = \frac{\sum_{k=1}^{n} \widetilde{d^{k}_{ij}}}{K} \tag{1}$$

The next step is to calculate the geometric mean ($\widetilde{r_i}$) values for each criterion, which can be obtained from the given equation.

$$\widetilde{r_i} = \left(\prod_{j=1}^{n} \widetilde{d_{ij}}\right)^{\frac{1}{n}}, fori = 1, 2, 3, \dots, n \tag{2}$$

Here, $\tilde{d}_{ij}$ is the DMs' preference of the i^{th} criterion over the j^{th} criterion.

The next step is to determine the fuzzy weights ($\widetilde{w_j}$) for each criterion, which are obtained from the vector summation of each $\widetilde{r_i}$, i.e., $(\widetilde{r_1} \oplus \widetilde{r_2} \oplus \dots \oplus \widetilde{r_n})$. The fuzzy weights are calculated by using the following formula:

$$\widetilde{w_j} = \widetilde{r_i} \otimes (\widetilde{r_1} \oplus \widetilde{r_2} \oplus \dots \oplus \widetilde{r_n})^{-1} = \left(lw_j, mw_j, uw_j\right) \tag{3}$$

The weight vector $\widetilde{w_j}$ is basically a TFN. TFN is required to defuzzification using CoA method (Chou & Chang, 2008). The de-fuzzified weights are denoted as M_j and are calculated using the following equation.

$$M_j = \left(\frac{lw_j + mw_j + uw_j}{3}\right) \tag{4}$$

3.2 The FTOPSIS Method

The classical TOPSIS method was first introduced by Hwang and Yoon (1981). It is a well-known and widely used method for ranking alternatives in MCDM problems. In this method, the optimal alternative should have the shortest and farthest distance from positive ideal solution and negative ideal solution, respectively. In real-life decision-making scenarios, ambiguities and vagueness are present in the experts' subjective judgements, which cannot be purely eliminated by using crisp data. However, in many circumstances, crisp data is not available. The classical TOPSIS method completely avoids those imprecise values that are difficult to define by crisp values. To overcome this problem, Chen (2000) introduced the FTOPSIS method. The FTOPSIS method fits human judgment of preference under real-world conditions (Kumar, Kumar, & Barman, 2018). The stepwise procedure of the FTOPSIS method is given below.

A fuzzy-decision matrix ($\tilde{A}$) is constructed in the following format: $\tilde{A} = \left[x_{ij}\right]_{m\times n}$,Where, m represents the number of alternatives and n represents the number of criteria. x_{ij} represents the DM's preference of i^{th} criterion over j^{th} criterion. DM's subjective preferences are measured using the linguistic variables as shown in Table 2. The linguistic variable x_{ij} can be described using TFN $\left(x_{ij} = a_{ij}, b_{ij}, c_{ij}\right)$.

Assume that there is a decision group with K numbers of DMs, then the fuzzy-decision matrix is as follows:

Table 2. Linguistic variables and corresponding fuzzy numbers.

Linguistic variables	Triangular fuzzy numbers
Very Low (VL)	(1,1,3)
Low (L)	(1,3,5)
Average (A)	(3,5,7)
High (H)	(5,7,9)
Very high (VH)	(7,9,9)

$$\tilde{A}^k = \begin{bmatrix} \tilde{x}^k_{11} & \tilde{x}^k_{12} & \cdots & \tilde{x}^k_{1n} \\ \tilde{x}^k_{21} & \tilde{x}^k_{22} & \cdots & \tilde{x}^k_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}^k_{m1} & \tilde{x}^k_{m2} & \cdots & \tilde{x}^k_{mn} \end{bmatrix}$$

Where, $\tilde{x}^k_{ij} = (a^k_{ij}, b^k_{ij}, c^k_{ij})$, $\tilde{x}^k_{ij}$ represents the performance rating of the i^{th} alternative with respect to the j^{th} criterion, evaluated by the k^{th} DM. In this study, three levels of DMs (strategic level, tactical level and operational level) are considered. Aggregated values of the preference of each DM ($\tilde{x}^k_{ij}$) are considered and formulated using following equations:

$$a_{ij} = \min_k \left\{ a^k_{ij} \right\}, b_{ij} = \frac{1}{K}\sum_{k=1}^{k} b^k_{ij}, c_{ij} = \max_k \left\{ c^k_{ij} \right\} \quad (5)$$

Compiling all the preferences of DMs, the final decision matrix with aggregated values of the preference can be reconstructed as follows:

$$\tilde{A} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} where, \widetilde{x_{ij}} = \left(a_{ij}, b_{ij}, c_{ij}\right)$$

Next, the fuzzy decision matrix ($\tilde{A}$) is normalized using the linear scale transformation method. To avoid complicated calculation steps of the classical TOPSIS method, some authors (Haldar et al., 2014) used a linear scale transformation method to transform various criteria scales into a comparable scale. Thereby, normalized fuzzy decision matrix ($\tilde{R}$) is obtained which can be expressed as, $\tilde{R} = \left[\widetilde{r_{ij}}\right]_{m\times n}$

For benefit criteria;

$$\widetilde{r_{ij}} = \left(\frac{a_{ij}}{c^*_j}, \frac{b_{ij}}{c^*_j}, \frac{c_{ij}}{c^*_j}\right)$$

where, $c^*_j = \max_i \left\{ c_{ij} \right\}$, for all $j \in$ B

For cost criteria;

$$\widetilde{r_{ij}} = \left(\frac{a^-_j}{c_{ij}}, \frac{a^-_j}{b_{ij}}, \frac{a^-_j}{a_{ij}}\right)$$

where, $a^-_j = \min_i \left\{ a_{ij} \right\}$, for all $j \in$ C

B and C are the sets of benefit and cost criteria respectively.

Next, the weighted normalized fuzzy decision matrix ($\tilde{V}$) is calculated as:

$\tilde{V} = \left[\widetilde{v_{ij}}\right]_{m\times n}, (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$

Next, the Fuzzy Positive Ideal Solution or FPIS ($\widetilde{A^+}$) & Fuzzy Negative Ideal Solution or FNIS ($\widetilde{A^-}$) are calculated as follows:

$$\widetilde{A^+} = \left(\widetilde{V_1}^+, \widetilde{V_2}^+, \ldots.., \widetilde{V_N}^+\right), \text{ where } \tilde{V}_j^+ = \max_i \left\{ V_{ij} \right\}$$

$$\widetilde{A^-} = \left(\widetilde{V_1}^-, \widetilde{V_2}^-, \ldots.., \widetilde{V_N}^-\right), \text{ where } \tilde{V}_j^- = \min_i \left\{ V_{ij} \right\}$$

Next, the separation measure is calculated. The distance of separation of FPIS and FNIS from each alternative are calculated using positive ideal separation and negative ideal separation.

Positive ideal separation:

$$\widetilde{d_i^+} = \sum_{J=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), fori = 1, 2, \ldots., m \quad (6)$$

Negative ideal separation:

$$\widetilde{d_i^-} = \sum_{J=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), fori = 1, 2, \ldots., m \quad (7)$$

According to Dalalah, Hayajneh, and Batieha (2011), the distance between two TFNs $A_1 = (a_1, b_1, c_1)$ and $A_2 = (a_2, b_2, c_2)$ is measured with the vertex method

$$d(A_1, A_2) = \sqrt{\frac{1}{3}\left[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2\right]}$$

Finally, the closeness coefficient is calculated to rank all alternatives in order. The closeness coefficient (CC_i) is calculated as follows:

$$\widetilde{CC_i} = \frac{\widetilde{d_i^-}}{\widetilde{d_i^+} + \widetilde{d_i^-}}, fori = 1, 2, \ldots.., m \quad (8)$$

According to the $\widetilde{CC_i}$ values, the ranking of the alternatives can be determined.

4. RESEARCH DESIGN

The entire research is garnished with the four basic steps of the PDCA cycle. The PDCA cycle is basically a four-step problem-solving technique used in process improvement and continuous evaluation of management practises (Brau, Gardner, Webb, & McDonald, 2019). It is one of the quality control tools used in a supply chain context (Nguyen, Nguyen, Schumacher, & Tran, 2020). It encompasses the basic tenets of strategic management. The PDCA cycle (Figure 1) can be broken down into four steps: 'Plan', 'Do', 'Check', and 'Act'. The 'Plan' phase includes establishing goals and designing processes to improve results; 'Do' phase includes plan execution and performance measurement; 'Check' phase includes review and monitoring the outcomes; and 'Act' phase includes decision-making for continuous improvement. To emphasise the relevance of the study, the four steps of the PDCA cycle are engraved with names; 'Define & Design', 'Perform & Analysis', 'Review & Monitor' and 'Actions & Measures' respectively.

The four steps of the PDCA cycle, designed specifically for this research, are briefly summarised in the following stanzas:

Step-1: plan (define & design)

This step includes mapping out the desired goal and presenting the best way to meet it. In this research, the planning phase comprises various activities such as criteria identification, questionnaire development, and DM committee formation. Significant criteria are identified from the extant literature review. A questionnaire is developed in order to

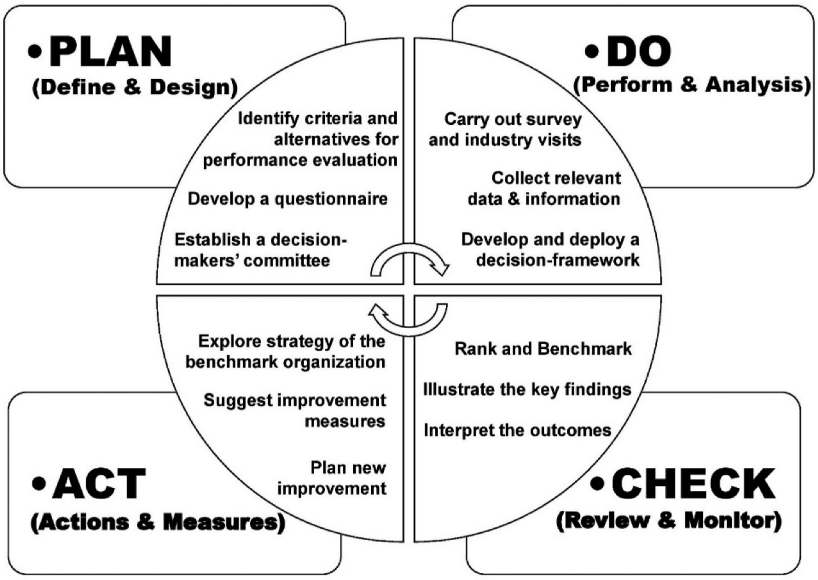

Figure 1. The PDCA cycle.

gather relevant data and information. An expert committee or a group of DMs is established in order to carry out the survey. The expert committee consists of selected members from the case organizations.

Step-2: do (perform & analysis)

This step includes activities like industry visits, surveys, and data collection. An integrated FAHP and FTOPSIS methodology (Figure 2) has been developed. First, a pairwise comparison matrix is constructed. Then a fuzzy pairwise comparison matrix is developed by converting the crisp numbers into TFN. Then the FAHP method is employed to determine the criteria weights. Next, a fuzzy-decision matrix is developed by aggregating DMs' ratings. Then a fuzzy-normalized decision matrix is formed. Weights obtained from the FAHP method are used to calculate the weighted normalised fuzzy-decision matrix in the FTOPSIS method. Subsequently, alternatives are prioritised and ranked according to the closeness coefficients.

Step-3: check (review & monitor)

In this step, results obtained from the above methodology are reviewed and monitored. If any error or inconsistency is found in the final outcome, then the original data and calculations of the previous step are checked carefully. Also, key findings are illustrated.

Step-4: act (actions & measures)

In this step, improvement measures are suggested and relevant strategies are explored. Basically, this step identifies the bottlenecks or system constraints and finds opportunities for improvement. Root causes of poor performance are also analysed. Planning for better improvement is also introduced at this stage. As it promotes continuous improvement, therefore, check for new problems and adopt the PDCA cycle again.

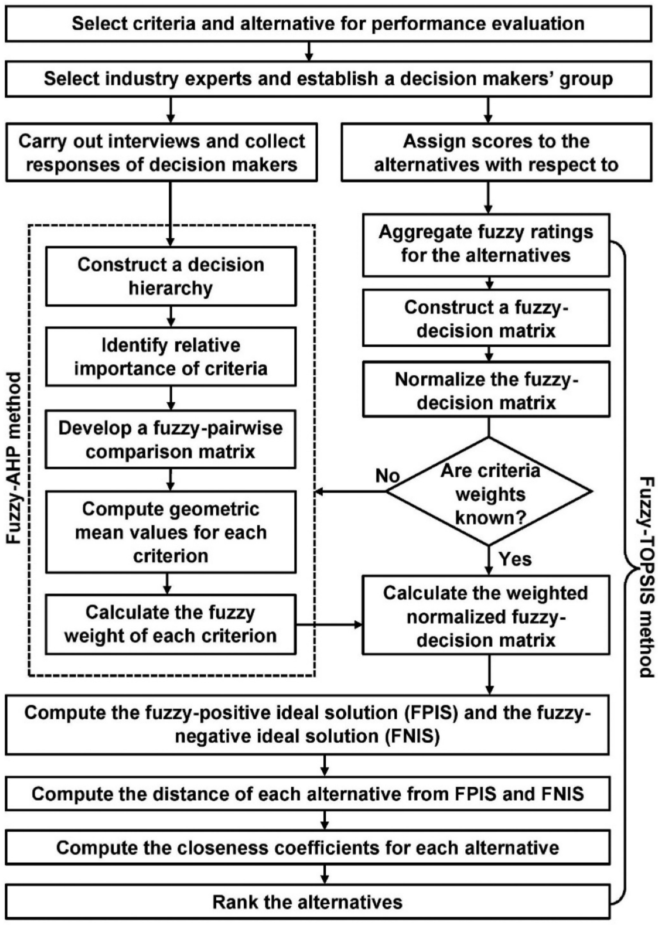

Figure 2. Integrated FAHP and FTOPSIS methodology.

5. AN EMPIRICAL CASE STUDY

To demonstrate the aptness of the proposed model, a real-world problem of GSCMPE is considered. Three prominent India-based manufacturing organization from three different industrial segments (leather, pharmaceutical, and steel) have been considered for GSCMPE. The prime reason behind selecting these organizations is the distinction and variability in their supply chain characteristics. The selected organizations are esteemed manufacturers with a worldwide market in their respective domains. All three organizations have taken many GSCM initiatives to pursue sustainability in business. All the organizations are ISO-certified. Due to the privacy policies of the organizations, the names, locations, and other identifiable details are kept anonymous in this study. Three organizations are abbreviated as Organization A, Organization B, and Organization C, respectively. The brief descriptions of the organizations are given in Table 3

Step-1: Five significant criteria are selected for GSCMPE in this study. The choice of criteria for GSCMPE is not trivial. Initially, twenty criteria are identified from an extensive literature review, which have been frequently used by several researchers. Then, principal component analysis (PCA) is applied. PCA (Sutono, Rashid, Taha, Subagyo, & Aoyama, 2017) is a data reduction tool for the evaluation of a small set of variables within a large portion of data. PCA mainly deals with linear combinations of variables and is used as a popular ranking method for multi-criteria analysis (Wang et al., 2000). In this study, PCA is used to identify the significant criteria that have maximum variations in the data. Thus, out of twenty criteria, only five are selected. The criteria, along with their details, are shown in Table 4.

The next step is questionnaire development. A questionnaire is a basic research tool that consists of a series of questions for extracting relevant information from the respondents (Ray, Ghosh, & Mandal, 2021). In this research, a questionnaire has been developed to collect experts' opinions. A few sample questions that are included in the questionnaire are shown in Table 5.

A DM, or appraisers' committee, is then established in the study to carry out the survey. The committee includes managerial representatives and industry executives selected from all three levels (strategic, tactical, and operational) of the selected organizations. All selected members of the DM committee are highly skilled professionals with more than twenty years of corporate expertise. The representative from the strategic level is abbreviated as 'DM1' here. Similarly, representatives from the tactical level and operational levels are abbreviated as 'DM 2', and 'DM 3', respectively.

Table 4. Criteria description.

Criteria	Notations	Type	Dimension	Sources
Design for proper utilization of resources	C1	Benefit	Operational	Foo et al. (2018)
Optimization of process parameters to increase quality and reduce scrap & wastes	C2	Benefit	Operational	Wang, Pan, Wang, and Zhou (2020)
Environmental impact of harmful emissions released from production	C3	Cost	Environmental	Frank et al. (2016); Acquaye et al. (2018)
Use of eco-friendly packaging material	C4	Benefit	Environmental	Sari et al. (2017); Tosun et al. (2014)
Utilization of renewable energy	C5	Benefit	Economic	Ghosh et al. (2021a)

Table 5. Sample questionnaires.

Questions	Yes/no	Measure/how much?
Are liquid and solid wastes harmful to the environment?		
Do you have a green procurement policy?		
Do you design products for the proper utilization of resources?		
Do you use energy-efficient technologies?		
How much recyclable content is present in your construction materials?		
Do you optimize transportation operations to reduce carbon footprint?		
Do you optimize processes to enhance quality and minimize waste?		
Do you use renewable energy?		
Have you a wastewater treatment plant?		
What is top management's commitment to GSCM implementation?		
How do you design safety features to reduce hazardous consequences?		

Step-2: The survey has been carried out in order to collect relevant data and information. The survey and structured interviews with industry personnel have been completed after getting consent from the corresponding officials. Communications with industry experts have been

Table 3. Brief overview of the selected organizations.

Organizations	Organization A	Organization B	Organization C
Industrial segment	Leather industry	Pharmaceutical industry	Steel industry
Turnover (US $)	22 billion (approx.)	13 billion (approx.)	41 billion (approx.)
Type of goods produced	Leather-aided premium quality products, such as bags, footwear, lifestyle accessories, shirts, coating materials, household essentials, fashion instruments, and custom-made products	Drugs, essential and emergency medicines, Healthcare products, medical equipment, nutrients, and supplements	TMT bars, galvanized roofing sheets, rails, bridge structures, gas cylinders, metal containers, screws and fastener equipment, agricultural equipment, bearing, springs, electric wires, pipes, household utensils, and furniture
Number of associate suppliers of raw material, components and sub-assemblies	860	668	2200
Total number of plants/ Sales outlets across the country	11	8	6
Number of workers employed by the organization	44,277	27,880	62,450

established through e-mails, telephones, and frequent site visits. Attempts have been made to make the survey free from personal bias, such as arranging meetings with different people and examining the responses very carefully. Not everyone in the industry wants to participate in the survey. Again, participants may not agree to disclose information regarding internal policies and sensitive issues. Therefore, the entire survey is based on mutual agreement. Responses and feedback are taken from DMs at all three levels and aggregated for collective response. Thus, a pairwise comparison matrix (Table 6) is constructed that comprises the relative preferences of the criteria.

In Table 6, the data is in the form of crisp or real numbers. Now the FAHP methodology is applied in order to calculate the criteria weights. The crisp numbers are converted into fuzzy numbers (TFN) using the scale transformation (Table 1). Thereafter, the fuzzy pairwise comparison matrix (Table 7) is constructed. The average value for preferences is calculated using Equation 1. Now the geometric mean is calculated using Equation 2 and shown in Table 8. Next, fuzzy weights for each criterion are calculated using Equation 3.

Table 6. Pairwise comparison matrix.

	C1	C2	C3	C4	C5
C1	1	3	$\frac{1}{5}$	$\frac{1}{4}$	$\frac{1}{2}$
C2	$\frac{1}{3}$	1	$\frac{1}{6}$	7	3
C3	5	6	1	4	2
C4	4	$\frac{1}{7}$	$\frac{1}{4}$	1	$\frac{1}{5}$
C5	2	$\frac{1}{3}$	$\frac{1}{2}$	5	1

Table 7. Fuzzy pairwise comparison matrix ($\tilde{D}$).

	C1	C2	C3	C4	C5
C1	(1,1,1)	(2,3,4)	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	$\left(\frac{1}{5},\frac{1}{4},\frac{1}{3}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$
C2	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(1,1,1)	$\left(\frac{1}{7},\frac{1}{6},\frac{1}{5}\right)$	(6,7,8)	(2,3,4)
C3	(4,5,6)	(5,6,7)	(1,1,1)	(3,4,5)	(1,2,3)
C4	(3,4,5)	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{5},\frac{1}{4},\frac{1}{3}\right)$	(1,1,1)	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$
C5	(1,2,3)	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(4,5,6)	(1,1,1)

Table 8. Fuzzy geometric mean of variables ($\tilde{r}_i$).

	C1	C2	C3	C4	C5	$\tilde{r}_i$
C1	(1,1,1)	(2,3,4)	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	$\left(\frac{1}{5},\frac{1}{4},\frac{1}{3}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(0.467,0.596,0.803)
C2	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(1,1,1)	$\left(\frac{1}{7},\frac{1}{6},\frac{1}{5}\right)$	(6,7,8)	(2,3,4)	(0.844,1.032,1.262)
C3	(4,5,6)	(5,6,7)	(1,1,1)	(3,4,5)	(1,2,3)	(2.268,2.993,3.630)
C4	(3,4,5)	$\left(\frac{1}{8},\frac{1}{7},\frac{1}{6}\right)$	$\left(\frac{1}{5},\frac{1}{4},\frac{1}{3}\right)$	(1,1,1)	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	(0.416,0.491,0.587)
C5	(1,2,3)	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	$\left(\frac{1}{3},\frac{1}{2},\frac{1}{1}\right)$	(4,5,6)	(1,1,1)	(0.803,1.108,1.552)

Table 9. Fuzzy weights of criteria ($\tilde{w}_j$).

	Fuzzy Geometric Mean Value ($\tilde{r}_i$)	Fuzzy Weights ($\tilde{W}_i$)	Defuzzied weight
C1	(0.467,0.596,0.803)	(0.060,0.096,0.167)	0.108
C2	(0.844,1.032,1.262)	(0.108,0.166,0.263)	0.179
C3	(2.268,2.993,3.630)	(0.290,0.481,0.757)	0.509
C4	(0.416,0.491,0.587)	(0.053,0.079,0.122)	0.085
C5	(0.803,1.108,1.552)	(0.102,0.178,0.323)	0.201

Table 10. Performance rating of alternatives with respect to each criterion.

	Organization A			Organization B			Organization C		
Criteria	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
C1	VH	H	VH	H	A	H	H	L	VH
C2	H	A	H	A	VL	L	H	H	VH
C3	H	A	A	A	L	A	A	A	L
C4	A	A	A	H	H	A	L	L	A
C5	A	L	L	VL	L	L	A	L	H

Table 11. Fuzzy-decision matrix using aggregated values ($\tilde{A}$).

Criteria	C1	C2	C3	C4	C5
Organization A	(5,8.334,9)	(3,6.334,9)	(3,5.667,9)	(3,5,7)	(1,3.667,7)
Organization B	(3,6.334,9)	(1,3,7)	(1,4.334,7)	(3,6.334,9)	(1,2.334,5)
Organization C	(1,6.334,9)	(5,7.667,9)	(1,4.334,7)	(1,3.667,7)	(1,5,9)

Criteria weights are de-fuzzified or converted into crisp numbers using Equation 4. Both fuzzy weights and de-fuzzified weights are shown in Table 9.

Next, the FTOPSIS methodology is applied. DMs' ratings for alternatives correspond to each criterion are shown in fuzzy matrices (Table 10). Criteria values (obtained from DMs' ratings) are aggregated using Equation 5 and are shown in a fuzzy-decision matrix (Table 11). Then the fuzzy-decision matrix using aggregated values is normalised using Equation 6 and Equation 7 ands shown in Table 12. Then criteria weights, obtained from the FAHP method (Table 9), are employed in the FTOPSIS method to construct a weighted normalised fuzzy-decision matrix. The weighted normalised fuzzy-decision matrix is calculated using equation (8) and shown in Table 13. FPIS and FNIS values are calculated using Equation 9 and Equation 10 and shown in Table 14. Equation 6 and (Equation 7) are used to calculate the fuzzy positive ideal separation matrix (Table 15) and the fuzzy negative ideal separation matrix (Table 16), respectively. Finally, closeness coefficients are calculated using Equation 8, and the ultimate ranking (Table 17) is done according to the closeness coefficient values.

Step 3: The organizations are ranked according to the order of closeness coefficients (Table 17). The rankings of the organizations are as follows: Organization C (Steel Industry) > Organization B (Pharmaceutical Industry) > Organization A (Leather Industry). Closeness coefficients for Organization C, Organization B, and Organization A are 0.914, 0.656, and 0.250, respectively. Organization C is closer to FPIS and farther from FNIS. Organization C has the maximum closeness coefficient. Hence, Organization C secures the first rank. The performance of Organization B is average and it holds the second rank. But the performance of Organization A is not up to the mark. Therefore, it can be concluded that Organization C is the benchmark organization. Organization C has adopted GSCM policies successfully in its supply chain. On the other hand, fuzzy weights of the criteria are determined using the FAHP method. From the table, it can be seen that

Table 12. Normalized fuzzy-decision matrix ($\tilde{R}$).

Criteria	C1	C2	C3	C4	C5
Organization A	0.556, 0.926, 1	0.334, 0.704, 1.000	0.112, 0.176, 0.334	0.334, 0.556, 0.778	0.112, 0.407, 0.778
Organization B	0.334, 0.704, 1	0.112, 0.334, 0.778	0.143, 0.231, 1.000	0.334, 0.704, 1.000	0.112, 0.259, 0.556
Organization C	0.112, 0.704, 1	0.556, 0.852, 1.000	0.143, 0.231, 1.000	0.112, 0.407, 0.778	0.112, 0.556, 1.000

Table 13. Weighted normalized fuzzy-decision matrix ($\tilde{V}$).

Criteria	C1	C2	C3	C4	C5
Organization A	0.033,0.089,0.167	0.036,0.117,0.263	0.032,0.085,0.253	0.018,0.044,0.095	0.011,0.072,0.251
Organization B	0.020,0.068,0.167	0.012,0.055,0.205	0.041,0.112,0.757	0.018,0.056,0.122	0.011,0.046,0.180
Organization C	0.007,0.068,0.167	0.060,0.141,0.263	0.041,0.112,0.757	0.006,0.032,0.095	0.011,0.099,0.323

Table 14. FPIS $\left(\widetilde{A^+}\right)$ and FNIS $\left(\widetilde{A^-}\right)$ values.

Criteria	C1	C2	C3	C4	C5
A^+	0.033,0.089,0.167	0.060,0.141,0.263	0.041,0.112,0.757	0.018,0.056,0.122	0.011,0.099,0.323
A^-	0.007,0.068,0.167	0.012,0.055,0.205	0.032,0.085,0.253	0.006,0.032,0.095	0.011,0.046,0.180

Table 15. Fuzzy positive ideal separation ($\widetilde{d_i^+}$) matrix.

Criteria	C1	C2	C3	C4	C5	d_i^+
Organization A	0.000	0.020	0.291	0.017	0.044	0.372
Organization B	0.014	0.066	0.000	0.000	0.088	0.168
Organization C	0.019	0.000	0.000	0.022	0.000	0.041

Table 16. Fuzzy negative ideal seperation matrix.

Criteria	C1	C2	C3	C4	C5	
Organization A	0.019	0.051	0.000	0.010	0.044	0.124
Organization B	0.007	0.000	0.291	0.022	0.000	0.320
Organization C	0.000	0.057	0.291	0.000	0.088	0.436

Table 17. Closeness coefficients ($\widetilde{CC_i}$) and ranking.

Organizations	d_i^+	d_i^-	CC_i	Rank
Organization A	0.372	0.124	0.250	3
Organization B	0.168	0.320	0.656	2
Organization C	0.041	0.436	0.914	1

C3 (Environmental impact of harmful emissions released from production) gains maximum weight (0.509), hence it is the critical criteria for GSCM performance. Policymakers should predominantly consider this criterion for GSCM performance improvement. On the contrary, C5 (utilisation of renewable energy) gains the least weight, so it has no significant influence on GSCM performance.

Step-4: strategies of the benchmark organization

Organization C embeds GSCM principles into each of its supply chain activities. All of its factories and vendors are periodically audited by competent organizations in order to check their level of compliance. It has a rigid corporate social responsibility (CSR) policy that ensures that the organization continues and expands its business in an economically, socially, and environmentally sustainable way. The organization has increased its expenditure on R&D in the current year. It has established many R&D centres to bring up new innovations. The following are few significant achievements of the benchmark organization in the last financial year.

(i) There is a 13% reduction in water consumption in its processing and a 35% water savings at operational levels.
(ii) Investment in environmental protection has increased by 11%.
(iii) Total waste generation decreased by 15%, while recycling increased from 48% to 52%.
(iv) 30% of total energy is extracted from renewable energy sources.
(v) Savings in energy costs worth 8.5 million after using energy-efficient technology.
(vi) 12% reduction in the value chain's carbon footprint.
(vii) Metal scrap worth 10,000 metric tonnes has been recycled.

Improvement measures

All three organizations have adopted various GSCM practises in their business activities. But in this study, the GSCM performance of Organization C is the best. Other organizations should consider Organization C as a pioneer organization and emulate its strategies. Both Organization C and Organization B have established strong and collaborative relationships with suppliers for green procurement. Organization A should put more emphasis on supplier collaboration. The GSCM performance of Organization B is satisfactory, whereas, the performance of Organization A is lagging. The benchmark organization has adopted some innovative steps towards GSCM implementation. Organization C has set its target to attain a minimum waste production by implementing the 3 R policy (reduce, reuse, and recycle). In comparison with other organizations, Organization C optimised its processes more effectively to reduce defects, waste, and scrap. It is clear from the above analysis that, apart from putting stress on the operational part, the benchmark organization also put emphasis on other subsidiary aspects, such as R&D, CSR, sustainable planning, energy and resource conservation, and supplier collaboration. As a result of this, it has been able to reduce hazardous emissions, metal scrap, energy costs, and so on, while also achieving customer satisfaction through the development of new products, considering cost factors, quality, and durability. Organization C has achieved high-capacity utilization and optimum design, whereas Organization B has achieved it partially, but it is a bit difficult for Organization A to achieve this due to the requirement of highly customized products. Organization C conducts on-site sustainability assessments of suppliers. Procurement costs for Organization B are a major concern. It has a wide supplier network and procures more than 35% of its turnover; it also conducts sustainable supplier engagement programs. Organization A sources raw materials locally, and it entirely depends on local suppliers. For this reason, Organization A is vulnerable to supply chain disruption. It should build a wide and healthy network of suppliers. Organization C has taken the following steps to improve quality: establishing a QA/QC team, employee training, and concurrent process mapping. The quality enhancement programmes of both Organization

B and Organization A are not significant. Organization B should adopt practises like regular quality audits, frequent inspections, and using precision tools. Organization A should track product quality levels and define quality from a customer perspective. Organization C has already implemented a 3 R (reduce, reuse, recycle) policy for effective waste management. Incineration and landfill disposal are two waste management techniques used by Organization B. As a disposal strategy, Organization A employs the landfill method. Biological treatment should be used as an effective waste management strategy in both Organization A and Organization B. It has been found that Organization B and Organization A have paid less attention to replacing existing, convenient technologies with updated, energy-efficient technologies. The use of energy-efficient technology has the potential to significantly reduce total energy costs as well as the total carbon footprint. Organization C utilizes a large portion of the waste heat through a waste heat recovery plant. As energy-efficient measures, Organization B can use membrane filtration, IR radiation heating, cold process pasteurization, and electron beam sterilization, whereas, Organization A can go for PLC devices.

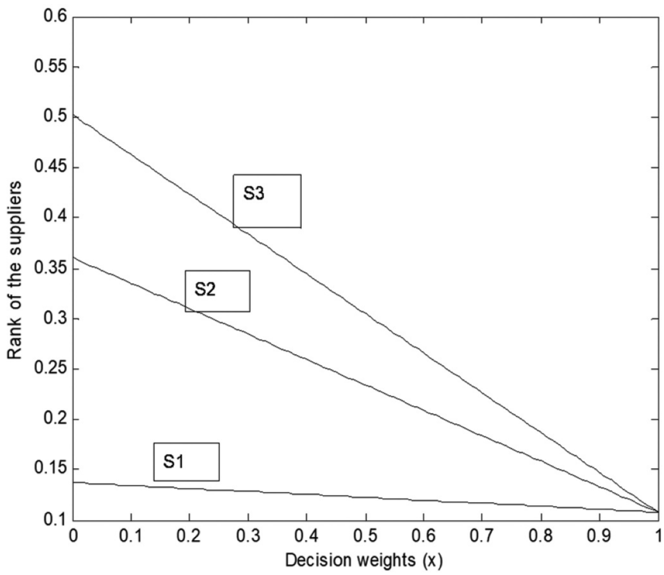

Figure 3. Case 1.

6. DISCUSSIONS

This study offers holistic constructs for performance evaluation, encompassing the entire dimensions of supply network sustainability. Thus, it evaluates environmental, economic, and operational criteria simultaneously. Existing models mostly focus on qualitative data without considering the DM's attitude towards evaluation criteria. But the current research emphasises the DM's attitude towards the criteria. The following figures (Figure 3– Figure 7) show the variation of selection priority of Organization A, Organization B, and Organization C with respect to the variation in the priority of criterion. In the figures, the ordinate denotes the rank of the alternatives, and the abscissa denotes the decision weights. The relative preference of alternatives varies from 0 to 1. In Figs.3–7, supplier organizations are abbreviated as follows: Organization A as S1, Organization B as S2 and Organization C as S3.

Case 1: If the DM has a high priority over C1, then Organization C or S3 is the best

If the DM solely considers C1 for performance evaluation, then Organization C gains the maximum relative preference. In this case, the rankings of the organizations are as follows: Organization C > Organization B > Organization A. This implies that Organization C prioritized C1 (design for proper utilization of resources) more than other organizations.

Case 2: If the DM has a high priority over C2, then Organization A or S1 is the best

If the DM solely considers C2 for performance evaluation, then Organization A gains the maximum relative preference. In this case, the rankings of the organizations

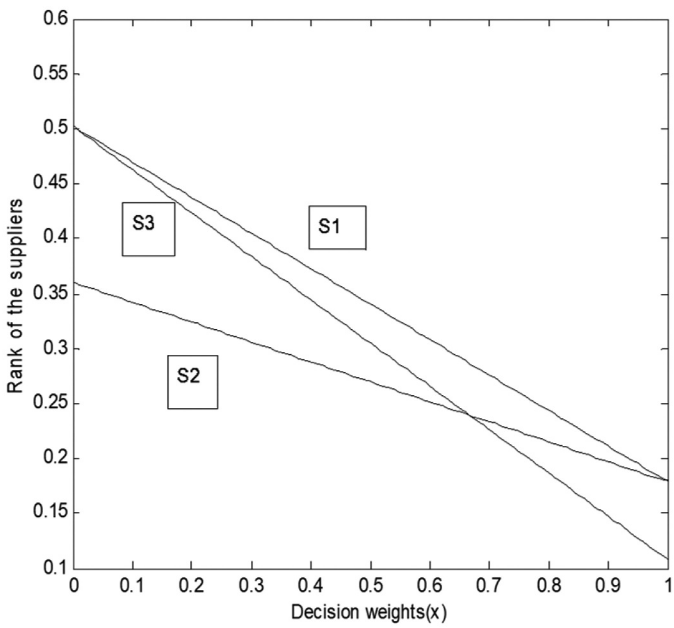

Figure 4. Case 2.

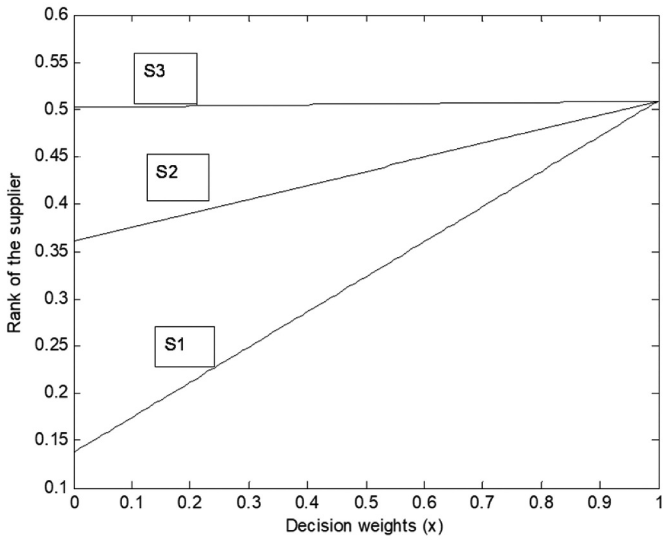

Figure 5. Case 3.

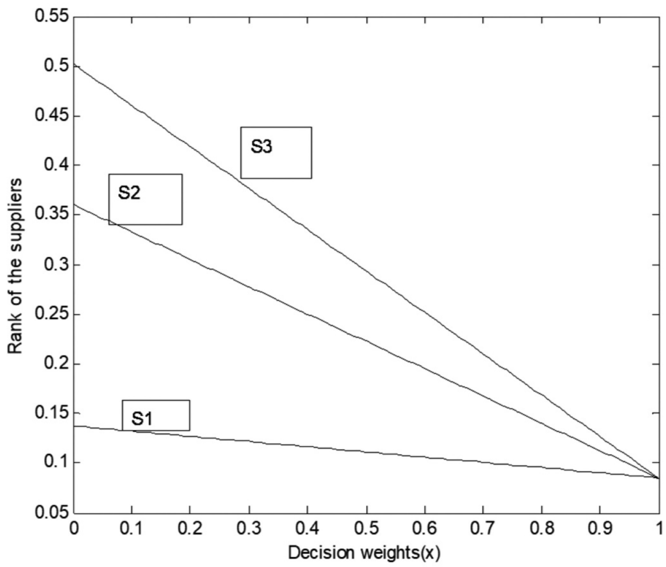

Figure 6. Case 4.

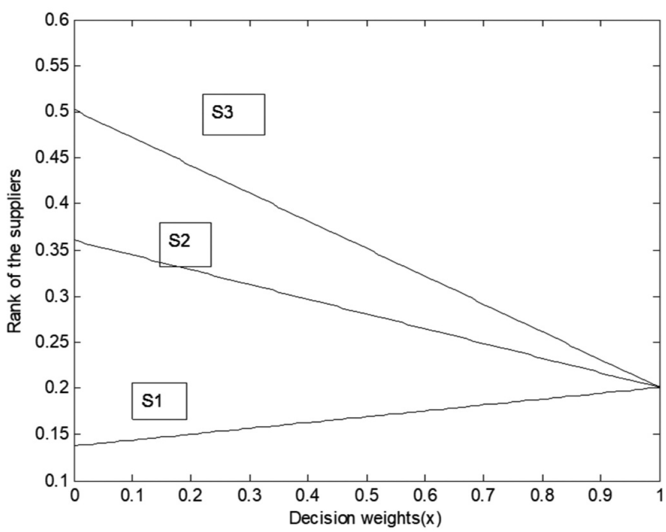

Figure 7. Case 5.

are as follows: Organization A > Organization C > Organization B. As a result, Organization A places a greater emphasis on C2 (optimization of process parameters to increase quality and reduce scrap and waste) than other organizations.

Case 3: If the DM has a high priority over C3, then Organization C or S3 is the best

Case 4: If the DM has a high priority over C4, then Organization C or S3 is the best

Case 5: If the DM has a high priority over C5, then Organization C or S3 is the best

For cases 3, 4, and 5, Organization C gains the maximum relative preference when DM prefers C3, C4, and C5 respectively for performance evaluation. In this case, the rankings of the organizations are as follows: Organization C > Organization B > Organization A, which is similar to that of Case 1. This implies that Organization C put more stress on C3 (environmental impact of harmful emissions released from production), C4 (use of eco-friendly packaging material), and C5 (utilization of renewable energy) than other organizations. Therefore, Organization C (steel industry) is the best. MATLAB programming is used to generate these priority graphs. The degree of effects of each criterion has been presented in the analysis which supports the best organization

Thus, this research subsequently fills the aforementioned research gaps and addresses all the research questions that are ascertained in Section 1. The result reveals that Organization C is ahead of other organizations in terms of GSCM performance, while the performance of Organization B is relatively poor and the performance of Organization A is not up to the mark. Organization B and Organization A must improve their GSCM performance by incorporating various improvement measures. Strategy of the benchmark organization has been explored, which may guide other industries for GSCM performance improvement. Hence, research questions (i), (ii) and (iii) get addressed. The FAHP method determines the weights of the criteria considered in this study. According to the weights (Table 9), the criteria may be ranked as follows: C3 > C5 > C2 > C1 > C4. So, C3 (environmental impact of harmful emissions released from production) is the most influential parameter for GSCMPE. Therefore, organisations assess the impact of harmful emissions at each and every stage of the supply chain in order to build a cleaner production system. Hence, the research question (iv) gets addressed. On the other hand, the proposed framework consists of FAHP and FTOPSIS methodologies, which are highly capable of removing vagueness in judgment, and these methodologies can handle qualitative data efficiently. Moreover, a PDCA-based group decision-making approach can reduce the inconsistency and randomness of redundant data. Hence, the research question (v) gets resolved.

6.1 Comparison of the proposed work with existing works based on important key parameters

Firstly, the current study findings recommend that the steel industry as the best when DM prefers d*esign for proper utilization of resources* more than other criteria. The steel industry mostly focuses on life cycle assessment during the design phase. That's why it has been able to properly utilise resources in its production processes. This is in line with the findings of Foo, Lee, Tan, and Ooi (2018), who argued that organizations should consider design for durability, design for scrap and waste reduction, and design for reusability and recyclability in order to effectively implement GSCM. Secondly, findings of this research suggest that the *environmental impact of harmful emissions released from production* is the most influential criteria. This corroborates the findings of Acquaye et al. (2018), who stated that the cumulative impact of potentially hazardous emissions and the carbon footprint of all industries are increasing, and the development of low-carbon supply chain management strategies can help organisations reduce the impact of emissions. Again, results reveal that *utilization of renewable energy* is the second most influential criteria. This is in line with the findings of Ghosh et al. (2021a), who found that energy used from renewable resources plays a vital role in the selection of environmentally-conscious sourcing. The above analysis indicates that key findings of this research are in alignment with previous research carried out in the field of GSCM.

6.2 Research implications

The utility of the proposed decision-making framework is evidently acceptable to management because the proposed tools and models are relatively easy to use and implement. Computations in various steps are also comprehensive. The proposed framework will facilitate decision-making with a magnitude of uncertainties and imprecision in performance evaluation. This research offers a valid mechanism that can be efficiently used by DMs to measure the GSCM performance of various industrial sectors, which, in turn, can help them enhance their GSCM performance by developing strategies. The proposed model can accommodate any number of criteria and alternatives, which will allow managers to perform sensitivity analysis at different stages and thus obtain a more robust and precise result. Again, this technique can provide strategic guidance to policymakers and practitioners. It can be proficiently used to assess suppliers' performance and develop sourcing strategies.

7. Conclusion

The literature review reveals the deficiency of field-based studies, which corroborates the viability of the proposed research methodology. So far, to the authors' knowledge, there is no such study on the GSCMPE of manufacturing organizations in the context of developing countries. An attempt has been made in this research to evaluate the GSCM performance of three India-based manufacturing organizations, namely, Organization A (leather industry), Organization B (pharmaceutical industry) and Organization C (steel industry). An integrated fuzzy-based MCDM approach has been developed and deployed in this study, where FAHP is used to determine criteria weights and FTOPSIS is used to rank the organizations according to their closeness coefficients. The result reveals that Organization C (steel industry) is the best organization in the ranking as it is closest to FPIS and farthest from FNIS. Again, it can be noticed that out of 5 cases in sensitivity analysis, Organization C secures the top rank in 4 cases. Therefore, Organization C is the benchmark organization. On the other hand, Table 9 shows that criteria C3 (environmental impact of harmful substances released from production) and C5 (utilisation of renewable energy) gain higher weights than other criteria. Therefore, it can be concluded that these criteria are influential criteria for GSCMPE. The key implications of this research are summarised as follows:

(i) The performance evaluation framework in this research encompasses the entire dimensions of sustainability (environmental, social, and operational). Therefore, the benchmark organization's strategy will have a direct impact on overall sustainability.
(ii) This research utilises fuzzy set theory for measuring the GSCM performance of manufacturing organizations, which can eliminate vagueness and ambiguities that are inherently present in traditional performance evaluation approaches.
(iii) The data collection process in AHP includes the active involvement of all the stakeholders concerned. It integrates stakeholders from all levels of organizations (strategic, tactical, and operational). Therefore, it is possible to implement all the improvement measures across the supply chain.
(iv) The model proposed in this research is relatively easier to understand and implement. This method can be applied easily without putting so much effort into it, even without having sound knowledge of the complicated decision-making processes. This approach can be profoundly applied in any industrial decision-making process involving any number of criteria and alternatives.

8. LIMITATION & SCOPE FOR FUTURE RESEARCH

Some limitations have been identified in this research, which lays the foundation for further investigation. First, given that all case organizations in this research are selected from the same country. Since the regulatory framework, geographical positioning, and political background could influence GSCM practise implementation and their performance, this may limit the generalizability of the results. A replication of this research, nevertheless, can be adopted in the context of other countries in a future course of action that would provide this unexplored field with new contributions. Based on this, future studies might consider a specific type of supply chain. Secondly, the measurement approach in this research is limited; the application of GSCM practises is measured by evaluating the opinions of industry experts and business professionals from selected organizations. Hence, future research might examine the experts' opinions together or apply the Delphi technique. Again, this study uses an integrated decision-making approach that seems to be quite accurate, yet errors may be present due to an expert's perception of preference. There are also other shortcomings, like a field-based study that includes a survey, industry visits, and interviews with management personnel, which is a tedious process and consumes a lot of time. The research can be concluded by indicating a few research avenues like:

(i) Further research can be carried out by adding more attributes and alternatives.
(ii) The proposed methodology can be coupled with other soft computing approaches and applied to the same case, and the outcomes can be compared to justify the result.
(iii) Future research could be focused on other key metrics and criteria for GSCMPE.
(iv) Future research could replicate this case study-based research across a broader periphery of manufacturing organizations in India as well as abroad.

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Credit authorship

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