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A Hybrid Decision-Making Method based on Interval-Valued Fermatean Fuzzy Sets and a Green Supplier Chain Management Application

Ali Kablan [1], Serdar Kuzu [2] & Murat Kirişci [3]

[1] İstanbul University-Cerrahpaşa, Department of Foreign Trade, İstanbul, Türkiye
[2] İstanbul University-Cerrahpaşa, Accounting and Tax Department, İstanbul, Türkiye
[3] İstanbul University-Cerrahpaşa, Department of Biostatistics and Medical Informatics, İstanbul, Türkiye

Abstract

There is a growing need to integrate environmentally sound choices into supply-chain management research and practice. Choosing the most sustainable suppliers in the context of green supply chain management is a decision-making problem that frequently entails uncertainty and differing viewpoints among decision-makers. Regulatory bodies that describe regulations to meet societal and ecological concerns and facilitate the growth of business and economy also need to be made aware of their absence. This study presents an integrated multi-criteria decision-making method based on an interval-valued Fermatean fuzzy set. The integrated multi-criteria decision-making methods include the SWARA and WASPAS techniques based on an interval-valued Fermatean fuzzy set. The new method has been applied to the problem of selecting a candidate for a position in green supplier chain management. The results were analysed and compared across various parameters. The performance was then assessed and validated using a sensitivity analysis. The method proposed in this study was compared with previously known methods, and the new method's advantages were demonstrated. In addition, the study's findings and their consequences for lawmakers, businesspeople, technologists, and practitioners are examined. In the future, these stakeholders can concentrate on these deficiencies and provide long-term remedies.

Keywords Decision Making · Green Supplier Chain · Interval-valued Fermatean Fuzzy Set · SWARA · WASPAS

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Corresponding author: Ali Kablan ali.kablan@iuc.edu.tr

A Hybrid Decision-Making Method based on Interval-Valued Fermatean Fuzzy Sets and a Green Supplier Chain Management Application

In today's world of limited natural resources and environmental pollution, the green supply chain management (GSCM) idea integrates green practices and environmentally friendly energy sources into business operations as a mitigation technique to minimise ecological damage. Government regulations, the SCM partners' emphasis on sustainable partnerships, and other green practices, such as green manufacturing, -design, -logistics, etc., are all gaining traction to support sustainable production in the industries. Because GSCM techniques significantly positively affect the economy and human well-being, implementing them may be essential to achieving the Sustainable Development Goals (Debnath et al., 2023).

As a component of managerial and sustainable industrial practices, various industries in rising economies are constantly under oppression to enforce GSCM principles worldwide (Kirişci et al., 2025). This sector needs a steady rise in supply chain operations that deplete many natural resources, contaminate the environment, and disrupt the ecology. In such circumstances, implementing GSCM techniques can help all industries by optimising waste degradation, crosscutting, and energy usage, increasing productivity, and maximising profit (Alkandi et al., 2025).

Multi-criteria decision-making (MCDM) is employed in separate situations with well-defined and limited options. The number of solutions to the MCDM problems is fixed (Taherdoost & Madanchain, 2023). For example, cost and process quality are among the most commonly used factors in many DM situations (Shahsavarani & Abadi, 2015). Additionally, in these situations, expert groups give the criteria different weights (W) according to their importance in that specific situation.

Motivation

In human cognition and DM processes, quantifying the M and degrees of non-membership (N) in a single numerical value is only partially justifiable or technically sound. Interval numbers can be used when information needs to be presented as intervals rather than single-valued numbers.

Measuring the M and degrees of non-membership (N) in a single numerical value is only partially technically sound or justified in human cognition and DM processes. When it is necessary to portray information as intervals rather than single-valued numbers, interval numbers might be used. Intervals are a more convenient way for the decision-maker to state her/his choice for the M and N functions. In some real-world DM situations, decision makers may have difficulty conveying their opinions with a precise number due to a lack of information, which can be represented by an interval number between 0 and 1. The M and N to have an interval value for a given set is necessary to introduce the idea of interval-valued Fermatean fuzzy sets (IVFFS).

A mathematical structure used in modelling situations and DM, including imprecision and uncertainty, is called the IVFFS (Jeevaraj, 2021). In situations when it is challenging to assign a precise M, IVFFS adds an extra degree of flexibility and expressiveness to regular FSs. It is advantageous in the following situations: In MCDM situations with ambiguous or imprecise decision criteria, IVFFS is frequently used. By encoding M and N as intervals, it facilitates the handling of subjective judgments. IVFFS offers a framework for modelling and reasoning with IV- M and N while working with data sets that contain intrinsic ambiguity or partial info. By taking the IV-degrees of agreement and disagreement into account, IVFFS may synthesise differing viewpoints in scenarios involving numerous stakeholders or experts (Kirisci, 2024b). Systems with unclear or ambiguous operating parameters, such as process control or robotics, can be modelled using IVFFS.

Applications such as image processing and data clustering that need to handle ambiguous or overlapping patterns robustly use IVFFS.

The following succinctly describes the causes for selecting IVFFS on alternative fuzzy systems. IVFFS ensures a more flexible framework by letting the declaration of M and N and hesitation degrees as intervals. Better suited for situations in which the exact membership values are not known. It is helpful when uncertainty is a natural part of the situation (Jeevaraj, 2021). IVFFS offers a more adaptable model in situations where DEs lack complete information or have concerns about the veracity of data from several sources. It is especially preferred when it must occasionally convey the ambiguity of expert viewpoints. When assessing numerous factors, IVFFS presents a more adaptable depiction for every criterion. When human judgments or preferences are ambiguous, interval values yield more realistic results. Intervals can more accurately portray fluctuating situations when information is ambiguous because of a system's time-varying nature (Rani & Mishra, 2022). IVFFS simulates uncertain data in data analysis procedures, intensive learning, and artificial intelligence systems that rely on fuzzy logic. In systems with partial data, vagueness may be stated using interval values.

IVFFS offers a strong mathematical framework for handling complex uncertainty by fusing the benefits of IV-representations and Fermatean FSs (FFS) (Kirisci, 2024b). This strategy makes more robust and trustworthy decisions possible, enabling DEs to communicate and manage uncertainty across a broader spectrum.

Decision-makers can select their priorities using the expert-oriented Step-wise Weight Assessment Ratio Analysis (SWARA) technique. This method's primary characteristic is its ability to estimate expert opinions of the criteria's important rates while determining the Ws criteria. To answer the problem, the Weighted Aggregated Sum Product Assessment (WASPAS) method employs the criterion Ws and performance values depending on the alternatives. Additionally, the procedure may verify the consistency in the alternative ranks by conducting a sensitivity analysis within its operation.

Literature

Zadeh's (1965) notion of an FS was used to show the ambiguity and uncertainty of the M. By connecting a component's M to an element, Atanassov's IFS (1986) offers a more thorough interpretation of the assessment data. Yager (2013, 2014) created the Pythagorean FS (PFS) concept. The FFS was the first to broaden the scope of information claims by including the cubic sum of M and N (Senapati & Yager, 2020). Thus, compared to IFS and PFS, FFS handles ambiguous decision circumstances more effectively and practically. Senapati and Yager created the FFS (2019a, 2019b). Because of their benefits in giving professionals more alternatives and elucidating information, researchers have pushed for improving many DM systems to address real-world DM and evaluation concerns—many studies on FS, IFS, and PFS, including studies (Alrasheesi & et al., 2022; Atnassov & Gargov, 1989; Garg, 2016a; 2016b; 2016c; 2017; Ji et al., 2021; Kirisci, 2019; 2021; Kirisci & Simsek, 2022; Liu, Ali & Mahmood, 2023; Ma & Zeng, 2014; Pan et al., 2022; Peng & Yang, 2016; Rahman, Ayub & Abdullah, 2021; Xian, Wan & Yang, 2020; Yager, 2013, 2014; Yager & Abbasov, 2013). FFS studies quickly established themselves in the literature (Deveci & et al., 2023; Garg et al., 2023; Garg, Shahzadi & Akram, 2020; Jeeveraj, 2021; Kirisci, 2023a, 2023b, 2023c, 2024; Kirisci, Demir & Simsek, 2022; Rani & Mishra, 2022; Seikh & Chatterjee, 2024; Senapati & Yager, 2019a, 2019b, 2020; Shahzadi & Akram, 2021; Simsek & Kirisci, 2023. It shows the M and N by the closed subinterval of the interval [0,1]. Jeevaraj (2021) defined the IVFFS.

Previous research frequently presumed that decision-makers knew the criteria well and out and had complete faith in their evaluations. This, however, requires attention to the fact that real-world decision-making frequently involves information gaps and uncertainty. Nevertheless, there are instances in actual life where this presumption is incorrect. One must figure out how to manage this restriction to prevent such circumstances. As a result, the idea of confidence levels came into being. Some academics have given certain confidence levels to aggregation operations. Yu (2014) coupled many IF averaging and geometric aggregation operations with a confidence level. The confidence level, IF a hybrid averaging operator was applied to a DM issue by Ma & Zeng (2014), dependent on trapezoidal IFN; Rahman et al. (2021) introduced a variety of Einstein aggregation operations dependent on confidence levels. Subsequently, to tackle the MADM problem, Liu et al. (2023) improved the confidence level for sophisticated PF-based aggregating operations. Ji et al. (2021) offered a two-stage MADM technique according to the IVPF aggregation operators with self-confidence levels. Pan et al. (2022) employed IVPF hybrid weighted algorithms according to the self-confidence level to select shared bicycles from green recycling suppliers. Garg et al. (2023) recently investigated cubic FF aggregation operators according to confidence levels and their use in MADM issues. Seikh and Chatterjee (2024) have given confidence level-based aggregation operators in the IVFF structure.

In 2010, Kersuliene, Zavadskas, and Turskis wrote the SWARA method. The goal is to find each property's relative value and the options that should be prioritised for each attribute. They achieve this by obtaining the decision-maker's perspective through a weighted method. This helps establish the initial priority and determine the proportionate value of each feature. Many decision-making scenarios have recently been modified to use the SWARA technique. Stevic et al. (2022) thoroughly examined the fuzzy SWARA technique, highlighting its drawbacks for decision-making processes. Their research made it clear how important it is to understand the limitations of the fuzzy SWARA approach. They looked at risk analysis in this dynamic environment and demonstrated how supply chain risk management may benefit from SWARA. Deveci et al.'s (2023) evaluation of the hazards in sustainable mining operations broadened the use of SWARA. Their work created the FF scoring function-based SWARA method, a revolutionary approach to risk assessment and management in sustainable mining. Their study showed how effective SWARA is in supporting environmental decision-making, especially in risk assessment for groundwater pollution. Ulutas et al. (2020) employed the F-SWARA and -CoCoSo techniques to determine the locations of logistics facilities. Seikh and Chatterjee (2024) used the IVFF-based SWARA approach to determine the attribute Ws. Professionals can state their ideas more freely because the SWARA technique is not scalable.

The WASPAS framework is a creative utility measure-based method frequently used in many real-world situations (Zavadkas et al., 1965). It combines the Weighted Product Model (WPM) with the Weighted Sum Model (WSM). Therefore, compared to these two models, it is more accurate. Mishra and Rani (2018) extended the WASPAS framework with IVIFSs. Pamucar et al. (2019) have used a linguistic neutrosophic WASPAS model to assess the safety consultants' study of carrying hazardous chemicals. Gundogdu and Kahraman (2019) have utilized the WASPAS model to evaluate industrial robot assessment problems. Rani and Mishra (2022) presented a new WASPAS method for assessing choices from an IVFF standpoint. By selecting the most feasible alternative e-waste recycling partner, the novel IVFF-WASPAS strategy seeks to expand the application domains of the WASPAS methodology.

Necessity

In most emerging economy nations, the GSCM idea is still in its infancy and is relatively new. To put such methods into action, it is necessary to have a deeper comprehension of the factors that could accelerate the adoption process. The issues that need to be investigated in this study are as follows: CSFs that support the implementation of GSCM practices in the industry should be determined. The correlation between CSFs should be known for implementing GSCM practices in a developing economy. The classification of CSFs into cause-and-effect groups should be shown. Suggestions should be presented to industrial managers and policymakers to facilitate the implementation of GSCM practices.

Contribution

An approach according to IVFFSs has been devised to order the options for SCM according to the work's methodological component. The best provider was chosen using an MCDM approach. Additionally, comparative studies have been conducted to verify the precision of the choices and practices. The primary contributions are as follows:

1. The MCDM framework model, which integrates the SWARA and WASPAS methodologies based on IVFFS, effectively models and ranks the GSCM, ensuring a facility for practitioners and society. Using the recommended techniques, the professionals may determine a range of two scale points from the pre-established language scale. After converting the interval data into IVFF values, the evaluation's confirmed and indeterminate components are further discussed in lower and higher approximations.
2. The criteria for each alternative evaluate the GSCM-related data independently.
3. The efficacy of the proposed model in ranking GSCM will be evaluated with a comparison.
4. Based on the results, detailed implications are given.

Preliminary

Let $I[0,1]$ show the set of all closed subintervals of the unit interval. The set $F = \{(a,\ m_F(a), n_F(a)) : a \in E\}$ is called IVFFS, where $m_F(a), n_F(a) \in I[0,1]$ with $0 < \sup_a (m_F(a))^3 + \sup_a (n_F(a))^3 \leq 1$ (Jeeveraj, 2021).

The IVFFS can be given as $F = \left\{\left(a, \left[m_{F_L}(a), n_{F_L}(a)\right], \left[m_{F_U}(a), n_{F_U}(a)\right]\right) : a \in E\right\}$. Here, $0 < \sup_a (m_{FU}(a))^3 + \sup_a (m_{FU}(a))^3 \leq 1$, $h_F = \left[h_{F_L}, h_{F_U}\right] = \left[\left(1 - m_{F_L}^3 - n_{F_L}^3\right)^{1/3}, \left(1 - m_{F_U}^3 - n_{F_U}^3\right)^{1/3}\right]$.

For F, F_1, F_2,

- $F_1 \cup F_2 = \left(\left[\max\left(m_{F_{1L}}, m_{F2_L}\right), max\left(m_{F_{1U}}, m_{F2_U}\right)\right], \left[\min\left(n_{F_{1L}}, n_{F2_L}\right), min\left(n_{F_{1U}}, n_{F2_U}\right)\right]\right)$,
- $F_1 \cap F_2 = \left(\left[\min\left(m_{F_{1L}}, m_{F2_L}\right), min\left(m_{F_{1U}}, m_{F2_U}\right)\right], \left[\max\left(n_{F_{1L}}, n_{F2_L}\right), max\left(n_{F_{1U}}, n_{F2_U}\right)\right]\right)$,
- $F_1 \oplus F_2 = \left(\left[\begin{array}{c}\sqrt[a]{(m_{F1L}(a))^3 + (m_{F2L}(a))^3 - (m_{F1L}(a))^3 (m_{F2L}(a))^3} \\ \sqrt[a]{(m_{F1U}(a))^3 + (m_{F2U}(a))^3 - (m_{F1U}(a))^3 (m_{F2U}(a))^3}\end{array}\right], \left[n_{F_{1L}} n_{F2_L}, n_{F_{1U}}, n_{F2_U}\right]\right)$,
- $F_1 \otimes F_2 = \left(\left[m_{F_{1L}} n_m, m_{F_{1U}}, m_{F2_U}\right], \left[\begin{array}{c}\sqrt[a]{(n_{F1L}(a))^3 + (n_{F2L}(a))^3 - (n_{F1L}(a))^3 (n_{F2L}(a))^3} \\ \sqrt[a]{(n_{F1U}(a))^3 + (n_{F2U}(a))^3 - (n(a))^3 (n_{F2U}(a))^3}\end{array}\right]\right)$,
- $\lambda F = \left(\left[\sqrt[a]{1 - \left(1 - m_{F_L}^3\right)^\lambda}, \sqrt[a]{1 - \left(1 - m_{F_U}^3\right)^\lambda}\right], \left[n_{F_L}^\lambda, n_{F_U}^\lambda\right]\right)$,
- $F^\lambda = \left(\left[m_{F_L}^\lambda, m_{F_U}^\lambda\right], \left[\sqrt[a]{1 - \left(1 - n_{F_L}^3\right)^\lambda}, \sqrt[a]{1 - \left(1 - n_{F_U}^3\right)^\lambda}\right]\right)$.

The score, accuracy, and normalised score functions are defined as

$$\cdot SC(F) = \frac{1}{2}\left(\left[(m_{FL}(a))^3 + (m_{FU}(a))^3\right] - \left[(n_{FL}(a))^3 + (n_{FU}(a))^3\right]\right), \tag{1}$$

$$\cdot AC(F) = \frac{1}{2}\left(\left[(m_{FL}(a))^3 + (m_{FU}(a))^3\right] + \left[(n_{FL}(a))^3 + (n_{FU}(a))^3\right]\right), \tag{2}$$

$$\cdot \overline{SC}(F) = \frac{1}{2}(SC(F) + 1). \tag{3}$$

where $SC(F) \in [-1,1],\ AC(F), \overline{SC}(F) \in [0,1]$ (Rani & Mishra, 2022). For ω_k, the IVFF-weighted geometric operator is characterised by

$$IVFFWG(F_1, F_2, \ldots, F_n) =$$

$$\left(\left[\prod_{i=1}^{n} (m_{FiL}(a))^{\omega_i}, (m_{FiU}(a))^{\omega_i}\right], \left[\sqrt[a]{\left(1 - \prod_{i=1}^{n}\left(1 - (n_{FiL}(a))^3\right)^{\omega_i}\right)} \sqrt[a]{\left(1 - \prod_{i=1}^{n}\left(1 - (n_{FiU}(a))^3\right)^{\omega_i}\right)}\right]\right). \tag{4}$$

Table 1
Linguistic Terms and IVFFNs

	m_L	n_L	m_U	n_U
Certainly High Importance (CH)	0.95	0	0	0
Very H I (VH)	0.8	0.1	0.9	0.2
H I (H)	0.7	0.2	0.8	0.3
Slightly More I (SM)	0.6	0.35	0.65	0.4
Equally I (E)	0.5	0.5	0.5	0.5
Slightly Less I (SL)	0.35	0.6	0.4	0.65
L I (L)	0.2	0.7	0.3	0.8
Very L I (VL)	0.1	0.8	0.2	0.9
Certainly L I (CL)	0	0.95	0	1

These formulas

$$\omega_t^O = \frac{\sqrt{\frac{1}{2}\left[(1-h_{tL})^2 + (1-h_{tU})^2\right]}}{\sum_{t=1}^{k}\sqrt{\frac{1}{2}\left[(1-h_{tL})^2 + (1-h_{tU})^2\right]}}, \tag{5}$$

$$\omega_t^S = \frac{k-\phi_t+1}{\sum_{t=1}^{k}(k-\phi_t+1)}, \tag{6}$$

is called the Rank-Sum formula for the objective (OW) and subjective weights (SW), where $t = 1, 2, ..., k$ and ϕ_t indicates the rank of *the tth* professional. For the final W, combine the OW and SW:

$$f\omega_t = \beta\omega_t^O + (1-\beta)\omega_t^S, \tag{7}$$

where $\beta \in [0, 1]$.

The relative significance of the score values(SCV) is computed from the second maximum SCV. The relative significance of the v^th^ criterion is computed as the difference between the v^th^ alternative and the (v+1)^th^ alternative SCs. For $v = 1, 2, ...\alpha$,

$$\chi_v = \begin{cases} 1, & v = 1, \\ r_{v+1}, & v > 1 \end{cases} \tag{8}$$

where r_v is the relative significance of the alternative v^{th} .

$$P_v = \begin{cases} 1, & v = 1, \\ \frac{P_{v-1}}{\chi_v}, & v > 1 \end{cases} \tag{9}$$

The ultimate Ws of the criteria

$$\omega O_v = \frac{P_v}{\sum_{v=1}^{\alpha} P_v}, \tag{10}$$

For the i^{th} alternatives over j^{th} criteria, the IVFF decision matrix $Z = (z_{ij})_{m\times n}$ as

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \vdots & \vdots \\ z_{m1} & \cdots & z_{mn} \end{bmatrix} \tag{11}$$

The elements of the normalised decision matrix $U = (u_{ij})_{m\times n}$ as

$$u_{ij} = \begin{cases} z_{ij}, & for\ benefit\ criteria \\ (z_{ij})^c, & for\ cost\ criteria \end{cases} \tag{12}$$

Using Equation (3), the SC matrix $\overline{S} = (s_{ij})_{m\times n}$ can be given:

$$\overline{S} = \overline{SC}(F)_{ij} = \begin{bmatrix} \overline{SC}(F)_{11} & \cdots & \overline{SC}(F)_{1n} \\ \vdots & \vdots & \vdots \\ \overline{SC}(F)_{m1} & \cdots & \overline{SC}(F)_{mn} \end{bmatrix} \tag{13}$$

Determining criteria Ws accurately is essential to the MCDM process because of the demonstrated substantial association between criteria Ws and the prioritised outcome of selections. Therefore, during the MCDM process, a suitability function (UF)Q(Si) is formed for each attribute, where its SCV is multiplied by its W:

$$Q(S_i) = \Sigma_{j=1}^{n} \omega_j \overline{SC}(F)_{ij} \tag{14}$$

The term ω_j in this formula indicates the W of attribute V_j and the partially known W subset, which denotes *N*. The function $Q(S_i)$ is used to find the *UF* to which a substitute satisfies the parameters of the experts. A precise W value for each alternative should yield the most significant feasible assessment $Q(S_i)$. This concept illustrates how to configure a linear programming method to assess the W in the way outlined below:

$$(M-I): \begin{cases} \max m = \Sigma_{i=1}^{m} Q(S_i) = \Sigma_{i=1}^{m} \Sigma_{j=1}^{n} \omega_j \overline{SC}(F)_{ij}, \\ s.t. \quad \Sigma_{j=1}^{n} \omega_j = 1, \quad \omega_j \geq 1, \quad and \quad \omega_j \in N. \end{cases} \tag{15}$$

Here, $Q(S_i)$ signifies the overall SCV for each S_i. The W vector is produced following the model (M-I).

The formulas

$$\Upsilon_i^{(1)} = \Sigma_{j=1}^{n} \omega_j (F)_{ij} \tag{16}$$

$$\Upsilon_i^{(2)} = \prod_{j=1}^{n} ((F)_{ij})^{\omega_j} \tag{17}$$

$$\Upsilon_i = \upsilon \Upsilon_i^{(1)} + (1-\upsilon)\Upsilon_i^{(2)} \tag{18}$$

Is called WSM, WPM, and WASPAS, where $\upsilon \in [0,1]$. If υ=0 and υ=1, then WASPAS becomes WPM and WSM.

Proposed Method

In this study, SWARA and WASPAS approaches are combined, and a new MCDM methodology is given. The best technique for GSCM was modified using IVFFSs to choose the best. SWARA and WASPAS in the IVFF context are covered in this section, along with IVFFs and the offered MCDM technique. *Figure 1* depicts the GSCM problem in the MCDM architecture.

Algorithms

Algorithm 1: Finding the Ws of Experts

Input: Number of alternatives and criteria

Output: Final Ws of the experts

Begin

For t=1; d **do**

1. Table 1 shows the corresponding IVFFNs for each expert.
2. Equation 5 is used to characterise the OWs of experts using the entropy method.
3. Equation 6 is used to identify the expert's SWs using the Rank-Sum approach.
4. Equation 7 is used to determine the final expert Ws.

Algorithm 1: Finding the Ws of Experts

End For

End

Algorithm 2: IVFF-SWARA

Input: Number of alternatives and criteria

Output: The W of the criteria

Begin

For v=1; a and t=1; d **do**

1. Find the corresponding IVFFNs from the experts that reflect the Significance of each criterion.

2. Using Equation 4, combine the IVFFNs for every criterion.

End For

For v=1; a **do**

3. Equation 3 is used to determine the normalised SC.

4. Rank the criteria in descending order based on their normalised SCs.

5. Beginning with the criterion that received the second-highest SC,

Determine the relative importance of each criterion.

6. Using Equation 8, determine each criterion's relative coefficient.

7. Apply Equation 9 to the evaluation of the penultimate Ws.

8. Using Equation 10, determine the final Ws of the criteria.

End For

End

Algorithm 3 IVFF-WASPAS

Input: Number of alternatives and criteria

Output: The ranking of the alternatives.

Begin

For t=1; d **do**

1. Create the matrix of choices (Matrix 11).

2. Find the choice matrix (Matrix 12) that has been normalised.

3. The SCVs transform the normalised choice matrix into the SC Matrix (Matrix 13).

4. Build Model 15, a linear model, to calculate the attribute Ws.

5. Analyse Equation 16's WSM measure.

6. Use Equation 17 to estimate the WPM metric.

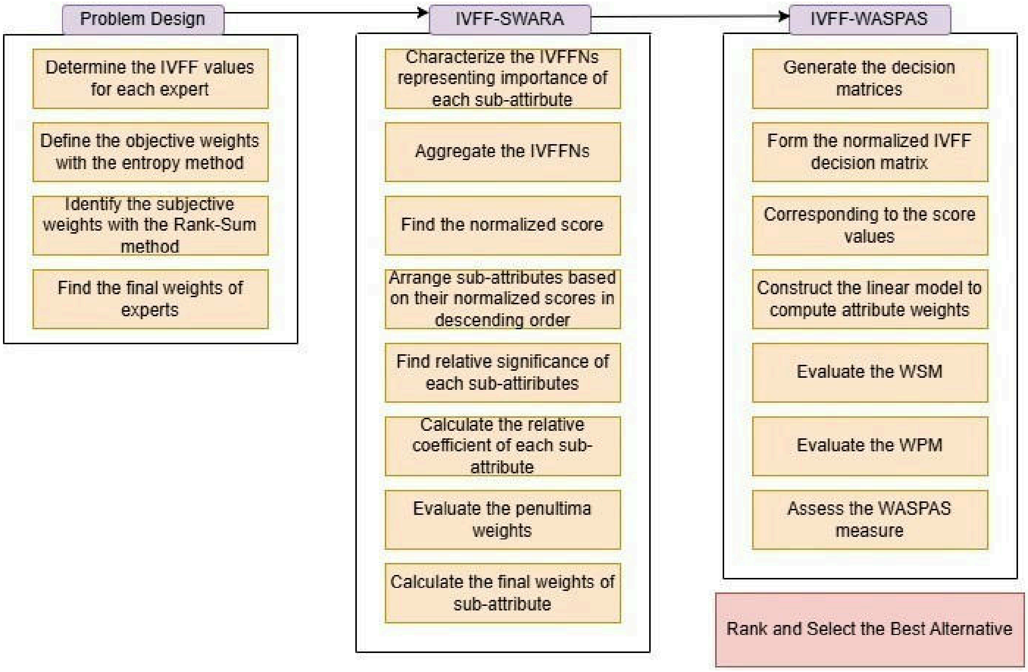
7. Evaluate each option using the combined or WASPAS metric(Equation 18)

End For

End

Figure 1

Proposed Method



Application

Because of the growing corporate activity in the globalised economy and a lack of environmental knowledge, exposure to environmental protection investment capacity has expanded. Numerous industrial companies have adopted green marketing and investment strategies. As the global period evolves, investments are evolving in many ways to be sustainable regarding finances, society, and the environment. In order to improve the healthiest business performance and create a green economy, green marketing, CSR, and green investment are crucial. According to earlier academics, green investment is the adaptation of legislative and policy measures to draw private capital into green business sectors.

GSCM is gaining more and more attention from scholars and supply-chain management professionals. The leading cause of GSCM's growing importance is the deteriorating environment, which includes rising pollution levels, overflowing waste sites, and the depletion of raw material resources. However, GSCM is more than just being green; it is also about increasing earnings and making smart business decisions. It drives the company's value rather than being a cost centre. Moreover, regulatory requirements and customer pressure are what propel GSCM.

A manufacturer must select the best supplier from the following five options: F_1, F_2, F_3, F_4, and F_5. A senior member gathered three specialists to supervise the supplier selection procedure. Three criteria were used to evaluate the options: E_1 stands for the management system, E_2 stands for the manager's dedication to GSCM, and E_3 stands for applying green technology. Based on the information provided, it is necessary to determine the optimal solution in GSCM.

Computations

Stage of Finding Ws of Experts: Table 1 displays the linguistic variables and the IVFF values corresponding to them. *U1–CH, U2–VH, and U3–H* are the linguistic variables of each expert's significance. Using the experts' importance and Equation 5, the OWs are found as $\omega_t^O = \{0.62, 0.23, 0.15\}$. The SWs are acquired to be $\omega_t^S = \{0.5, 0.33, 0.17\}$. If the professionals' Ws are consolidated with Equation 7, $f_{\omega_k} = \{0.56, 0.28, 0.16\}$ is acquired.

Stage of the IVFF-SWARA: Table 1 lists the linguistic criteria for determining the alternatives' relative relevance. Table 2 lists the experts' confidence levels for each criterion. Table 3 shows the SCV, aggregate value, and linguistic values as defined by the professionals for each criterion. The criteria's normalised SCs are calculated. In Table 4, the criteria SCs are listed in decreasing order. The criteria's relative importance is determined. The relative coefficient for each criterion was computed. The penultimate Ws for each criterion are established. The final Ws of the criteria are evaluated. Important details about the criteria under consideration are given(Table 4). Notably, the analysis highlights the importance of various criteria in DM.

Table 2

Confidence Levels

Experts	U_1	U_2	U_3
Criteria			
E_1	0.7	0.6	0.5
E_2	0.9	0.7	0.7
E_3	0.7	0.8	0.7

Table 3

Experts	U_1	U_2	U_3	Aggregate Value	SCVs
Criteria					
E_1	*H*	*SM*	*E*	$[(0.02, 0.21), (0.02, 0.26)]$	-0.013
E_2	*CH*	*VH*	*VH*	$[(0.05, 0.05), (0.06, 0.1)]$	-0.0004
E_3	*SM*	*SL*	*L*	$[(0.005, 0.36), (0.008, 0.4)]$	-0.032

Table 4

Calculation of Ws of the Alternatives

	SCVs	r_υ	χ_ν	P_ν	ω_{O_υ}
E_2	-0.0004	0	1	1	0.139
E_1	-0.013	0.0001	1.0001	0.99	0.137
E_3	-0.032	0.0017	1.0017	0.98	0.136

Stage of the IVFF-WASPAS: In Table 5, the IVFF-decision-matrix is given. The normalised IVFF decision matrix was obtained (Table 6). The collective SC matrix was generated from the normalised IVFF-decision matrix (Table 7). Consider that the Ws of the criterion are distributed as follows:

$$0.18 \le \omega_1 \le 0.27,\ \ 0.10 \le \omega_2 \le 0.20,\ \ 0.15 \le \omega_3 \le 0.258,\ \ \ 0.20 \le \omega_4 \le 0.30,\ \ 0.12 \le \omega_5 \le 0.18,$$

$$s.t.\ \ \sum_{j=1}^{n} \omega_j = 1, \qquad \omega_j \ge 1.$$

The model

$$\max m = 3.51\omega_1 + 4.38\omega_2 + 5.69\omega_3 + 4.27\omega_4 + 4.36\omega_5,$$

$$s.t.\ \begin{cases} 0.18 \le \omega_1 \le 0.27,\ \ 0.10 \le \omega_2 \le 0.20,\ \ 0.15 \le \omega_3 \le 0.258,\ \ 0.20 \le \omega_4 \le 0.30,\ \ 0.12 \le \omega_5 \le 0.18 \\ \sum_{j=1}^{n} \omega_j = 1, \qquad \omega_j \ge 1 \end{cases}.$$

It is given as a linear programming. Hence, $\omega = \{0.27, 0.20, 0.15, 0.20, 0.18\}^T$ is shown as the attribute Ws. Table 8 provides the IVFF-WSM, -WPM, and -WASPAS values.

Therefore, $F_1 > F_4 > F_5 > F_3 > F_2$ is the order of precedence for the GSCM approach choices, and F_1 is the most desirable alternative.

Table 5
IVFFS Decision Matrix

Criteria	F_1	F_2	F_3	F_4	F_5
E$_2$	$[(0.42, 0.66), (0.50, 0.74)]$	$[(0.70, 0.28), (0.80, 0.33)]$	$[(0.85, 0.35), (0.92, 0.18)]$	$[(0.36, 0.72), (0.39, 0.77)]$	$[(0.33, 0.68), (0.44, 0.78)]$
E$_1$	$[(0.43, 0.68), (0.49, 0.70)]$	$[(0.29, 0.73), (0.34, 0.85)]$	$[(0.56, 0.39), (0.68, 0.40)]$	$[(096, 0.10), (0.32, 0.66)]$	$[(0.42, 0.61), (0.40, 0.72)]$
E$_3$	$[(0.57, 0.44), (0.67, 0.51)]$	$[(0.61, 0.45), (0.74, 0.35)]$	$[(0.80, 0.32), (0.85, 0.27)]$	$[(0.86, 0.10), (0.91, 0.13)]$	$[(0.75, 0.28), (0.80, 0.35)]$

Table 6
Normalised IVFFS Decision Matrix

Criteria	F_1	F_2	F_3	F_4	F_5
E$_2$	$[(0.42, 0.66), (0.50, 0.74)]$	$[(0.70, 0.28), (0.80, 0.33)]$	$[(0.85, 0.35), (0.92, 0.18)]$	$[(0.36, 0.72), (0.39, 0.77)]$	$[(0.33, 0.68), (0.44, 0.78)]$
E$_1$	$[\ (0.49, 0.70), (0.43, 0.68)]$	$[(0.34, 0.85), (0.29, 0.73)]$	$[(0.68, 0.40), (0.56, 0.39)]$	$[(0.32, 0.66), (096, 0.10)]$	$[(0.40, 0.72), (0.42, 0.61)]$
E$_3$	$[(0.67, 0.51), (0.57, 0.44),]$	$[(0.74, 0.35), (0.61, 0.45)]$	$[(0.85, 0.27), (0.80, 0.32)]$	$[\ (0.91, 0.13), (0.86, 0.10)]$	$[(0.80, 0.35), (0.75, 0.28)]$

Table 7
Collective SC Matrix

Criteria	F_1	F_2	F_3	F_4	F_5
E$_2$	0.38	0.70	0.84	0.32	0.33
E$_1$	0.38	0.27	0.60	0.66	0.38
E$_3$	0.57	0.62	0.77	0.85	0.72

Table 8
WSM, WPM and WASPAS

	$\Upsilon_i^{(1)}$	$\overline{SC}(\Upsilon_i^{(1)})$	$\Upsilon_i^{(2)}$	$\overline{SC}(\Upsilon_i^{(2)})$	Υ_i	Rank
F_1	$[(0.584, 0.599), (0.372, 0.420)]$	0.490411	$[(0.693, 0.798), (0.485, 0.611)]$	0.427657	0.4590	1
F_2	$[\ (0.355, 0.712), (0.327, 0.685)]$	0.349335	$[(0.383, 0.877), (0.368, 0.698)]$	0.272856	0.3138	5
F_3	$[(0.376, 0.844), (0.458, 0.711),]$	0.297148	$[(0.282, 0.844), (0.280, 0.715)]$	0.269709	0.2833	4
F_4	$[(0.687, 0.749), (0.457, 0.581)]$	0.450844	$[(0.562, 0.792), (0.477, 0.596)]$	0.394383	0.4225	2
F_5	$[(0.405, 0.733), (0.369, 0.596)]$	0.377783	$[(0.427, 0.738), (0.470, 0.604)]$	0.389845	0.3837	3

Discussion

This section discusses the sensitivity and comparative analyses of the new method.

Sensitivity Analysis

Sensitivity analysis aims to apply changes in the inputs and check their effect on the outputs and findings. Nevertheless, employing a specific MCDM strategy might limit sensitivity to that approach and fail to take into account how modifications may affect the results. Additionally, validating results entails using many MCDM techniques to compare and assess various outcomes. It is impossible to use a particular MCDM strategy, compare the outputs, and validate the results using other techniques. Therefore, expanded fuzzy logic must be included in the MCDM approach in addition to taking uncertainty into account when determining the best option based on GSCM. To verify the correctness and stability of the results, which were overlooked in the studies, it is also crucial to look at the sensitivity analysis and validation using various MCDM techniques.

A sensitivity analysis of the υ parameter's range of values has been carried out(Adamu et al., 2025; Bouraimai et al., 2024; Debshiri et al., 2024; Ghoushchi et al., 2024; Kaspar & Kallyaperumal, 2024; Triantaphyllou & Sanchez, 1997). Now, we methodically investigate the influence of the parameters on the selection of GSCM. A range of υ values is considered in the investigation. The purpose of this evaluation is to illustrate the effectiveness of the newly created framework. Professionals may determine how responsive the presented model is to variations in WSM versus WPM by varying the υ parameter. The analysis results (Table 9 and Figure 2) show that the optimal option, F_1, is the same for all parameter values. As a result, υ values are sensitive to and dependent upon the GSCM evaluation. As a result, the proposed model is sufficiently stable over a range of parameter values.

The alternatives' relative sensitivity to shifts in priority Ws is highlighted by the radar charts (and line charts), which show their performance rankings under various evaluation criteria. This investigation highlights the robustness and dependability of the chosen approaches in determining the best mix designs under various decision-making circumstances. Stability and robustness in its evaluation are demonstrated by the radar chart's (and line chart's) comparatively balanced performance across all approaches. The rankings are reliable and accurately represent the relative positions of the options. WSM and WPM displayed comparable patterns. The criteria that each technique emphasises impact the ranking. It has been demonstrated that when a manufacturer wishes to choose the best supplier among the five options, the proposed method has a strong structure and remains sensitive to parameter changes.

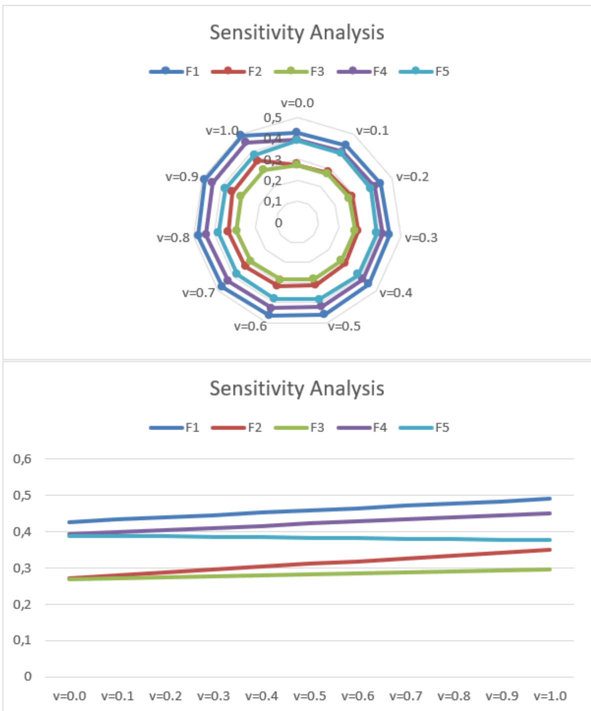
Table 9

Sensitivity

	$\upsilon=0,0$ (WSM)	$\upsilon=0,1$	$\upsilon=0,2$	$\upsilon=0,3$	$\upsilon=0,4$	$\upsilon=0,5$	$\upsilon=0,6$	$\upsilon=0,7$	$\upsilon=0,8$	$\upsilon=0,9$	$\upsilon=1,0$ (WPM)
F_1	0.4276	0.4339	0.4402	0.4464	0.4527	0.4590	0.4653	0.4715	0.4778	0.4841	0.4904
F_2	0.2728	0.2805	0.2881	0.2958	0.3034	0.3138	0.3187	0.3263	0.3340	0.3416	0.3493
F_3	0.2697	0.2724	0.2752	0.2779	0.2806	0.2833	0.2861	0.2889	0.2916	0.2944	0.2971
F_4	0.3943	0.4000	0.4056	0.4113	0.4169	0.4225	0.4282	0.4339	0.4395	0.4451	0.4508
F_5	0.3898	0.3886	0.3874	0.3862	0.3850	0.3837	0.3826	0.3814	0.3801	0.3789	0.3777

Figure 2

Sensitivity Analysis



Comparative Analysis

The duration of selecting and evaluating alternatives from a small or big pool based on relevant characteristics is known as MCDM. A wide range of options are assessed using several criteria as part of MCDM. MCDM techniques are applied to help DMs find the best and most desirable solution to these types of problems. As a result, researchers have introduced many MCDM strategies. We experimented with two MCDM techniques in the FFS framework in this part. The validity and accuracy of the new approach have been confirmed by comparing them with known methodologies.

To verify the robustness of the presented approach, a comparison with IVFF-WASPAS (Rani & Mishra, 2022), IVFF-SWARA (Seikh & Chatterjee, 2024), and Pythagorean fuzzy entropy-SWARA-WASPAS (Alrashadi et al., 2022) will be carried out.

The identical decision matrices and sub-criteria Ws were used in the computations of the comparison approaches. In Table 10, the outputs of the comparisons are shown. The differences between the compared methodologies are shown in Table 10. With a few differences, the results of the method proposed in this work are comparable to those of the IVFF-WASPAS, -SWARA methods, and PF-entropy-SWARA-WASPAS. Since the new methods analyse criteria and alternatives using IVFFSs rather than traditional techniques, they aid in addressing MCGDM issues more sensibly and practically.

Various MCDM approaches may yield various outcomes when applied to a particular situation. Because different methods have different methodological effects and purposes, it makes perfect sense to have varied outcomes (Table 10). Given the distinct features of every decision-making process, it is clear from the results that there have also been some minor tweaks, which makes perfect sense. FFS's structure and many membership levels allow it to produce accurate and flexible results. As a result, the analysis confirms the accuracy of the outputs of the new method.

Table 10

Ranking

Method	F_1	F_2	F_3	F_4	F_5
IVFF-WASPAS	1	2	5	3	4
IVFF-SWARA	1	3	4	5	2
PF-entropy-SWARA-WASPAS	1	4	5	3	2

Conclusion

Governments, businesses, and international organisations care about sustainability and the environment. Because of this, companies are having a hard time becoming more sustainable in reducing the negative environmental impacts of industrial processes without compromising energy efficiency, dependability, performance, quality, or paradigm change. Choosing suppliers and setting supplier priorities have always been difficult for supply chain professionals. It increases the overall economic profit while minimising ecological impact. However, this field is still challenging and requires a more thorough study. Numerous important internal and external components can be found in an organisational supply chain. These components are necessary for planning and implementing the GSCM concepts.

The F, IF, and PF sets are all generalised into the FFS. One of the most popular expansions of FS, PFS, has criteria that state that an object's M and N must be squared and equal to or less than 1. In certain situations, the decision-maker may specify the extent of a feature's M and N to make the sum of the squares bigger than 1. Consequently, the PFS inappropriately handles this scenario. One of the more comprehensive theories is FFS. It can handle incomplete, ambiguous, and inconsistent data commonly found in real-world cases. Hence, FF information DM is more appropriate for valid scientific and technical applications. Making decisions or developing solutions for real-world problems is difficult and perplexing. Therefore, reducing uncertainty is crucial for choosing the best course of action. Effective management of the relationships between the inputs is also necessary for DM to be most beneficial.

This work establishes a unique DM process for the SC system and addresses the challenge of choosing a GSCM. Therefore, the SWARA combined WASPAS methods based on IVFFSs were developed. The Ws of the attributes are determined using the SWARA approach. Decision experts can voice their opinions more freely because the SWARA approach is not scalable. SWARA is easier to calculate and understand because it does not require the solution of intricate linear goal functions. The WASPAS technique ranks the options according to professional judgments regarding particular parameters.

However, to define the robustness and consistency of the suggested methodology, a sensitivity analysis is offered to analyse the impact of the threshold parameter value on the WASPAS technique, the criteria, and the decision-expert Ws. The sensitivity analysis showed that the new model produced balanced outcomes across all tests. In addition, the validity and effectiveness of the new method were evaluated by comparing them with previous studies.

In this study, the algorithms belonging to the methods were integrated and operated with expert knowledge. This shows that the new technique can be successfully implemented when selecting supplier alternatives for GSCM based on the criteria.

The business community can learn how implementing green practices can benefit their company from this study. Businesses can benefit both financially and environmentally by embracing and implementing green strategies. Businesses may boost their productivity, competitiveness, and profitability by implementing green practices. To reduce waste, businesses employ sustainable practices. Customers are more likely to trust businesses that use green practices, which increases optimism, enhances reputational capital, and leads to a larger and more loyal customer base. Regulations, tax benefits, and government subsidies increase the appeal of sustainability. Therefore, buying managers should be aware of suppliers' advantages and emphasise the significance of green cooperation and the necessity of continuous cooperation to develop green practices during every green transaction between a buyer and a supplier. The secret to success is simple, but it requires hard work, leadership, and organisational commitment. Teaching everyone concerned that sustainable and green concepts are more than just a trend is one way to implement green principles. By encouraging sustainable practices, businesses may boost their output, profitability, and competitiveness. Merely being "a good thing to do" is not enough. When adopting green practices, professionals should focus on developing a waste reduction strategy because it will reduce operating costs. Practitioners need to understand that developing a green system involves more than just abiding by the law. An important component is adherence to environmental regulations. Working with elected officials and government regulatory agencies to cultivate goodwill and support from external stakeholders should be one of the primary goals. Experts should emphasise eco-friendly practices that save expenses and waste, increase productivity, and improve brand reputation. Their top priorities should be to hire and retain green-minded employees, create a healthy work environment for their employees, prepare for future laws and regulations that may alter operations, and take advantage of the financial and investment opportunities that come with green practices.

This study provides managers and policymakers with several crucial insights. Managers can use this study to identify the key elements they must prioritise to succeed in their companies and obtain a competitive advantage in the marketplace. Managers can introduce effective plans for reducing their environmental impact. It could entail acquiring more eco-friendly materials, streamlining production processes to use less energy and produce less waste, setting up eco-friendly logistics and transportation networks, etc. These contributions guarantee the continuation of traditional commercial and industrial operations while enhancing the overall resilience of the supply chain. Our analysis has revealed several insights that the top management may find helpful. According to the results, customer demand significantly influences the use of GSCM strategies to preserve sustainability. Environmentally friendly products and activities are becoming increasingly popular, and consumers are increasingly aiming for socially and environmentally sustainable items. Managers need to be aware of the needs and goals of their customers regarding sustainable operations and products. To guarantee that workers have the knowledge and skills necessary to perform GSCM operations effectively, increasing investments in environmentally friendly technologies and practices, staff training, and development are also required.

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Author Details

Ali Kablan (Assoc. Prof.)

[1] İstanbul University-Cerrahpaşa, Department of Foreign Trade, İstanbul, Türkiye

0000-0003-2711-0034 ali.kablan@iuc.edu.tr

Serdar Kuzu (Assoc. Prof.)

[2] İstanbul University-Cerrahpaşa, Accounting and Tax Department, İstanbul, Türkiye

0000-0001-8178-8749 serdar.kuzu@iuc.edu.tr

Murat Kirişci (Prof. Dr.)

[3] İstanbul University-Cerrahpaşa, Department of Biostatistics and Medical Informatics, İstanbul, Türkiye

0000-0003-4938-5207 murat.kirisci@iuc.edu.tr

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