A Hesitant Fuzzy SAW-MULTIMOORA Approach for ESG-Oriented Supplier Risk Ranking

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Abstract—**Environmental, Social, and Governance (ESG) risks have a growing impact on supply chain continuity and compliance. However, assessing ESG risks among existing suppliers is frequently hindered by heterogeneous data and uncertain expert judgments. This paper aims to rank suppliers based on ESG risks by introducing a hesitant fuzzy Multi-Criteria Decision-Making (MCDM) framework. Expert evaluations are represented using hesitant fuzzy sets. To weigh the ESG factors, the hesitant fuzzy Simple Additive Weighting (SAW) method is used. To rank suppliers, the hesitant fuzzy MULTIMOORA method is employed. A case study of a wool fabric producer illustrates the practical application of the approach. The results are then compared by applying the hesitant fuzzy VIKOR method. The proposed framework facilitates supplier monitoring, audit planning, and targeted improvement actions by offering a transparent ESG risk ranking framework.**

I. Introduction

A critical component of supply chain management, Environmental, Social, and Governance (ESG) performance affects operational continuity, reputational risk, and regulatory compliance. In this context, sustainability reporting is a critical process for companies to describe their strategies, measure their environmental and social impacts, and improve corporate governance standards. Therefore, in today's business world, financial success alone is not considered sufficient; companies are expected to have an ethical and sustainability-focused approach. Businesses can control present and future operational risks by using sustainability reporting, which provides a clear roadmap to meet these requirements. Since ESG-related deficiencies can lead to disruptions, quality issues, and cost fluctuations across supplier portfolios, ESG is not just a reporting item but also an essential part of supplier monitoring and improvement planning. At the same time, operational measures including waste management, energy efficiency, emissions reduction, and adherence to environmental regulations are critical. These methods directly translate into quantifiable risk factors in supplier relationships [1].

Ranking ESG risk among current suppliers is still difficult despite the growing emphasis on ESG for two pragmatic reasons. First, the evidence for ESG is varied and frequently lacking; some criteria rely on qualitative audits and subjective observations, while others are backed by quantitative data. Second, assessments frequently reveal expert hesitation when assessors struggle to assign a single score and instead vacillate among several reasonable conclusions. According to earlier research, ESG evaluations encompass a variety of criteria, including labor standards, health and safety, transparency, anti-corruption, governance compliance, and risk management. The relative significance of these criteria sets varies depending on the situation and the stakeholders' interests [2]. Additionally, supplier-oriented sustainability evaluation streams specifically recognize the importance of disclosure-related factors and capability-building methods, highlighting the need for decision models that account for expert input uncertainty [3].

To address these challenges, this study addresses a supplier monitoring problem rather than a new supplier selection or prediction problem. Given a set of existing tier-1 suppliers, ESG risk criteria, and hesitant expert evaluations, the objective is to obtain a transparent risk ranking to prioritize audits and supplier development actions. This paper proposes a hesitant fuzzy Multi-Criteria Decision-Making (MCDM) framework where hesitant fuzzy sets are used to convey expert assessments, enabling evaluators to define several membership degrees for each combination of criteria and suppliers. The resulting hesitant information is aggregated and transformed into numerical values, which are then processed by two methods. The hesitant fuzzy Simple Additive Weighting (SAW) method is used for prioritizing the ESG factors. The hesitant fuzzy MULTIMOORA is used for ranking the suppliers.

This study makes three primary contributions: Based on relevant literature, we operationalize an ESG risk ranking methodology for current supplier portfolios [1], [2], [3]. We integrate hesitant expert judgments into the ranking process via hesitant fuzzy modeling, enhancing realism under incomplete/ambiguous ESG evidence. We provide insights to practitioners to support transparent, decision-centric supplier risk prioritization.

The rest of this paper is structured as follows. In Section II, relevant literature is reviewed. The proposed methodology approach is presented in Section III. The application and comparative findings are presented in Section IV. Implications and future study directions are discussed at the end of Section V.

*Research supported by Galatasaray University.

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II. Background

A. ESG Studies on Supplier Assessment

Studies on ESG and supplier assessment have become widespread due to a notable rise in supply chain management. Cao et al. [4] demonstrate that collaboration among competing buyers in conducting ESG audits on a common supplier can enhance consumer confidence. However, a dominant buyer's efforts may be exploited by a less influential buyer. This underscores that supplier ESG risk management extends beyond mere measurement to encompass incentives and managerial decisions. Diego and Montes-Sancho [5] indicate that sustainability information disclosures by second-tier "nexus suppliers" can mitigate buyers' ESG risk, contingent on network access and supplier type. The notion that transparency can serve as a "double-edged sword" underscores the significance of transparency and traceability criteria in risk assessment. Karaman et al. [6] demonstrate how supplier ESG training increases the reduction of carbon emissions caused by sustainable supply chain practices. This implies that environmental performance should be addressed through supplier development tools. Osintsev and Rakhmangulov [1] highlight the confusion in measurement caused by the regulation of green logistics tools and advocate prioritizing these tools using MCDM-based ranking. This provides a methodological foundation for ranking ESG risk indicators. Shen and Sun [2] observe that many criteria in ESG-focused supplier evaluations contain missing data and that uncertainty poses a significant challenge for decision-making.

The related literature suggests that ranking with MCDM is appropriate, but most studies on ESG risk ranking remain limited to a single method; applications that integrate two methods are relatively rare. Consequently, while these studies strongly highlight the supply chain dynamics and governance challenges of ESG, a transparent, comparative ESG risk-ranking framework remains limited by heterogeneous evidence and expert uncertainty. Therefore, to fill this literature gap, this study proposes a hesitant fuzzy SAW–MULTIMOORA methodology to rank ESG-oriented supplier risks.

B. ESG Studies and MCDM

The MCDM approach is appropriate for ESG assessment due to its multi-dimensional and analytical nature. The ESG studies employing MCDM methods are listed in Table 1.

According to Table 1, on the ESG ranking and measurement side, investment- and company-performance-focused practices are common. ESG assessment under uncertainty for electronics companies using SF-AHP, SF-WASPAS [7], transparent ESG ranking in data-scarce markets using TOPSIS [8], weighting that makes criterion contributions visible in country ESG scoring [9], integrated ESG sustainable business performance in companies using IT2FAHP–IT2F-CoCoSo [3], ESG constrained portfolio optimization using TODIM, ML forecasting, and optimization [10]. There are studies on ESG disclosure in the Turkish textile/garment/leather sector, with a transparency and accountability perspective, using the CRITIC, MABAC, and COPRAS methods [11].

On the supply chain side, there are fewer studies. The PLTS-based TODIM is used for the EV battery recycling area [2], and the green logistics instruments are ranked using fuzzy AHP and TOPSIS [1].

TABLE I. Literature Table of ESG Studies and MCDM

Ref.	Properties of Articles		
	Purpose	***Methods***	***Application Domain***
[7]	To identify the key ESG criteria affecting investment decisions in the global electronics industry.	SF-AHP, SF-WASPAS	Global electronics companies
[8]	To develop a transparent, low-data ESG measurement and ranking model.	TOPSIS	20 firms listed in the MASI ESG Index
[9]	To rank countries by ESG performance and transparently reveal the contribution of each criterion to country scores.	Entropy weights	Country-level application across many countries
[3]	To evaluate the ESG-based sustainable business performance of listed companies within an integrated framework.	IT2FAHP IT2F-CoCoSo	Medical companies
[10]	To develop an ESG-constrained, multi-objective portfolio optimization framework that integrates asset selection, return forecasting, and optimization.	TODIM, BN-XGBoost forecasting, TLBO optimizatio n	Nifty 100 firms
[2]	To develop a decision framework for ESG-oriented supplier selection.	PT-VRCD-TODIM PLTS	Electric vehicle battery recycling
[1]	To systematize existing green logistics methods and instruments in supply chains and determine their importance rankings.	Fuzzy AHP, TOPSIS, MABAC, MARCOS	Illustrative example
[11]	To evaluate the ESG disclosure-based performance of firms in the Turkish textile, apparel, and leather sectors.	CRITIC, MABAC, COPRAS	Turkish textile/appar el/leather companies

Previous ESG studies have primarily focused on firm-level measurement and ranking, such as investment-oriented evaluations and disclosure-based performance assessments, using single MCDM pipelines, including TOPSIS, TODIM variants, and interval type-2 fuzzy extensions [3], [7], [8], [10], [11]. Supply chain–specific research either systematizes green logistics instruments [1] or addresses ESG-oriented supplier selection under uncertainty using advanced consensus and risk-perception modeling [2]. Nonetheless, ESG risk ranking for existing supplier portfolios remains underexplored, especially when expert judgments are hesitant, yielding multiple plausible scores rather than a single value. Furthermore, the literature lacks a decision framework that more effectively models uncertainty and consensus in ESG-focused supplier selection. To address these gaps, this study presents a hesitant-fuzzy framework for ranking supplier ESG risks and integrates SAW with MULTIMOORA.

III. Methodology

The study's methodology comprises three primary stages. Initially, the problem is identified, and an evaluation framework is developed through a review of literature, industry reports, and expert input. This evaluation model includes 12 ESG risk factors and seven suppliers. In the second stage, experts assess the factors, and their weights are determined using the hesitant fuzzy SAW technique. In the final stage, experts evaluate the suppliers, and the hesitant fuzzy MULTIMOORA technique is used to rank them. The steps involved in the proposed hesitant fuzzy SAW-MULTIMOORA method are as follows [12], [13]:

Step 1. DMs assess ESG factors using the linguistic terms outlined in Fig. 1, along with similar expressions such as "*At most s_i*", "*Lower than s_i*", "*At least s_i*", "*Greater than s_i*", and "*Between s_i and s_j*".

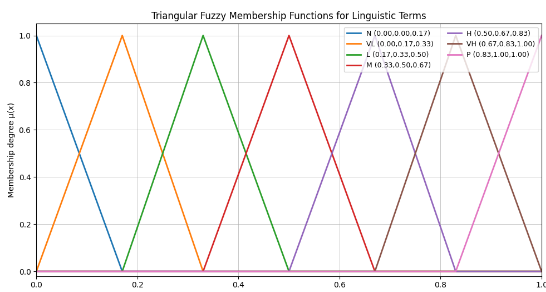

Figure 1. The fuzzy linguistic scale.

Step 2. Let I_t be the degree of importance assigned to each DM, where $0 \leq I_t \leq 1$, for $t = 1,2,...,k$, and $\sum_{t=1}^{k} I_t = 1$ $\widetilde{\omega t}$ let denote the fuzzy weight of the DMs. I_t is determined as:

$$I_t = \frac{d(\widetilde{w_t})}{\sum_{t=1}^{k} d(\widetilde{w_t})}, t = 1,2,\ldots,t \quad (1)$$

where $d(\widetilde{w_t})$ returns the fuzzy weight's defuzzified value using the signed distance.

Step 3. The combined fuzzy weights $(\widetilde{W_j})$ for each individual attribute are calculated.

$$\widetilde{W_j} = (I_1 \otimes \widetilde{W_{j1}}) \oplus (I_2 \otimes \widetilde{W_{j2}}) \oplus \ldots \oplus (I_k \otimes \widetilde{W_{jk}}) \quad (2)$$

where $a_j = \sum_{t=1}^{k} I_t a_{jt}$, $b_j = \sum_{t=1}^{k} I_t b_{jt}$ $c_j = \sum_{t=1}^{k} I_t c_{jt}$.

Step 4. The fuzzy weights of criteria are defuzzified. The defuzzification of $\widetilde{W_j}$ is denoted as $d(\widetilde{W_j})$ and computed.

$$d(\widetilde{W_j}) = \frac{1}{3}\left(a_j + b_j + c_j\right), j = 1,2,\ldots,n \quad (3)$$

Step 5. Normalized weight of criterion C_j is represented as W_j and calculated.

$$W_j = \frac{d(\widetilde{W_j})}{\sum_{j=1}^{n} d(\widetilde{W_j})}, j = 1,2,\ldots,n \quad (4)$$

where $\sum_{j=1}^{n} W_j = 1$ the weight vector W=$(W_1, W_2, \ldots, W_n)$ is built.

Step 6. DMs evaluate supplier alternatives using the linguistic terms outlined in Fig. 1, along with similar expressions such as "*At most s_i*", "*Lower than s_i*", "*At least s_i*", "*Greater than s_i*", *and "Between s_i and s_j"*.

Step 7. The OWA operator is used to aggregate and construct the fuzzy envelope for HFLTS, as described by Liu and Rodríguez [14]. This process leads to the formation of a trapezoidal fuzzy number.

Step 8. Let $\tilde{x}_{ij}^* = \left(x_{ij1}^*, x_{ij2}^*, x_{ij3}^*, x_{ij4}^*\right)$ is a trapezoidal fuzzy number; it is normalized:

$$x_{ijk}^* = x_{ijk} \Big/ \sqrt{\sum_{i=1}^{m} \sum_{k=1}^{4} (x_{ijk})^2} \quad (5)$$

Step 9. The weighted normalized matrix is computed:

$$\tilde{\tilde{x}}_{ij} = \tilde{\tilde{x}}_{ij} \tilde{w}_j \text{ , } i=0,1,\ldots,m \quad (6)$$

Step 10. The summarizing ratios $\tilde{y}_i^*$ are calculated:

$$\tilde{y}_i^* = \sum_{j=1}^{g} \tilde{x}_{ij}^* \ominus \sum_{j=g+1}^{n} \tilde{x}_{ij}^* \quad (7)$$

Step 11. Let $\tilde{y}_i^* = (y_{i1}^*, y_{i2}^*, y_{i3}^*, y_{i4}^*)$ is a summarizing ratio. Then, each ratio is defuzzified:

$$BNP_i = \frac{y_{i1}^* + 2y_{i2}^* + 2y_{i3}^* + y_{i4}^*}{6} \quad (8)$$

The alternatives are ranked in descending order by BNP.

Step 12. The j^{th} coordinate point of the reference point is calculated as:

$$\begin{cases} \tilde{x}_j^+ = (max_i x_{ij1}^*, max_i x_{ij2}^*, max_i x_{ij3}^*, max_i x_{ij4}^*), j \leq g \\ \tilde{x}_j^+ = (min_i x_{ij1}^*, min_i x_{ij2}^*, min_i x_{ij3}^*, min_i x_{ij4}^*), j > g \end{cases} \quad (9)$$

Step 13. The distances from the reference vector $\tilde{r}$ are computed. Consider $\tilde{A} = (a, b, c, d)$, and $\tilde{B} = (e, f, g, h)$ as two trapezoidal numbers. The calculation of the distances between these numbers is as follows:

$$d(\tilde{A}, \tilde{B}) = \sqrt{1/4[(a-e)^2 + (b-f)^2 + (c-g)^2 + (d-h)^2]} \quad (10)$$

Step 14. The min-max metric of Tchebycheff is ranked:

$$min_i(max_j d(\tilde{r}_j, \tilde{x}_{ij}^*)) \quad (11)$$

Step 15. The overall utility is calculated:

$$U_i' = \frac{A_i}{B_i} \quad (12)$$

Step 16. Alternatives are ranked in descending order according to their U_i' values.

IV. Application

The case company is a full-service manufacturer of wool fabrics, including yarn manufacturing, weaving, dyeing, and finishing. The business shall be referred to as Company ABC from now on for privacy reasons. A supply chain comprising raw fibers, chemical inputs, shipping, packaging, and services for managing regulated waste is required for this configuration. The firm's essential input categories, which comprise wool and recycled fibers, dyestuffs and finishing auxiliaries, packaging, third-party logistics, and regulated waste disposal, are thus represented by seven current tier-1 suppliers (i.e., S1–S7). The goal is to assess these current suppliers based on ESG risk to help prioritize audits and focus on supplier development.

The ESG criteria are determined through a literature review, examination of industry reports, and consultation with experts. The proposed ESG risk factors can be listed as:

Environmental (E)

- **E1. Carbon/Logistics emissions risk:** exposure to high transport/process emissions; aligned with green logistics emphasis on emissions/carbon management [15], and supply-chain carbon mitigation work [6].
- **E2. Energy inefficiency risk:** weak energy efficiency and monitoring practices; frequently cited as an operational sustainability lever [6], [15].
- **E3. Waste management risk:** poor waste/chemical management practices; common in green logistics/supply-chain sustainability instruments [15].
- **E4. Environmental compliance/standards risk:** likelihood of non-compliance with environmental regulations/standards; linked to ESG compliance and disclosure pressure [1], [15].

Social (S)

- **S1. Occupational health & safety (OHS) risk:** accident/unsafe workplace exposure [2].
- **S2. Labor practices/standards risk:** working conditions, excessive overtime, labor-rights exposure [2], [5].
- **S3. Supplier ESG training weakness:** limited ESG training/capability building; shown to strengthen sustainability outcomes in supply chains [6].
- **S4. Social responsibility & disclosure weakness:** low transparency on social practices; aligned with transparency-driven ESG risk exposure discussions [1].

Governance (G)

- **G1. Anti-corruption/ethics risk:** exposure to unethical practices [2].
- **G2. Corporate governance compliance risk:** weak governance controls and policy compliance [2], [4].
- **G3. Risk management capability weakness:** limited risk identification/mitigation capability; critical for preventing ESG incidents [2], [5].
- **G4. Transparency/disclosure risk:** limited ESG disclosure and traceability; shown to condition buyer ESG risk exposure in multi-tier networks [1], [2].

Information on Company ABC's suppliers is summarized in Table 2. The expert panel consists of two academics and one textile procurement expert. Their expertise covers sustainable supply chain management, ESG governance, MCDM, and supplier monitoring. This composition supports both methodological rigor and practical relevance.

TABLE II. The Information About Suppliers.

Supplier	Role	Main ESG risk
S1	Wool/wool blend raw material	Traceability/certification
S2	Recycled/sustainable fiber	Recycled-content verification, greenwashing
S3	Dyestuffs and auxiliaries	Hazardous chemical management
S4	Finishing chemicals	SDS, labeling, restricted substances
S5	Packaging materials	Waste reduction, packaging claims
S6	3PL/logistics	Emissions reporting and documentation
S7	Waste/sludge disposal	Licensing, traceable disposal chain

A. *The Hesitant Fuzzy SAW Method for ESG Ranking*

The experts evaluated ESG risk factors using comparative terms and the linguistic scale shown in Fig. 1. An example evaluation is provided in Table 3.

TABLE III. The Experts' Evaluations Of ESG Factors.

ESG Factors	DM1	DM2	DM3
E1	Between VH and H	At least VH	At least M
E2	At least VH	At least M	At least VH
E3	Between VH and H	Between H and P	At least VH
E4	At least VH	Between M and H	At least VH
S1	Between VH and H	Between VH and H	Between VH and H
S2	At least VH	At least VH	Between M and H
S3	Between M and H	Between M and H	Between VH and H
S4	At least M	At least M	Between M and H
G1	At least VH	At least VH	Between M and H
G2	Between M and H	Between M and H	Between VH and H
G3	At least VH	At least M	At least VH
G4	Between VH and H	Between H and P	At least VH

Since the expert panel includes two academics and one industry practitioner with complementary expertise, equal decision-maker weights were adopted to avoid privileging one perspective over another; thus, ($\lambda_1 = \lambda_2 = \lambda_3 = 1/3$).

To calculate the weights of the ESG factors, the steps of the hesitant fuzzy SAW method are followed as outlined in *Steps 1-5*. The final weights and ranking of ESG factors are provided in Table 4.

TABLE IV. THE ESG WEIGHTS.

Factors	Defuzzified Weigths	Normalized Weights	Rank
E1	0.722	0.079	7
E2	0.722	0.079	7
E3	0.907	0.100	1
E4	0.778	0.085	4
S1	0.833	0.091	3
S2	0.778	0.085	4
S3	0.722	0.079	10
S4	0.556	0.061	12
G1	0.778	0.085	4
G2	0.722	0.079	10
G3	0.722	0.079	7
G4	0.870	0.095	2

According to the results, the most risky ESG factor for Company ABC is waste management risk (i.e., E3), followed by transparency/disclosure risk (i.e., G4), and then occupational health & safety risk (i.e., S1). In the wool fabric manufacturer, where dyeing, finishing, chemical use, and sludge disposal create important environmental and regulatory exposure. The high importance of transparency/disclosure risk also indicates that traceability, documentation, and reliable ESG reporting are critical for supplier monitoring.

B. The Hesitant Fuzzy MULTIMOORA Method for Suppliers Ranking

The experts assessed seven suppliers of Company ABC for ESG risks using a linguistic scale (Fig. 1) and reached a Delphi-based consensus among the three experts. Then, *Steps 6-16* are applied to determine suppliers' rankings. The results are provided in Table 5.

The results indicate that the Supp. 7 is the most risky supplier for Company ABC, Supp. 3 is the second, and Supp. 2 is the third. Supp. 7, as the waste management and sludge disposal contractor, involves high regulatory, licensing, and traceability risks, making it the first. Supp. 3, the dyestuffs and auxiliaries supplier, is also critical due to concerns related to hazardous chemical management, safety documentation, and environmental compliance. Supp. 2 ranks third because recycled-content verification, traceability, and potential greenwashing risks are important issues for sustainable fiber supply.

TABLE V. THE RANKING OF SUPPLIERS.

Supplier	The Fuzzy Reference Point Approach		The Fuzzy Ratio System Ranking		The Fuzzy Full Multiplicative Form Ranking	
	max d(r)	*Rank*	*BNP*	*Rank*	*BNP*	*Rank*
Supp. 1	0.013	6	0.154	6	1.262E-22	6
Supp. 2	0.013	6	0.179	3	2.675E-22	3
Supp. 3	0.009	1	0.188	2	4.957E-22	2
Supp. 4	0.009	3	0.170	5	2.514E-22	5
Supp. 5	0.010	4	0.150	7	1.049E-22	7
Supp. 6	0.009	3	0.174	4	2.621E-22	4
Supp. 7	0.009	1	0.200	1	7.026E-22	1

C. Comparison

To compare the results, the hesitant fuzzy VIKOR method is applied. This method is based on the idea of ideal and compromised solutions and uses linear normalization. Hesitant fuzzy MULTIMOORA is based on a utility-based function and uses the root of the sum of squares.

MULTIMOORA identifies S7–S3–S2 as the highest-risk group, whereas VIKOR ranks S3–S2–S7. Both methods consistently identify S1 and S5 as low-risk suppliers. MULTIMOORA has an advantage: because ratio, reference point, and multiplicative forms are used together, it does not rely on a single criterion; it assesses high-risk suppliers from multiple perspectives. However, interpretation can be difficult when the three sub-approaches give different signals. VIKOR's advantage is its ease of explanation using the ideal/compromise solution logic. However, it is sensitive to normalization and compromise parameters; therefore, it is used as a validation/comparison tool rather than as the main method. The findings indicate that while both methods consistently identify the low-risk suppliers (Supp. 1 and Supp. 5), they diverge at the high-risk alternatives.

D. Sensitivity Analysis

A sensitivity analysis was conducted to assess the robustness of the supplier ranking to changes in criterion weights. The base-case ranking was compared with alternative scenarios, including equal weights and increased emphasis on selected ESG dimensions. This analysis aims to verify whether the highest-risk supplier group remains stable under reasonable changes in the criteria's importance. The results of the sensitivity analysis are provided in Table 6.

TABLE VI. RESULTS OF THE SENSITIVITY ANALYSIS.

Scenario	Top-ranked supplier	Top-3 order
Base weights	S7	S7–S3–S2
Equal weights	S7	S7–S3–S2
Environmental +10%	S7	S7–S3–S2
Social +10%	S7	S7–S3–S2
Governance +10%	S7	S7–S3–S2

The sensitivity results indicate that the high-risk supplier group remains stable across weighting scenarios. This supports the robustness of the proposed ESG risk-ranking framework.

V. CONCLUSION

The results indicate that waste management, transparency/disclosure, and OHS are the most critical ESG risk factors, while S7, S3, and S2 form the highest-risk supplier group. In related literature, pollution/waste and GHG emissions were critical [7]. Political stability and voice/accountability were critical ESG factors [9]. Health and safety were the most critical factors [3]. Public disclosure of social responsibility was the most critical factor [11]. Our results are similar with these studies as waste management risk, transparency/disclosure risk, and occupational health & safety risk are the most important factors.

This study contributes to the literature by providing a transparent and comparative decision framework that models uncertainty and consensus in ESG-focused supplier risk ranking. The findings should be interpreted as analytical rather than statistical generalization, since the application is based on a single wool fabric manufacturer and a small expert panel. Nevertheless, the framework is transferable to other sectors by redefining criteria, suppliers, and expert weights. Expert bias was mitigated through a heterogeneous panel, hesitant linguistic evaluations, Delphi-based consensus, and sensitivity analysis. The model can also be dynamically adapted by periodically updating evaluations with new audit results, incident records, emissions data, and corrective-action outcomes.

Future research may extend the framework through multiple case studies across different sectors, alternative aggregation operators, and dynamic ESG monitoring approaches. In particular, digital twins and multi-agent/game-theoretic models may complement the proposed framework by capturing real-time data flows and strategic interactions among buyers, suppliers, logistics providers, and regulators. Integrating such approaches may improve real-time ESG monitoring and scenario-based supplier development decisions.

ACKNOWLEDGMENT

The Scientific Research Projects Commission of Galatasaray University has financed this study (FBA-2026- 1342).

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