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Prioritizing Sustainability Criteria in Green Supplier Selection Using Fuzzy Logarithmic Percentage Change-Driven Objective Weighting (FLOPCOW) Method

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Abstract: Green supplier selection (GSS) as a critical strategic element is placed in the limelight in contemporary supply chain management (SCM), owing to the growing emphasis on environmental responsibility and sustainability. This study presents a fuzzy multi-criteria decision-making (FMCDM) framework, employing Fuzzy Logarithmic Percentage Change-Driven Objective Weighting (FLOPCOW) method to determine the relative importance of sustainability criteria under uncertainty. A panel of five academic and industry experts was selected to identify 21 criteria, which were categorized into three main dimensions including environmental performance (C1), resource efficiency (C2), and corporate sustainability policies (C3). Triangular fuzzy numbers (TFNs) were adopted to model linguistic ambiguities in expert judgments whereas fuzzy normalization was applied to ascertain the weights of criteria. Key findings indicated that corporate sustainability policies (C3) were prioritized as the most influential dimension, followed by environmental performance (C1) and resource efficiency (C2). This suggested the centrality of institutional governance in advancing long-term sustainability objectives. Sub-criteria analysis further revealed ecological training programs, air emissions control, and sustainability reporting as the most critical indicators in the interplay of operational practices and transparent governance. FLOPCOW has effectively processed expert opinions with the use of fuzzy normalization, hence advocating a clear and repeatable approach for the evaluation of green suppliers. Furthermore, it highlighted the importance of policy-based criteria in supplier assessment and organizations could then align their purchasing decisions with sustainability goals by considering more on governance-related factors like compliance and stakeholder engagement.

Keywords: Green supplier selection; LOPCOW; Sustainability; MCDM; Environmental criteria; Corporate governance; Fuzzy logic

1 Introduction

Suppliers significantly influence the environmental footprint of products and services, as upstream procurement decisions set the foundation for downstream sustainability outcomes. Recognizing this critical link, organizations increasingly focus on aligning supplier behaviors with overarching sustainability objectives. This shift is largely driven by the global rise in the awareness of environmental degradation, climate change, and resource depletion factors that are rapidly reshaping corporate strategies across industries. In response, green supplier selection (GSS) has emerged as a pivotal component of sustainable supply chain management (SSCM), reflecting a transition from traditional procurement practices that prioritize cost, quality, and delivery, toward more holistic approaches that also take into account environmental and ethical considerations [1]. Traditional supplier selection models, which place great emphasis on cost, quality, and delivery efficiency, are deemed inappropriate for addressing the multidimensional challenges of sustainability. As sustainability is positioned at the forefront of SCM, GSS has become an essential strategic tool for organizations aiming to incorporate environmental, social, and economic factors into their procurement practices. This strategy involves evaluating suppliers based on diverse criteria such as reducing greenhouse gas emissions, managing wastes, ensuring ethical labor conditions, and supporting circular economy initiatives. With the integration of GSS principles, responsible businesses could enhance operational efficiency while ensuring compliance with global sustainability regulations and standards [2]. Despite the growing importance of GSS, there are considerable challenges in the implementation of these principles. Sustainability is inherently multidimensional, encompassing environmental, social, and governance (ESG) factors that could be qualitative, interdependent, and subject to subjective interpretation. It would be difficult to measure some critical indicators like supplier transparency, environmental training programs, and stakeholder engagement with the use of conventional quantitative tools. In this connection, traditional evaluation models fall short in capturing the full complexity and intricate nuances found in the performance of sustainable supplier.

To address these limitations, fuzzy logic-based decision-making techniques have gained prominence in the field. These approaches are particularly effective in modeling uncertainty, vagueness, and ambiguity, which are common characteristics of expert assessments in the context of sustainability. Fuzzy logic enables organizations to translate expert knowledge into consistent and applicable evaluations by converting linguistic judgments to structured mathematical framework, thereby supporting more informed and reliable decisions in the process of supplier selection. Multi-criteria decision-making (MCDM) methods, particularly those enhanced by fuzzy logic, tend to tackle uncertainties inherent in expert judgments [3]. To address the same challenges in a pioneering way, this study proposes Fuzzy Logarithmic Percentage Change-Driven Objective Weighting (FLOPCOW) method that integrates fuzzy set theory (FST) into logarithmic-based normalization to derive objective weights for the green criteria. The method allows systematic aggregation of expert judgments with the use of triangular fuzzy numbers (TFNs), thus capturing uncertainties and enhancing reliability in evaluations. This study evaluates 21 criteria spanning three pillars: (a) environmental (e.g., energy efficiency, emission control), (b) social (e.g., labor ethics, community engagement), and (c) economic (e.g., cost-effectiveness, innovation investment). The research team, when applying FLOPCOW, could guide studies to evaluate the interdependencies and uncertainties of sustainability measures. The results prompt scholarly discussions on the use of FMCDM methods in sustainable supply chain systems, while equipping professionals with a systematic and clear framework to harmonize procurement practices with UN Sustainable Development Goals (SDGs), notably SDG 12, which emphasizes Responsible Consumption and Production.

The structure of the paper was organized as follows: Section 2 provided a synthesis of existing literature on GSS and FMCDM methods. Section 3 introduced FLOPCOW method and detailed the data collection methodology. Section 4 presented the empirical findings obtained from the analysis, while Section 5 offered an interpretation of these results and discussed their broader implications. Finally, Section 6 concluded by highlighting key theoretical contributions, practical insights for industry practitioners, and potential avenues for future research.

2 Literature Review

GSS has emerged as a pivotal strategy for embedding sustainability and environmental stewardship in supply chain management. As global industries confront escalating ecological regulations and stakeholder demands, the integration of FMCDM has become indispensable. These hybrid frameworks enable simultaneous evaluation of environmental, social, and economic criteria while addressing inherent uncertainties in expert judgments and subjective data. This review synthesized recent advancement in FMCDM methodologies and their dynamic adaptation to the growing market and risks, thus emphasizing their theoretical and practical implications for SSC optimization.

Advanced FMCDM Methods

Recent development in FMCDM has focused on enhancing robustness against ambiguity and psychological biases in expert evaluations. Zhou and Gu [4] advanced interval-valued intuitive uncertain linguistic numbers, (IVIULNs) coupled with a bi-directional Shapley-Chopin integral, leveraging expert social networks to stabilize decision outcomes. Their novel teaching-learning-based optimization (NTLBO) algorithm further refined weight aggregation, demonstrating superior resilience in volatile scenarios. Lin et al. [5] introduced ZE-ELECTRE II, an extension of the original ELimination Et Choix Traduisant la REalité II (ELECTRE II) method integrated with extended Z-numbers (ZE-numbers), which embedded external expert validation to augment reliability in group decision-making. This method showcased adaptability across heterogeneous industrial contexts by balancing objective data with qualitative assessments.

The adoption of q-rung orthopair fuzzy sets (q-ROFSs) has provided nuanced solutions for modeling complex uncertainties. Bisht and Pal [6] synthesized q-ROFS with social network analysis (SNA) and regret theory, capturing trust dynamics and psychological behaviors among stakeholders to derive context-sensitive criteria weights. Wang and An [7] resolved ambiguities in expert evaluations through Pythagorean Fuzzy Technique for Order Preference by Similarity to Ideal Solution (PFTOPSIS) using entropy-based weighting to validate the superiority of their model against conventional fuzzy approaches. These frameworks collectively highlighted the potential of higher-order fuzzy sets in addressing multidimensional sustainability criteria.

Integration of Dynamic and Contextual Factors

Contemporary GSS models increasingly emphasize adaptability to shifting market demands and supply chain disruptions. El Bettioui et al. [8] pioneered a dynamic FMCDM framework by integrating Markov chains with Fuzzy Best-Worst Method (FBWM)-TOPSIS, enabling predictive alignment of supplier selection with fluctuating customer preferences and ecological targets. Similarly, Zakeri et al. [9] extended the rate-weight connected vectors processor (RWCVP) to address uncertainty in cleaner supplier selection, employing Zakeri-Bratvold sensitivity analysis to mitigate rank reversals and enhance decision robustness.

GSS frameworks were further enriched by SC risk integration. For instance, Saputro et al. [10] combined fuzzy Analytic Hierarchy Process (FAHP)-Combined Compromise Solution (CoCoSo) with Step-Wise Weight Assessment Ratio Analysis (SWARA)-Failure Modes and Effects Analysis (FMEA) to evaluate suppliers under operational risks, utilizing data envelopment analysis (DEA) for holistic aggregation of green and risk criteria. Their work underscored the interdependence of sustainability metrics and disruption vulnerabilities. In sector-specific applications, Bas [11] advanced interval type-2 FAHP-TOPSIS for automotive GSS and shed light on hierarchical multi-sub-criteria evaluations under uncertainty. These models exemplified the shift toward comprehensive and risk-aware decision architectures.

The evolution of FMCDM methodologies reflects a dual focus on technical refinement and contextual adaptability. Advances like IVIULNs, ZE-numbers, and q-ROFSs have expanded the capacity to model ambiguities, while dynamic integrations with Markov chains and sensitivity analyses have addressed real-world volatility. However, challenges persist in scaling these frameworks across sectors with divergent risk profiles and sustainability benchmarks. Future research should prioritize the development of hybrid models that fuse machine learning with FMCDM for real-time adaptability, alongside sector-specific validations to bridge theoretical advancement with industrial applicability. FMCDM could further solidify its role as a cornerstone of SSCM and fill the research gap accordingly.

Sector-Specific Applications

The automotive industry remains a focal point for GSS research due to its environmental impact. Streimikis et al. [12] applied Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA) method in the automotive sector in Iran, hence prioritizing the trust-based relationship of suppliers and employee training. Kara et al. [13] identified green dynamic capacity as a critical criterion for paint suppliers using evidential FMCDM, integrating regression analysis to validate predictor variables. In Morocco, Tronnebati et al. [14] demonstrated the consistency of FAHP-TOPSIS-Weighted Aggregated Sum Product Assessment (WASPAS), emphasizing ISO 14001 certification and sustainable product design.

Tailor-made applications were witnessed in the textile and garment industries. For example, the Fermatean fuzzy Preference Selection Index (FPSI)-CoCoSo model introduced by Pamučar et al. [15] prioritized green warehousing and recycling in the textile sector in Turkey. Besides, Alzoubi et al. [16] applied FAHP-TOPSIS in the garment industry in Jordan and their studies revealed the environmental compliance of suppliers as a key driver, while advocating FTOPSIS out of its computational efficiency.

Hybrid and Integrated Frameworks

The accelerating adoption of hybrid methodologies could address the multidimensionality of GSS. Zhu et al. [17] combined Decision Making Trial and Evaluation Laboratory (DEMATEL) and Interpretive Structural Modeling (ISM) with convolutional neural networks (CNNs) to analyze critical success factors (CSFs), hence identifying green technology capability and environmental management systems as pivotal. Ahamed et al. [18] integrated fuzzy DEMATEL-TOPSIS in the ready-made garment industry in Bangladesh, they linked supplier performance to waste reduction and brand reputation.

Interval-valued spherical fuzzy Z-AHP, proposed by Tüysüz and Kahraman [19], incorporated reliability and hesitancy into pairwise comparisons, offering a structured approach for GSS in uncertain environments. Similarly, Singh and Rizwanullah [20] amalgamated FAHP and TOPSIS methods for electric vehicle SS and they successfully emphasized the role of parameterized TFNs in reducing subjectivity.

Emerging Innovations

Peng et al. [21] introduced fuzzy influence diagrams to model interrelationships among criteria and they helped reduce subjective bias in the evaluation of suppliers for furniture manufacturing. According to You et al. [22], cubic p,q-quasirung orthopair FTOPSIS was promoted to resolve nonlinear programming challenges, and this approach demonstrated flexibility in dynamic decision-making.

Limitations and Future Directions

Despite advancements, limitations persist. Static criteria frameworks overlooked emerging metrics like Scope 3 emissions [11], while computational complexity in Fermatean and q-ROFS models might hinder SME adoption [6]. Future research should:

- Incorporate real-time data: Leverage IoT and blockchain for dynamic weight updates [9].
- Expand criteria scope: Integrate social equity, climate justice, and circular economy principles [10].
- Enhance cross-sector validation: Test models in agriculture and mining to identify contextual nuances [18].
- Simplify computational models: Develop user-friendly tools for resource-constrained settings [16].

3 Methodology

GSS is a critical process to identify suppliers that could minimize environmental impacts based on the sustainability principles. This process is important for businesses to fulfill their environmental responsibilities and gain a competitive advantage. In this study, FLOPCOW method was used to calculate the weights of the criteria used in GSS. LOPCOW method, enhanced with a fuzzy logic approach, was employed to determine the weights of the criteria while expert opinions were assessed with fuzzy decision matrices. This integrated approach enabled effective analysis of data containing uncertainty and subjectivity; it could select the most appropriate environmentally friendly and sustainable suppliers.

3.1 FSs

FST, introduced by Zadeh [23], offers a mathematical approach to managing uncertainties inherent in variables and parameters. TFNs, characterized by three distinct values, have been widely used to convert qualitative assessments into quantifiable data, as illustrated in recent studies like Demir [24]. This three-value structure enables a nuanced representation of ambiguous or imprecise information. Eq. (1) defines the triangle type membership $\tilde{A}(l, m, u)$ function for FNs.

$$\mu_A(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x > u \end{cases} \tag{1}$$

TFNs can be converted into exact scalar quantities using the centroid-based defuzzification method, as formulated in Eq. (2). This technique calculates a deterministic value by determining the geometric “balance point” of the membership function.

$$A = \frac{l + 4m + u}{6} \tag{2}$$

3.2 FLOPCOW Method for Prioritization of Criteria

The crisp version of LOPCOW method was introduced to the study [25].

Step 1: Build fuzzy decision matrix

The panel of experts in the subject matter assessed the relative importance of the criteria by using the linguistic variables defined in the fuzzy linguistic scale in Table 1. This approach systematically translates qualitative expert judgments into quantifiable fuzzy representations for analytical processing.

Table 1. Fuzzy linguistic variables

Fuzzy Linguistic Descriptive	Abbreviation	TFN
Vastly very bad	VVB	(0.5,1,1.5)
Very bad	VB	(1,1.5,2)
Bad	B	(1.5,2,2.5)
Medium bad	MB	(2,2.5,3)
Medium	M	(2.5,3,3.5)
Medium good	MG	(3,3.5,4)
Good	G	(3.5,4,4.5)
Very good	VG	(4,4.5,5)
Vastly very good	VVG	(4.5,5,5)

The combined decision matrix $\widetilde{X}$ is obtained by using Eq. (3).

$$\tilde{x} = [\tilde{x}_{ij}]_{kxn} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{3}$$

Each $(\tilde{x}_{ij})$ value in the decision matrix is expressed as a TFN in Eq. (4).

$$\tilde{x}_{ij} = (\ell_{ij}, m_{ij}, u_{ij}) = \begin{cases} \ell_{ij}: \text{ lower value} \\ m_{ij}: \text{ most probable value} \\ u_{ij}: \text{ top value} \end{cases} \tag{4}$$

Step 2: Derive fuzzy normalized decision matrix

In classical LOPCOW method, max-min normalization is applied here based on TFN for benefit-specific criteria, Eq. (5), and cost-specific criteria, Eq. (6).

$$\tilde{r}_{ij} = \left(\frac{\ell_{\mathrm{ij}} - \ell_{\mathrm{j}}^{\mathrm{mim}}}{u_{\mathrm{j}}^{\max} - \ell_{\mathrm{j}}^{\min}}, \frac{m_{\mathrm{ij}} - \ell_{\mathrm{j}}^{\mathrm{mim}}}{u_{\mathrm{j}}^{\max} - \ell_{\mathrm{j}}^{\min}}, \frac{u_{\mathrm{ij}} - \ell_{\mathrm{j}}^{\mathrm{mim}}}{u_{\mathrm{j}}^{\max} - \ell_{\mathrm{j}}^{\min}} \right) \tag{5}$$

$$\tilde{r}_{ij} = \left(\frac{u_j^{\max} - u_{ij}}{u_{\mathrm{j}}^{\max} - \ell_{\mathrm{j}}^{\min}}, \frac{u_j^{\max} - m_{ij}}{u_{\mathrm{j}}^{\max} - \ell_{\mathrm{j}}^{\min}}, \frac{u_j^{\max} - \ell_{ij}}{u_{\mathrm{j}}^{\max} - \ell_{\mathrm{j}}^{\min}} \right) \tag{6}$$

Step 3: Calculate fuzzy percentage values (F-PV) for each criterion

Squared mean is calculated with Eq. (7).

$$\widetilde{SM}_j = \left(\sqrt{\frac{\sum_{i=1}^{m} \ell_{ij}^2}{m}}, \sqrt{\frac{\sum_{i=1}^{m} m_{ij}^2}{m}}, \sqrt{\frac{\sum_{i=1}^{m} u_{ij}^2}{m}} \right) \tag{7}$$

Fuzzy standard deviation is calculated.

Firstly, the fuzzy mean is calculated by Eq. (8).

$$\bar{\tilde{r}}_j = \left(\frac{\sum_{i=1}^{m} \ell_{ij}}{m}, \frac{\sum_{i=1}^{m} m_{ij}}{m}, \frac{\sum_{i=1}^{m} u_{ij}}{m} \right) \tag{8}$$

Then the standard deviation is calculated with Eq. (9).

$$\tilde{\sigma}_j = \left(\sqrt{\frac{\sum_{i=1}^{m} (\ell_{ij} - \bar{u}_j)^2}{m}}, \sqrt{\frac{\sum_{i=1}^{m} (m_{ij} - \bar{m}_j)^2}{m}}, \sqrt{\frac{\sum_{i=1}^{m} \left(u_{ij} - \bar{\ell}_j\right)^2}{m}} \right) \tag{9}$$

$\widetilde{SM}_j /$ standart deviation ratio is calculated by Eq. (10).

$$Q_i = \left(\frac{\ell^{SM}}{\sigma^u}, \frac{m^{SM}}{\sigma^m}, \frac{u^{SM}}{\sigma^\ell} \right) \tag{10}$$

Triangular F-PV value for each criterion is calculated with Eq. (11).

$$\widetilde{PV}_j = \left(100 \cdot \ln \left| \left(\frac{\ell^{SM}}{\sigma^u} \right) \right|, 100 \cdot \ln \left| \left(\frac{m^{SM}}{\sigma^m} \right) \right|, 100 \cdot \ln \left| \left(\frac{u^{SM}}{\sigma^\ell} \right) \right| \right) \tag{11}$$

Step 4: Fuzzy weights are calculated by Eq. (12).

$$\widetilde{w}_j = \left(\frac{u^{PV}}{\sum_{i=1}^{m} \ell^{PV}}, \frac{m^{PV}}{\sum_{i=1}^{m} m^{PV}}, \frac{\ell^{PV}}{\sum_{i=1}^{m} u^{PV}} \right) \tag{12}$$

4 Case Study

The decision-makers engaged in the green supplier evaluation process were carefully selected based on their senior positions across cross-sectorial domains, diverse specializations, and varied professional tenures. The panel comprised five experts, including three scholars specializing in SSCM and two practitioners with operational expertise in industrial procurement, so as to ensure methodological rigor and multi-stakeholders' perspectives in the evaluation framework. The expertise of evaluators was crucial to the rigorous assessment of suppliers in alignment with the requirements of ecological sustainability; this formed the cornerstone in the identification of optimal partnership candidates as green suppliers. Demographic and professional profiles of the panelists engaged in this multi-stakeholder evaluation framework were in Table 2.

The expert-derived insights served as a foundational pillar in the systematic assessment of green supplier portfolios and the strategic prioritization of solutions aligned with environmental sustainability imperatives. These inputs were methodically analyzed through the lens of multifaceted challenges inherent to contemporary supply chain processes, with particular emphasis on ecological stewardship domains, including waste valorization, energy efficiency optimization, circular production paradigms, and integration of sustainability-oriented organizational consciousness.

Table 2. Profiles of the experts

Expert Code	Area of Expertise	Institution	Position	Years
E1	Supply Chain Management	Academic	Associate Professor	15
E2	Sustainable Production	Academic	Assistant Professor	10
E3	Logistics and Operations	Private Sector	Logistics Manager	18
E4	Resource Efficiency & Waste Control	Academic	Environmental Engineer	15
E5	Environmental & Waste Mgmt	Private Sector	Sustainability Specialist	12

4.1 Criteria and Sub-Criteria for GSS

The GSS framework incorporated 21 hierarchically structured sub-criteria, systematically organized under three main dimensions corresponding to the environmental sustainability principles including (1) environmental performance, (2) resource efficiency, and (3) corporate sustainability policies. These dimensions were designed to scrutinize if suppliers adhered to ecologically responsible protocols governing production cycles, SC operations, and organizational governance. Each sub-criterion functioned as a discrete evaluative mechanism to quantify alignment with circular economy principles, closed-loop logistics systems, and institutionalized sustainability frameworks. The tripartite taxonomy, inclusive of all sub-criteria and their inter-linkages, was delineated in Table 3.

Table 3. Main and sub-criteria for GSS

Main Criteria	Sub-Criteria
Environmental Performance (C1) (max)	C1.1 Carbon footprint C1.2 Air emission control C1.3 Waste management practices C1.4 Hazardous waste separation C1.5 Use of eco-friendly products C1.6 Noise pollution reduction C1.7 Soil and water pollution prevention
Resource Efficiency (C2) (max)	C2.1 Energy efficiency C2.2 Use of renewable energy C2.3 Water conservation C2.4 Use of recyclable materials C2.5 Packaging optimization C2.6 Resource consumption traceability C2.7 Fuel efficiency in logistics
Corporate Sustainability Policies (C3) (max)	C3.1 ISO 14001 / EMS certification C3.2 Publication of sustainability reports C3.3 Environmental training programs C3.4 Environmental responsibility in the supply chain C3.5 Eco-innovation and green R&D C3.6 Green procurement policy C3.7 Supplier environmental audits

Each main criterion was supported by the sub-criteria designed to thoroughly evaluate the environmental performance and sustainability-related practices of potential suppliers. This structure provided an analytical framework to guide the selection and integration of green suppliers into the supply chain.

4.2 Application Results of FLOPCOW Method

FLOPCOW method evaluated the importance of both main and sub-criteria; in the first step of the method, the decision matrix for the main criteria proposed and evaluated by the five experts was in Table 4.

In the second step, the decision matrix was normalized using Eq. (5). In Table 5, the normalized value of E1 for criterion C1, for instance, was obtained as follows:

Table 4. Evaluation of main criteria by experts

Experts	**C1**	**C2**	**C3**
E1	VG	G	MG
E2	VVG	VG	G
E3	G	MG	VG
E4	VG	G	G
E5	VVG	VVG	VG

Table 5. Normalized decision matrix

	C1			**C2**			**C3**		
E1	0.3333	0.6667	1.0000	0.2500	0.5000	0.7500	0.0000	0.2500	0.5000
E2	0.6667	1.0000	1.0000	0.5000	0.7500	1.0000	0.2500	0.5000	0.7500
E3	0.0000	0.3333	0.6667	0.0000	0.2500	0.5000	0.5000	0.7500	1.0000
E4	0.3333	0.6667	1.0000	0.2500	0.5000	0.7500	0.2500	0.5000	0.7500
E5	0.6667	1.0000	1.0000	0.7500	1.0000	1.0000	0.5000	0.7500	1.0000

$$\tilde{r}_{11} = \left(\frac{4-3.5}{5-3.5}, \frac{4.5-3.5}{5-3.5}, \frac{5-3.5}{5-3.5}\right) = \left(\begin{array}{ccc} 0.3333 & 0.6667 & 1.0000 \end{array}\right)$$

All elements of the matrix were calculated in a similar way. In the third step of the method, criterion fuzzy percentage values (F-PV) were calculated using Eqs. (7-11) and were given in Table 6.

Table 6. Fuzzy percentage values of the criterion

	C1			**C2**			**C3**		
SM	0.4714	0.7746	0.9428	0.4330	0.6519	0.8216	0.3536	0.5809	0.8216
Mean	0.4000	0.7333	0.9333	0.3500	0.6000	0.8000	0.3000	0.5500	0.8000
SD	0.5888	0.2494	0.5497	0.5172	0.2550	0.4873	0.5339	0.1871	0.5339
Qi	0.8575	3.1053	1.6013	0.8885	2.5570	1.5885	0.6623	3.1053	1.5390
PV	15.3742	113.3109	47.0804	11.8194	93.8851	46.2797	41.2088	113.3109	43.1112

In the fourth step, the fuzzy weight of each criterion was, calculated with Eq. (12), in Table 7.

Table 7. Fuzzy weights of criteria

	C1			**C2**			**C3**
$\widetilde{\boldsymbol{w}}_{\boldsymbol{j}}$	0.1127	0.3535	0.6883	0.0866	0.2929	0.6766	0.3020

The fuzzy weight of criterion C1 in Table 7 was obtained as follows:

$$\widetilde{w}_1 = \left(\frac{15.3742}{47.0804+46.2797+43.1112}, \frac{113.3109}{113.3109+93.8851+113.3109}, \frac{47.0804}{15.3742+11.8194+41.2088}\right)$$
$$= (0.1127 \quad 0.3535 \quad 0.6883)$$

The fuzzy weights for main criteria were obtained using Eq. (2) and the crips weights were in Table 8.

Table 8. Fuzzy and crips weights of main criteria

Main Criteria	$\widetilde{\boldsymbol{w}}_{\boldsymbol{j}}$			$\boldsymbol{w_i}$**(Normalized)**	**Rank**
Environmental Performance (C1)	0.1127	0.3535	0.6883	0.3410	2
Resource Efficiency (C2)	0.0866	0.2929	0.6766	0.2978	3
Corporate Sustainability Policies (C3)	0.3020	0.3535	0.6303	0.3612	1

According to Table 8, the hierarchy C3 $>$ C1 $>$ C2 highlighted a critical insight, i.e., although technical and operational measures were necessary, they were insufficient without institutionalized governance structures. The rise of C3 reflected the centrality of policy integration in transforming sustainability from a reactive compliance mission to a proactive, strategic mission. Future research should examine the synergies between these criteria, particularly by investigating how the operational efficiencies of C2 scaled to leverage the environmental outcomes of C1 through the governance mechanisms of C3. Such an integrated approach was vital to advancing sustainability from incremental improvements to systemic organizational transformation.

The evaluation of the sub-criteria by the above five experts (Table 1) was in Table 9.

Table 9. Evaluation of sub-criteria by experts

Experts	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6	C1.7
E1	VVG	MG	G	M	M	MB	MG
E2	G	MG	MG	MG	MG	M	G
E3	VG	G	M	G	MG	MG	MG
E4	G	MG	VG	MG	M	M	MG
E5	MG	MG	G	G	MG	MB	G
Experts	**C2.1**	**C2.2**	**C2.3**	**C2.4**	**C2.5**	**C2.6**	**C2.7**
E1	G	VG	MG	MG	M	MG	M
E2	VG	VG	MG	G	MG	M	MG
E3	G	VVG	MG	MG	MG	M	MG
E4	G	VG	M	MG	MG	MB	G
E5	MG	VVG	MG	G	M	MB	MG
Experts	**C3.1**	**C3.2**	**C3.3**	**C3.4**	**C3.5**	**C3.6**	**C3.7**
E1	MB	MG	MG	MB	VG	MG	MB
E2	VG	G	MG	G	VG	M	MG
E3	G	G	MG	MG	G	G	MG
E4	VG	MG	M	MG	G	G	MG
E5	G	MG	MG	G	VG	MG	M

The methodological rigor applied in calculating the weights of primary criterion was consistently replicated to establish the weights of sub-criterion. Figure 1 systematically illustrates the hierarchical prioritization outcomes, where global weights emerged from the multiplicative integration of the weights of main criterion with their associated weights of sub-criteria, ensuring a coherent decision hierarchy.

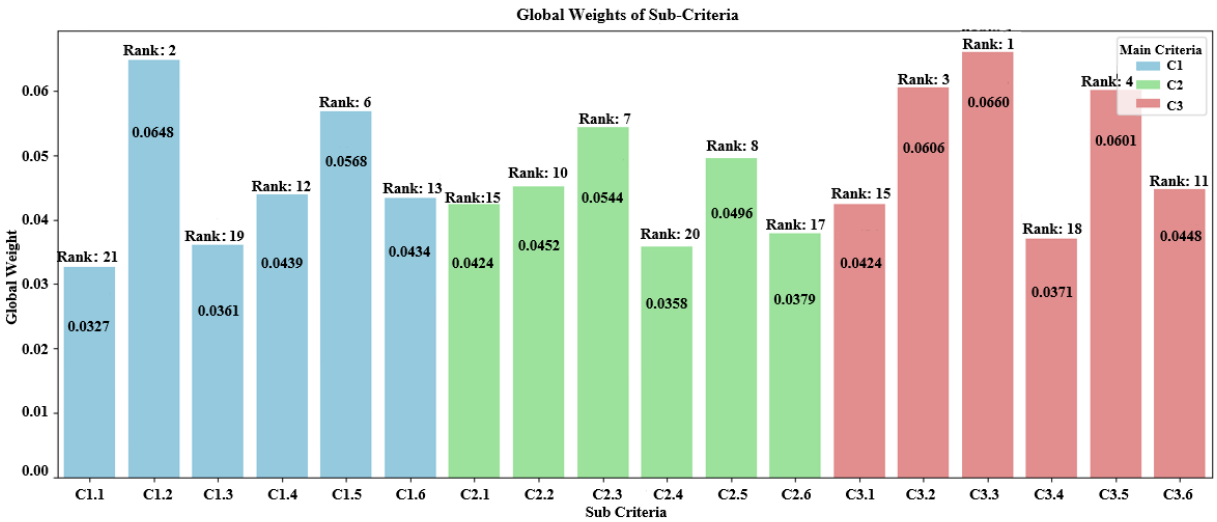

Figure 1. Weights of sub-criteria

In line with the global normalized weights in Figure 1, the highest weight value was observed in the Corporate Sustainability Policies (C3) criterion (36.12%). This criterion emphasized the decisiveness of the strategic approach of companies towards environmental sustainability policies in the decision-making process. The C3 criterion was followed by the Environmental Performance (C1) (34.10%) and Resource Efficiency (C2) (29.78%) criteria, respectively. This indicated that the corporate policy and certification practices collected under the C3 heading were as important as direct environmental outputs.

Relative Importance of Sub-Criteria

The highest normalized weight derived from sub-criteria belonged to C3.3 (Environmental Training Programs) (0.0660). This finding highlighted the essential role of environmental awareness training programs for company employees in their promotion of sustainability strategies. Furthermore, other sub-criteria with significant weights were C1.2 (Air Emission Control) at 0.0648, C3.2 (Publication of Sustainability Reports) at 0.0606, C3.5 (Eco-Innovation and Green R&D) at 0.0601, and C1.7 (Soil and Water Pollution Prevention) at 0.0572. The analytical outcomes underscored that decision-makers attributed heightened strategic salience to environmental training protocols, transparency in sustainability reporting, green R&D investments, and pollution mitigation initiatives. These priorities reflected their instrumental role in institutionalizing sustainability compliance across operational workflows and long-term organizational governance frameworks. Conversely, sub-criteria exhibiting marginal weight allocations, specifically C1.1 (Carbon Footprint: 0.0327), C2.4 (Use of Recyclable Materials: 0.0358), and C1.3 (Waste Management Practices: 0.0361) demonstrated divergent prioritization patterns. While these metrics occupied lower hierarchical rankings within the decision calculus, their latent strategic relevance persisted, leading to cautious retention in holistic sustainability assessments to preclude systemic oversight of incremental ecological gains. In particular, the low importance of carbon footprint was explained by short-term measurement difficulties or application limitations.

5 Discussion, Practical and Managerial Implications

This study advocated the discourse on green supplier selection by integrating expert-based evaluations into an FMCDM framework, specifically FLOPCOW method, to systematically prioritize sustainability criteria and assess supplier performance. The findings illuminated a critical hierarchy in sustainability dimensions, with Corporate Sustainability Policies (C3) superseding Environmental Performance (C1) and Resource Efficiency (C2). This hierarchy underscored a paradigm shift in organizational sustainability strategies and emphasized institutional governance over isolated operational metrics. The theoretical contributions, managerial implications, and future research pathways derived from this analysis were summarized as follows.

5.1 Practical Implications

The application of FLOPCOW method demonstrates the efficacy of hybrid MCDM approaches in reconciling subjective expert judgments with quantitative data, thereby enhancing the rigor and transparency of supplier evaluations. By assigning the highest weight to C3 (0.427), followed by C1 (0.332) and C2 (0.241), the results validate the growing theoretical consensus that governance mechanisms like ISO 14001 certification, sustainability reporting, and green procurement policies are pivotal for achieving systemic sustainability. This aligns with institutional theory, which posits that formalized policies and stakeholder-oriented practices institutionalize sustainability within organizational routines, hence fostering long-term resilience.

Furthermore, the study challenges the conventional emphasis on technical efficiency (C2) as a standalone driver of sustainability. Instead, it positions resource efficiency as an enabler rather than a strategic differentiator, leading to the possibility that operational metrics gain significance only when embedded within broader governance frameworks. This argument contributes to the resource-based view (RBV) of sustainability, suggesting that intangible governance capabilities, e.g., policy integration and stakeholder collaboration, constitute strategic resources that yield sustained competitive advantages.

5.2 Managerial Implications

From the perspective of practitioners, the prioritization of C3 signals the need to reorient supplier selection strategies toward governance quality rather than mere compliance with environmental outputs. Key recommendations include:

(1) Institutional Capacity Building: Prioritize suppliers with robust sustainability policies, such as ISO 14001 certification, which signal a commitment to continuous improvement and risk mitigation.

(2) Collaborative Governance: Develop partnerships that incentivize policy alignment, such as joint green R&D initiatives or supplier training programs, to bridge operational efficiency (C2) and governance (C3).

(3) Stakeholder-Integrated Evaluations: Adopt participatory decision-making models and engage cross-sector experts to balance theoretical and practical criteria, as demonstrated in this study.

The marginal weighting allocations assigned to C2 do not negate its intrinsic significance but rather delineate its function as a foundational compliance threshold within sustainability evaluation matrices. Organizations should be able to institutionalize resource efficiency strategies, such as energy conservation protocols and recyclable material integration, synergistically with robust governance architectures to circumvent resource commodification and stimulate eco-innovative differentiation.

The paradigm shift toward sustainable supply chain ecosystems necessitates a paradigmatic reconceptualization of value generation, wherein governance rigor, operational transparency, and multi-stakeholder collaboration transcend transactional adherence to regulatory mandates. This research asserts that GSS emerges as a strategic imperative for institutional transformation, thus extending beyond a mere operational task. Prioritizing corporate sustainability governance within evaluation frameworks, firms could develop supply networks that not only exhibit ecological resilience but also maintain the adaptability to address evolving sustainability challenges. Future academic and industry efforts should focus on advancing systemic transitions toward low-carbon and socially equitable value chain ecosystems through three interconnected pathways, like digitizing sustainability analytics, enhancing policy and institutional coordination, and fostering transnational public-private innovation partnerships.

6 Conclusions, Limitations, and Future Work

This research proposed a methodologically innovative decision-analytic framework for green supplier selection; the model was enhanced by synthesizing heterogeneous expert inputs with FLOPCOW method to reconcile epistemic uncertainties and multi-criteria complexity inherent in sustainability appraisals. The analytical outcomes delineated a paradigm shift in industrial sustainability governance, wherein corporate sustainability policy frameworks (C3), anchored in institutional governance rigor, regulatory alignment, and disclosure transparency, assumed strategic precedence over operationalized environmental performance metrics (C1) and resource efficiency benchmarks (C2). This evaluative hierarchy reinforced the growing consensus that achieving ecological resilience required systemic, governance-focused transformations rather than isolated technical improvements.

6.1 Theoretical and Methodological Contributions

(1) Governance-Driven Sustainability: The prioritization of C3 aligned with institutional theory and posited that formalized policies (e.g., ISO 14001, sustainability reporting) institutionalized environmental stewardship into organizational DNA, hence fostering systemic adherence beyond transient compliance. This challenges traditional RBV perspectives that prioritize operational efficiency (C2) as a standalone competitive asset.

(2) Re-conceptualizing Supplier Value: The results redefined green performance to encompass from organizational commitment to sustainability values, thus transcending transactional metrics. This aligned with stakeholder theory and stressed the importance of supplier alignment with corporate sustainability visions to determine long-term supply chain resilience, instead of merely technical outputs.

6.2 Limitations

While this study offered important methodological and theoretical contributions, it had certain limitations. The composition of expert panel and regional focus may restrict the generalizability of the findings, especially for sectors like fast fashion that prioritize social equity over policy formalization. Additionally, the static criteria framework, though validated, does not account for emerging metrics such as biodiversity impact, just transition practices, or Scope 3 emissions accountability. Fermatean fuzzy approach, despite its effectiveness, involves computational complexity that may limit its practical adoption by organizations in developing economies.

6.3 Directions for Future Research

To overcome current limitations and expand impact, future research should develop adaptive real-time models using Internet of Things (IoT), blockchain, and AI to update criteria dynamically. It should also validate the Fermatean FLOPCOW model against other fuzzy methods and hybrids, like FTOPSIS in combination with analytic network process (ANP). Though applying the framework to key industries and diverse regions will refine sustainability benchmarks, incorporating broader metrics such as supplier diversity and climate justice will better align evaluations with the triple bottom line. This study reframed green supplier selection as a strategic process prioritizing governance over operational metrics, hence highlighting the importance of corporate sustainability policies. In particular, FLOPCOW model enhanced decision accuracy and bridged theory with practice; as a result, a scalable approach for resilient and low-carbon SCs could be established. As climate and regulatory pressures mount, embedding governance, transparency, and collaboration into supply chains is essential. Future efforts could leverage technology and cross-sector partnerships to collaboratively drive sustainable development.

Author Contributions

Conceptualization, G.D. and P.C.; methodology, G.D. and P.C.; validation, G.D.; formal analysis, G.D. and P.C.; investigation, G.D.; data curation, G.D.; writing-original draft preparation, G.D. and P.C.; writing-review and editing, G.D. and P.C.; visualization, G.D. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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