



## A Novel Integrated MCDM Framework for ESG Risk Assessment in Manufacturing Firms: The LOGSTA-SPC-MUNRA Hybrid Model

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### ARTICLE INFO

#### Article history:

Received 27 February 2026

Received in revised form 1 April 2026

Accepted 7 April 2026

Available online 8 April 2026

#### Keywords:

ESG Risk Assessment; BIST Real Sector; Sustainable Finance; Risk Management; MCDM; LOGSTA; SPC; MUNRA.

### ABSTRACT

Environmental, social, and governance (ESG)-based risks have become key factors shaping firms' sustainability levels, competitive strength, and long-term resilience. Particularly in the manufacturing industry, where environmental obligations, energy intensity, operational sensitivities, and governance pressures interact simultaneously, the systematic measurement of these risks has gained growing importance. However, the multidimensional nature of ESG risks makes both inter-firm comparison and holistic performance assessment methodologically challenging. The aim of this paper is to develop an integrated decision-making model to assess firms' ESG risks and reveal their relative performance structure. For this purpose, an integrated weighting framework based on LOGarithmic normalization and STAndard Deviation (LOGSTA) and Symmetry Point of Criterion (SPC) was constructed to determine the importance levels of the criteria, while the relative ranking of firm performance was carried out through the Multiple Normalization Rating Analysis (MUNRA) approach. To assess the applicability of the developed model, an empirical case study was conducted on 13 manufacturing firms listed in the BIST Sustainability-25 Index. The results of the integrated weighting findings, as derived from the LOGSTA and SPC procedures, indicated that the ESG risk structure of the sampled firms is mainly constructed along the environmental dimensions. In this respect, carbon emission risk was identified as the most important criterion from the viewpoint of firm performance, whereas human capital risk was identified as the criterion that had the lowest relative discriminatory power. The ranking results, as derived from the proposed MUNRA approach, indicated that the top-performing firms were Ülker, Tüpraş, and Anadolu Efes, whereas the firms that had the lowest performance were Oyak Çimento, Çimsa, and Petkim. Finally, the proposed model was compared to other approaches, and it was indicated that the proposed model provides stable, consistent, and reliable results.

## 1. Introduction

In recent years, Environmental, Social, and Governance (ESG) considerations have moved to the forefront of corporate strategy and financial decision-making, a shift that has substantially changed the way firms are assessed in contemporary markets [1–3]. Firms are no longer assessed solely on

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<https://doi.org/10.59543/krgvw760>

the basis of conventional financial outcomes; rather, they are increasingly judged based on how effectively they manage environmental pressures, stakeholder expectations, and governance-related responsibilities, all of which have become central to long-term corporate sustainability [1–4]. This transformation has been especially visible in manufacturing industries, which are characterized by energy-intensive production processes, carbon exposure, resource dependence, labor-sensitive operations, and close regulatory scrutiny [5–7]. In such a setting, ESG-related issues are not merely symbolic concerns that influence reputation alone; they are materially relevant factors that can influence operating costs, access to external finance, business continuity, and long-term firm value [2], [5], [8].

Alongside the growing prominence of ESG performance, the notion of ESG risk has also gained increasing analytical importance, a development that has broadened the scope of firm-level sustainability analysis [7], [9]. Although ESG performance and ESG risk are closely related concepts, they should not be treated as interchangeable, since each refers to a different analytical domain [7], [10]. ESG performance generally reflects the extent to which firms exhibit favorable sustainability-related practices, whereas ESG risk refers to the vulnerabilities, exposures, and institutional weaknesses that emerge when environmental, social, and governance issues are not managed effectively [7], [10], [11]. For manufacturing firms, these vulnerabilities may stem from carbon-intensive production systems, inefficient energy use, climate-related physical threats, workplace safety deficiencies, supply-chain labor issues, weak disclosure practices, or governance failures, all of which may intensify firm-level fragility [8], [11], [12]. Such weaknesses may lead to higher compliance costs, greater operational instability, increased legal exposure, and weaker resilience in the face of market and regulatory change, outcomes that make ESG risk an essential component of strategic financial analysis [9], [12], [13].

The manufacturing industry provides a particularly suitable context for ESG risk assessment because it is a domain in which environmental, operational, and governance-related vulnerabilities interact in a highly visible manner [5], [6], [11]. Compared with many service-based industries, manufacturing firms are more directly exposed to environmental obligations, resource-use pressures, production-related disruptions, and compliance-intensive operating conditions, all of which increase the relevance of ESG-based risk evaluation [5], [8], [12]. In addition, the sector is characterized by complex supply networks and labor-dependent production systems, within which operational efficiency and governance quality are strongly interconnected [11], [13]. These features make manufacturing firms especially suitable for examining how ESG-related vulnerabilities differ across companies and how such differences shape overall risk profiles [8], [11]. Despite this relevance, the existing literature has more frequently emphasized ESG performance, disclosure quality, or general sustainability outcomes, whereas comparatively less attention has been devoted to the systematic and multidimensional assessment of ESG risk at the firm level, particularly in the case of real-sector manufacturing companies [9], [14], [15].

From a methodological standpoint, ESG risk assessment is inherently challenging because it deals with a multidimensional and interdependent set of vulnerabilities that cannot be adequately captured through a single financial ratio or a narrow group of operational indicators [7], [15], [16]. A meaningful assessment therefore requires an analytical structure that can incorporate multiple criteria simultaneously, preserve comparability across firms, and provide a transparent basis for weighting and ranking [15], [16]. In this regard, Multi-Criteria Decision-Making (MCDM) procedures offer a suitable methodological foundation, since they enable complex decision environments to be analyzed in a systematic and structured way [17], [18]. Their relevance becomes even more apparent in ESG-related contexts, in which the decision problem involves multiple dimensions, diverse

indicator types, and a need to identify both the relative importance of criteria and the comparative standing of alternatives [9], [17], [19].

Motivated by this need, the current manuscript introduces a combined MCDM methodology for the assessment of ESG risks in manufacturing firms. In the suggested structure, the weighting stage is based on the combined use of LOGarithmic normalization and STAndard Deviation (LOGSTA) and the Symmetry Point of Criterion (SPC) approach, while the ranking stage is carried out via the Multiple Normalization Rating Analysis (MUNRA) technique [17], [38]–[40]. The integration of LOGSTA and SPC offers a more robust basis for ascertaining criterion importance because it captures both distribution-sensitive variation and discriminatory power across criteria, two features that are particularly valuable in multidimensional decision settings [38], [39]. MUNRA, in turn, strengthens the ranking stage by incorporating multiple normalization structures into the evaluation process, a feature that reduces the dependence of final results on a single normalization procedure and improves the stability of the decision outcome [40].

The empirical application of the study concentrates on 13 manufacturing firms included in the BIST Sustainability-25 Index, which provides a relevant context for investigating ESG risk exposure in the Turkish capital market. This setting is particularly suitable because the selected firms operate in environmentally and operationally sensitive industries while also maintaining a visible sustainability profile that makes comparative assessment more meaningful. Within this framework, our study seeks to answer three main questions: which ESG risk criteria exert the strongest influence on the overall risk structure of the sampled firms; how these firms differ in terms of their environmental, social, and governance risk profiles; and whether the proposed integrated framework generates a stable and meaningful ranking of firm-level ESG risk exposure.

The study contributes to the literature in both empirical and methodological terms. Empirically, it provides a comparative ESG risk assessment for manufacturing firms, thereby extending the discussion beyond broad ESG performance narratives toward firm-level vulnerability analysis, which remains relatively underexplored in the existing literature [9], [14], [15]. Methodologically, it proposes an integrated decision-making tool that combines LOGSTA and SPC in the weighting stage and MUNRA in the ranking stage, thereby offering an alternative and structured route for assessing ESG-related risk exposure from a multidimensional perspective [38]–[40]. In doing so, our manuscript aims to enrich the growing literature on sustainable finance and ESG-based firm assessment by introducing a framework that is tailored to the risk-oriented realities of the manufacturing sector.

The rest of the paper is organized as follows. Section 2 presents the relevant literature and outlines the theoretical and empirical background of the study. Section 3 explains the integrated methodological framework. Section 4 introduces the sample and the indicators used in the analysis. Section 5 reports the empirical findings and discusses the results. Finally, Section 6 concludes with the main implications, limitations, and suggestions for future research.

### *1.1 Literature Review*

Previous literature focusing on the assessment of firm performance shows that MCDM procedures have substantially enhanced the analytical depth of this field. Empirical studies conducted across different industries and samples clearly reveal that performance cannot be adequately explained through one-dimensional measures alone and that more holistic assessment frameworks are needed. In this context, the general profile of some prominent studies in the relevant literature is presented in Table 1.

**Table 1**  
Related Literature

Author(s)	Weighting Procedure(s)	Ranking Procedure(s)	Period(s)	Country	Sample and Objective
Çakır and Perçin [19]	CRITIC	SAW, TOPSIS, VIKOR and Borda Count	2011	Türkiye	The performance level of 10 logistics firms included in the FORTUNE 500 list was tested.
Moghimi and Anvari [20]	F-AHP	TOPSIS	-	Iran	Within the scope of the research, the financial performance profile of 8 cement firms listed on the Tehran Stock Exchange was assessed.
Safaei Ghadikolaei <i>et al.</i> [21]	F-AHP	F-VIKOR, F- ARAS and F-COPRAS	2002–2011	Iran	The study examines the financial performance levels of six automotive firms listed on the Tehran Stock Exchange.
Erdoğan <i>et al.</i> [22]	Buckley's Column Geometric Mean Method	TOPSIS, VIKOR and ELECTRE	2011–2014	Türkiye	The performance of 21 food firms listed on BIST was investigated within a multi-criteria assessment framework.
Alimohamm adlou and Bonyani [23]	BWM	PROMETHEE II	2011–2015	Iran	A comparative assessment was conducted on the financial performance of the 14 largest firms in Iran's food industry.
Aldalou and Perçin [24]	Fuzzy Shannon's Entropy (FSE)	F-EDAS	2015–2017	Türkiye	The financial performance of firms listed in the BIST Food and Beverage Index in Türkiye was tested in the study.
Abdel-Basset <i>et al.</i> [25]	AHP	VIKOR and TOPSIS	-	Egypt	A performance analysis was carried out based on the financial statements of the 10 leading firms in the Egyptian iron and steel sector.
Baydaş and Elma [26]	Equal Weighting and Entropy	TOPSIS, WSA and PROMETHEE	2014–2018	Türkiye	The study examines the financial performance of 131 manufacturing firms listed on BIST and compares the MCDM weighting approaches employed.
İç and Yurdakul [27]	F-AHP	TOPSIS	-	Türkiye	The study aimed to reveal the performance levels of eight manufacturing companies in Türkiye.
Aduba [28]	F-AHP	TOPSIS	2010–2020	Japan	The study focuses on assessing the financial performance of the 18 largest construction firms in Japan.
Hoang <i>et al.</i> [9]	SF-AHP	SF-WASPAS	-	Global	Within the scope of the research, the ESG performance profile of the 10 largest firms in the global electronics industry was examined.
Işık <i>et al.</i> [29]	DEMATEL and CRITIC	EDAS, WASPAS and TOPSIS	2021	Türkiye	The market performance of 27 firms operating in the food and beverage sector listed on BIST was investigated comparatively.
Yu <i>et al.</i> [30]	IT2F-AHP	IT2F-CoCoSo	-	China and	A comparative analysis was carried out on the ESG metrics of five listed

				United States	medical firms operating in China and the United States.
Kaya <i>et al.</i> [31]	FUCOM	CoCoSo, GRA, MABAC, MAIRCA, MOOSRA, OCRA, TOPSIS, TODIM, VIKOR and Copeland	2019–2021	Türkiye	A comparative investigation was carried out on the financial criteria of 22 non-bank firms included in the BIST Sustainability Index.
Demir [32]	LOPCOW and MSD	CRADIS, MOOSRA, MAIRCA and Borda Count	2023	Türkiye	A comparative examination was conducted on the financial metrics of 13 cement firms listed on BIST.
Durdu [33]	SPC and LOPCOW	MARCOS	2023	Türkiye	A comparative assessment was conducted of the financial indicators of 16 real sector companies included in the BIST Sustainability 25 Index.
Adalar and Işık [17]	CRISUS	RAM	2022	Türkiye	The study aims to examine the sustainability performance of seven companies operating in the food and beverage sector listed on BIST.
Görçün <i>et al.</i> [34]	IT2F-AHP	CRADIS	2006–2020	Türkiye	The study investigated the financial performance structure of 11 companies from the Turkish textile and apparel industry listed on BIST.
Inanç <i>et al.</i> [35]	CRITIC and Entropy	MARCOS and TOPSIS	-	Global	A comparative analysis was employed to examine the ESG metrics of 10 firms included in the Fortune 500 list within the global logistics sector.
Belke <i>et al.</i> [36]	CRISUS and MAXC	CRADIS	2022	United Kingdom	A multidimensional performance comparison was carried out for eight beverage firms listed on the London Stock Exchange based on financial and ESG metrics.
Tutcu <i>et al.</i> [37]	CRITIC	MABAC and COPRAS	2024	Türkiye	A comparative assessment was conducted on the ESG implementation criteria of 23 firms operating in the textile, clothing, and leather industry in Türkiye.

## 2. Methodology

This section provides a detailed explanation of the algorithmic framework and operational logic of the integrated MCDM model proposed in the study. The ESG risk performance of real sector companies was systematically assessed through a sequence of interrelated methodological stages, as illustrated in Figure 1. First, a comprehensive decision matrix was created to enable the comparison of alternatives across environmental, social, and governance risk dimensions. Next, in order to minimize subjectivity in the weighting process and strengthen methodological robustness, the final criterion weights were calculated by employing the LOGSTA and SPC objective weighting procedures. After obtaining the final weights, the relative ESG risk performance of the alternatives was determined through the MUNRA ranking approach, and the alternatives were prioritized accordingly.

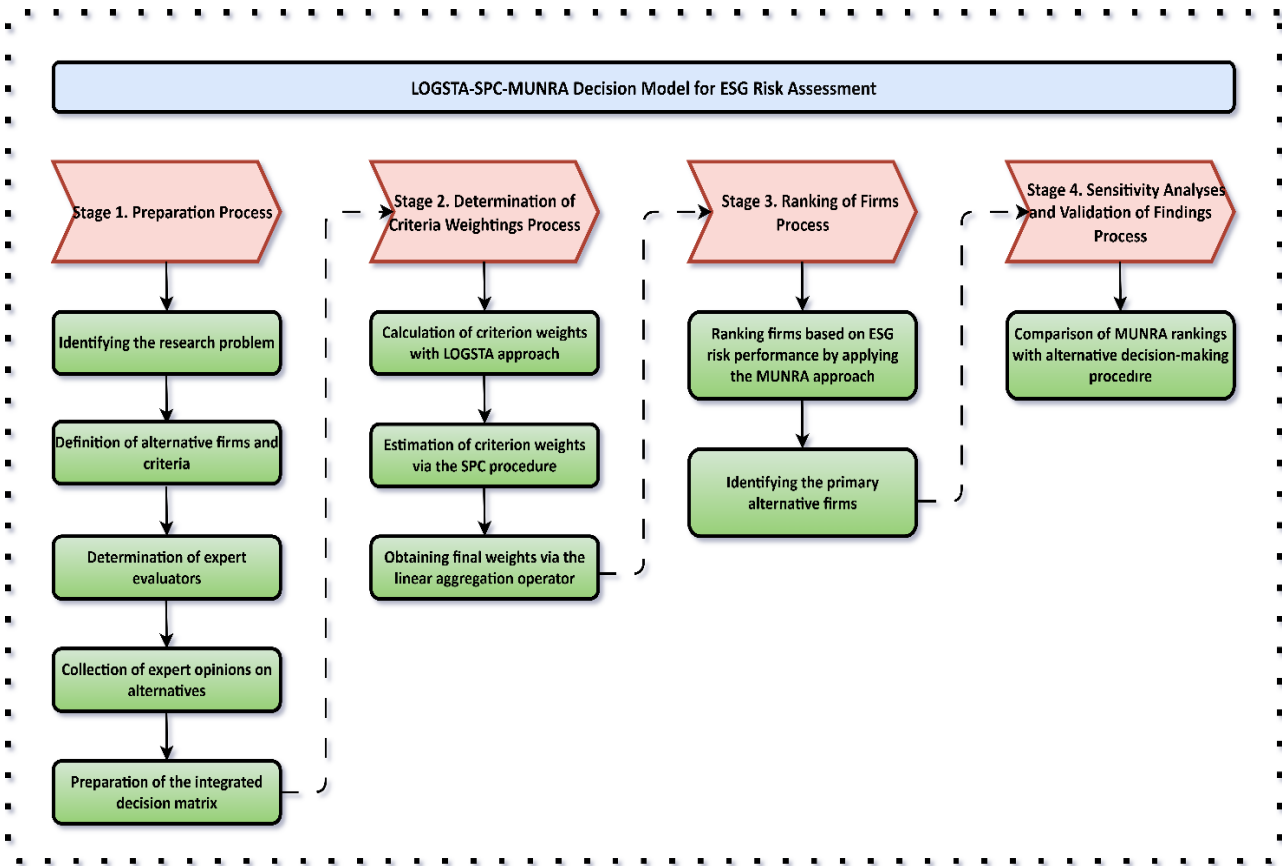


Fig. 1. Methodological framework

### 2.1 LOGSTA Approach

The LOGSTA approach is a new objective weighting algorithm introduced into the decision-making literature by Stević *et al.* [38] to determine criterion weights objectively based on quantitative data. The approach jointly employs logarithmic normalization and standard deviation, separately assessing beneficial and non-beneficial performance criteria while revealing the discriminating power of metrics based on the data structure. In this respect, LOGSTA differs from other objective weighting procedures by explicitly taking criterion type into account and by relying on a distinctive computational structure. The main advantage of the LOGSTA method lies in its ability to directly incorporate beneficial and non-beneficial criteria into the weighting process, thereby reflecting criterion direction and capturing the variation among criteria in a more sensitive manner. The implementation procedure of the approach consists of the following steps.

Step 1. For the solution of the decision problem, the initial matrix containing the alternatives and criteria is created in accordance with Eq. (1).

$$Z = |z_{ij}|_{m \times n} = \begin{vmatrix} A/C & C_1 & C_2 & \cdots & C_n \\ A_1 & z_{11} & z_{12} & \cdots & z_{1n} \\ A_2 & z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & z_{m1} & z_{m2} & \cdots & z_{mn} \end{vmatrix} \quad (1)$$

Step 2. In the next stage, the values in the decision matrix are subjected to logarithmic normalization. In this context, Eq. (2) is utilized for beneficial criteria, while Eq. (3) is applied to non-beneficial criteria.

$$n_{ij} = \left| \frac{\ln z_{ij}}{\ln(\prod_{i=1}^m z_{ij})} \right| \quad (2)$$

$$n_{ij} = \left| \frac{1 - \left| \frac{\ln z_{ij}}{\ln(\prod_{i=1}^m z_{ij})} \right|}{m-1} \right| \quad (3)$$

Step 3. In the third stage, the standard deviation scores are calculated for each criterion. Subsequently, by utilizing these scores, the G matrix is derived via Eq. (4). This procedure determines the discriminating power of the performance indicators.

$$g_j = \sigma_j \times \left( \left| \sum_{i=1}^m (\ln(n_{ij})) \right| \right)^{-1} \quad (4)$$

Step 4. Finally, the objective weights for each criterion are calculated by applying Eq. (5).

$$w_j = \frac{g_j}{\sum_{j=1}^n g_j} \quad (5)$$

## 2.2 SPC Approach

The SPC approach is an objective weighting procedure introduced into the decision-making literature by Gligorić *et al.* [39]. The method is based on the symmetry point approach, which takes the midpoint between the lower and upper values of each performance indicator as a reference and, in this way, provides a weighting procedure that considers the position of criteria within the data distribution. The main advantages of the SPC method include its simple and easy-to-understand computational structure, its applicability to complex decision problems, its flexibility to be integrated with conventional MCDM procedures, and its successful utilization across different scientific fields. Owing to these features, SPC stands out as both a practical and functional alternative in the weighting process. The application procedure of the method consists of six main steps.

Step 1. The initial decision matrix is built in accordance with Eq. (1).

Step 2. The symmetry points of the assessment criteria are calculated by applying Eq. (6).

$$SPC_j = \frac{\min\{z_{ij}\} + \max\{z_{ij}\}}{2} \quad (6)$$

Step 3. The absolute distance matrix is obtained on the basis of Eq. (7).

$$D = \left\| |d_{ij}| \right\|_{m \times n} = \begin{pmatrix} |z_{11} - SPC_1| & |z_{12} - SPC_2| & \cdots & |z_{1n} - SPC_n| \\ |z_{21} - SPC_1| & |z_{22} - SPC_2| & \cdots & |z_{2n} - SPC_n| \\ \vdots & \vdots & \ddots & \vdots \\ |z_{m1} - SPC_1| & |z_{m2} - SPC_2| & \cdots & |z_{mn} - SPC_n| \end{pmatrix} \quad (7)$$

Step 4. At this stage, the symmetric modulus matrix is derived through Eq. (8).

$$R = \left| |r_{ij}| \right|_{m \times n} = \begin{pmatrix} \left| \frac{\sum_{i=1}^m d_{i1}}{m} \right| & \left| \frac{\sum_{i=1}^m d_{i2}}{m} \right| & \dots & \left| \frac{\sum_{i=1}^m d_{in}}{m} \right| \\ x_{11} & x_{12} & \dots & x_{1n} \\ \left| \frac{\sum_{i=1}^m d_{i1}}{m} \right| & \left| \frac{\sum_{i=1}^m d_{i2}}{m} \right| & \dots & \left| \frac{\sum_{i=1}^m d_{in}}{m} \right| \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \left| \frac{\sum_{i=1}^m d_{i1}}{m} \right| & \left| \frac{\sum_{i=1}^m d_{i2}}{m} \right| & \dots & \left| \frac{\sum_{i=1}^m d_{in}}{m} \right| \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix} \quad (8)$$

Step 5. By utilizing the symmetric modulus matrix of the criteria, the vector matrix is obtained via Eq. (9).

$$Q_j = \left| \frac{\sum_{i=1}^m r_{ij}}{m} \right| \quad (9)$$

Step 6. Finally, the objective weights for each criterion are calculated by employing Eq. (10).

$$w_j = \frac{Q_j}{\sum_{j=1}^n Q_j} \quad (10)$$

### 2.3 Final Weighting Approach

Utilizing different decision-making methods to estimate the importance weights of criteria may lead to certain variations in the resulting scores. To address this issue, the current case study employs an aggregation operator that simultaneously integrates the effect of different approaches. In this framework, the criterion weights derived from the LOGSTA and SPC approaches were combined via Eq. (11). Through this integration, the final weights of each criterion were obtained. In this equation,  $w_j^{LOGSTA}$  and  $w_j^{SPC}$  denote the weights generated by the LOGSTA and SPC procedures, respectively.

$$w_j^{(final)} = \Psi w_j^{(LOGSTA)} + (1 - \Psi) w_j^{(SPC)} \quad (11)$$

### 2.4 MUNRA Approach

The MUNRA approach is a new alternative ranking method introduced to the decision-making literature by Ulutaş *et al.* [40]. The approach stands out by integrating three different normalization procedures—linear, vector, and nonlinear normalization—into the assessment of alternatives. The primary objective of MUNRA is to mitigate such problems as scale sensitivity, ranking instability, and the impact of extreme values, which may arise in ranking procedures based on a single normalization method, thereby producing more robust and balanced findings. In this respect, through its multiple-normalization structure, the method balances the effects of different data magnitudes, provides a more sensitive and stable ranking in complex decision problems, and differs from certain other ranking approaches through its easily applicable computational procedure and its relative resistance to the rank-reversal problem. The application procedure of the approach consists of the following four main steps.

Step 1. The decision matrix is generated via Eq. (1).

Step 2. In this stage, the decision matrix is normalized by applying three different procedures within a multiple-normalization framework. Accordingly, Eqs. (12)-(13) denote linear normalization, Eqs. (14)-(15) refer to vector normalization, and Eqs. (16)-(17) describe nonlinear normalization.

$$r_{ij} = \frac{z_{ij}}{\max(z_{ij})} \text{ if } j \in BNF \quad (12)$$

$$r_{ij} = \frac{\min(z_{ij})}{z_{ij}} \text{ if } j \in NBNF \quad (13)$$

$$y_{ij} = \frac{z_{ij}}{\sqrt{\sum_{i=1}^m (z_{ij})^2}} \text{ if } j \in BNF \quad (14)$$

$$y_{ij} = 1 - \frac{z_{ij}}{\sqrt{\sum_{i=1}^m (z_{ij})^2}} \text{ if } j \in NBNF \quad (15)$$

$$p_{ij} = \left( \frac{z_{ij}}{\max(z_{ij})} \right)^2 \text{ if } j \in BNF \quad (16)$$

$$p_{ij} = \left( \frac{\min(z_{ij})}{z_{ij}} \right)^3 \text{ if } j \in NBNF \quad (17)$$

Step 3. The values obtained from the linear, vector, and nonlinear normalization procedures are integrated with the criterion weights by applying Eqs. (18)–(20), thereby yielding separate weighted aggregate scores for each normalization structure.

$$r'_i = \sum_{j \in BNF} w_j \times r_{ij} + \sum_{j \in NBNF} w_j \times r_{ij} \quad (18)$$

$$y'_i = \sum_{j \in BNF} w_j \times y_{ij} + \sum_{j \in NBNF} w_j \times y_{ij} \quad (19)$$

$$p'_i = \sum_{j \in BNF} w_j \times p_{ij} + \sum_{j \in NBNF} w_j \times p_{ij} \quad (20)$$

Step 4. In the final stage, the weighted aggregate values are integrated to derive the final utility scores for the alternatives via Eq. (21).

$$v_i = \alpha r'_i + \beta y'_i + \gamma p'_i \quad (21)$$

In Eq. (21), the parameters  $\alpha$ ,  $\beta$ , and  $\gamma$  are defined within the interval  $[0, 1]$  and satisfy the condition  $\alpha + \beta + \gamma = 1$ . In the application of the approach, these parameters are assigned equal values; accordingly, the alternative with the highest final score is identified as the optimal choice.

### 3. Definition of alternatives and ESG risk

The empirical setting of this research was established on manufacturing firms listed in the BIST Sustainability-25 Index. The selection of this sample was not arbitrary; rather, it was guided by the need to investigate firms that exhibit a relatively advanced level of institutionalization in

sustainability practices, maintain publicly observable ESG-related structures, and provide a sufficiently comparable basis for risk-oriented assessment. Concentrating on firms included in the BIST Sustainability-25 Index offers an analytically meaningful context, since such firms are generally more visible in terms of sustainability disclosure, stakeholder engagement, and governance architecture than ordinary market participants. At the same time, restricting the analysis to a single manufacturing subsector could have reduced the explanatory breadth of the study and weakened the sectoral representativeness of ESG risk exposure. To this end, the sample was designed to include firms from different branches of manufacturing, thereby enabling a broader and more balanced assessment of environmental, social, and governance vulnerabilities across industrial structures. In total, 13 firms were included in the analysis, and each firm was assigned a specific alternative code for methodological clarity and operational convenience in the decision-making framework. The chosen firms and their corresponding codes are provided in Table 2.

**Table 2**  
 Firm Alternatives

Rank	Company Name	Stock Ticker	Code
1	Anadolu Efes Biracilik ve Malt Sanayii A.Ş.	AEFES	R <sub>1</sub>
2	Arçelik A.Ş.	ARCLK	R <sub>2</sub>
3	Aselsan Elektronik Sanayi ve Ticaret A.Ş.	ASELS	R <sub>3</sub>
4	Çimsa Çimento Sanayi ve Ticaret A.Ş.	CIMSA	R <sub>4</sub>
5	Doğuş Otomotiv Servis ve Ticaret A.Ş.	DOAS	R <sub>5</sub>
6	Enka İnşaat ve Sanayi A.Ş.	ENKAI	R <sub>6</sub>
7	Ford Otomotiv Sanayi A.Ş.	FROTO	R <sub>7</sub>
8	Mavi Giyim Sanayi ve Ticaret A.Ş.	MAVI	R <sub>8</sub>
9	Oyak Çimento Fabrikalari A.Ş.	OYAKC	R <sub>9</sub>
10	Petkim Petrokimya Holding A.Ş.	PETKM	R <sub>10</sub>
11	Tüpraş-Türkiye Petrol Rafinerileri A.Ş.	TUPRS	R <sub>11</sub>
12	Türkiye Şişe ve Cam Fabrikalari A.Ş.	SISE	R <sub>12</sub>
13	Ülker Bisküvi Sanayi A.Ş.	ULKER	R <sub>13</sub>

The criteria considered in this research were systematically organized under the three fundamental ESG dimensions—environmental, social, and governance—to adequately reflect the inherently multidimensional nature of ESG-related risk. Their selection was guided by three key considerations: their effectiveness in capturing the sustainability-driven risk exposure of manufacturing firms, their discriminative capability within a comparative decision-making framework, and their conceptual alignment with the operational, financial, and institutional characteristics of the real sector. Given that the present manuscript explicitly concentrates on risk exposure rather than favorable ESG performance, all criteria were modeled as minimization-oriented. In this context, higher indicator values correspond to increased vulnerability, elevated risk burden, and weaker institutional resilience, whereas lower values indicate a comparatively stronger position in terms of ESG risk management. This optimization structure is consistent with the primary objective of our paper, which is to identify firms exhibiting lower ESG-related risk exposure rather than those merely demonstrating stronger sustainability signaling. The complete set of ESG risk indicators, along with their respective codes and optimization directions, is given in Table 3.

The environmental dimension comprises five indicators designed to capture the main ecological and resource-based vulnerabilities of manufacturing firms. Carbon Emission Risk ( $E_1$ ) reflects the pressures associated with carbon-intensive production structures, particularly in terms of transition

costs, regulatory exposure, and reputational sensitivity. Energy Consumption and Efficiency Risk ( $E_2$ ) represents the firm’s vulnerability to energy-intensive operations and efficiency-related cost pressures, while Climate-Related Physical Damage Risk ( $E_3$ ) refers to the susceptibility of assets and production systems to climate-induced disruptions. Environmental Compliance Risk ( $E_4$ ) captures the potential burden arising from non-compliance with environmental regulations, whereas Waste Management and Resource Use Risk ( $E_5$ ) reflects the risks associated with inefficient resource utilization and inadequate waste practices.

The social dimension includes five criteria that represent stakeholder-related, workforce-related, and operationally embedded social risk channels. Product Responsibility Risk ( $S_1$ ) refers to the legal, reputational, and financial consequences that may arise from product quality and safety failures. Supply Chain Labor Practices Risk ( $S_2$ ) captures vulnerabilities linked to labor standards and ethical conditions throughout the supply network, while Cybersecurity and Data Privacy Risk ( $S_3$ ) reflects risks stemming from digital security breaches and information misuse. Human Capital Risk ( $S_4$ ) denotes firm-level exposure related to workforce capability, continuity, and organizational commitment, whereas Occupational Health and Safety Risk ( $S_5$ ) represents the risks associated with workplace safety deficiencies and labor-related operational disruptions.

The governance dimension consists of five indicators reflecting the institutional and managerial foundations of corporate sustainability risk. Board Independence Risk ( $G_1$ ) captures weaknesses in oversight and strategic monitoring resulting from limited board independence. Corruption and Ethical Misconduct Risk ( $G_2$ ) refers to vulnerabilities associated with unethical behavior and integrity-related failures, while Regulatory Compliance Risk ( $G_3$ ) represents the potential consequences of non-compliance with applicable legal and regulatory frameworks. Transparency and ESG Disclosure Risk ( $G_4$ ) reflects deficiencies in reporting quality and disclosure practices, and Internal Control and Audit Risk ( $G_5$ ) captures weaknesses in internal monitoring, audit quality, and managerial control mechanisms.

**Table 3**  
 ESG Risk Indicators

Rank	Dimension	Criteria	Code	Optimization
1	Environmental	Carbon Emission Risk	$E_1$	Min
2		Energy Consumption and Efficiency Risk	$E_2$	Min
3		Climate-Related Physical Damage Risk	$E_3$	Min
4		Environmental Compliance Risk	$E_4$	Min
5		Waste Management and Resource Use Risk	$E_5$	Min
6	Social	Product Responsibility Risk	$S_1$	Min
7		Supply Chain Labor Practices Risk	$S_2$	Min
8		Cybersecurity and Data Privacy Risk	$S_3$	Min
9		Human Capital Risk	$S_4$	Min
10		Occupational Health and Safety Risk	$S_5$	Min
11	Governance	Board Independence Risk	$G_1$	Min
12		Corruption and Ethical Misconduct Risk	$G_2$	Min
13		Regulatory Compliance Risk	$G_3$	Min
14		Transparency and ESG Disclosure Risk	$G_4$	Min
15		Internal Control and Audit Risk	$G_5$	Min

#### 4. Application of the Proposed Model

In this section, the application process of the developed integrated model is presented, and the empirical results regarding the ESG risk assessment of the selected manufacturing companies are reported.

##### 4.1 Findings Concerning the LOGSTA Approach

In the first stage of the application, the importance levels of the selected performance indicators were determined using the LOGSTA approach. For this purpose, an initial decision matrix including the alternatives and ESG risk indicators was constructed. In developing this matrix, evaluations were obtained from five experts with substantial professional experience and domain knowledge in ESG and corporate performance. The expert group consisted of a sustainability committee member, a supply chain and procurement manager, a corporate governance and compliance specialist, a finance/investor relations manager, and a deputy general manager. All experts had at least 15 years of professional experience in their respective fields. In terms of educational background, the panel included two experts with bachelor’s degrees, two with master’s degrees, and one with a doctoral degree. This composition helped incorporate diverse managerial perspectives together with experience-based expert judgments into the assessment process. A nine-point evaluation scale ranging from 1 (least important) to 9 (most important) was used to obtain expert assessments. At the final stage of this process, each expert was asked to evaluate the relevant alternatives with respect to the selected ESG risk criteria based on this scale. These individual assessments were then aggregated through arithmetic averaging to construct the final decision matrix. In this way, the decision problem was transformed into a quantitative matrix that integrates different expert judgments within a common framework and provides the basis for the subsequent weighting stage. The decision matrix used in the LOGSTA procedure is presented in Table 4.

**Table 4**  
 Integrated Decision Matrix

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
R <sub>1</sub>	2.800	2.800	3.200	3.200	4.000	4.600	7.600	5.600	4.600	4.000	4.000	4.200	4.200	4.600	4.200
R <sub>2</sub>	5.000	4.800	4.400	4.400	5.200	4.600	5.000	3.800	4.200	4.200	3.400	4.200	4.200	3.400	3.600
R <sub>3</sub>	3.200	4.200	3.400	3.400	4.200	4.600	4.600	7.600	3.400	3.400	3.800	4.200	4.200	3.600	4.200
R <sub>4</sub>	8.800	9.000	6.200	7.400	8.200	5.400	5.600	4.800	4.200	7.400	4.000	5.200	6.400	4.600	5.200
R <sub>5</sub>	6.000	6.200	6.800	5.400	5.200	4.000	6.400	3.800	4.400	6.400	4.000	4.200	5.200	4.200	4.200
R <sub>6</sub>	6.000	6.200	4.200	4.200	5.200	4.000	6.400	4.600	4.200	6.400	3.000	3.200	4.200	2.800	3.200
R <sub>7</sub>	4.200	5.200	4.200	4.200	5.200	4.400	5.600	3.800	4.200	4.200	4.000	4.200	4.200	4.200	4.200
R <sub>8</sub>	7.000	7.200	5.200	5.200	6.200	4.200	5.600	4.800	4.200	6.400	3.000	4.000	4.200	3.000	3.200
R <sub>9</sub>	9.000	9.000	7.200	8.400	8.200	5.400	5.600	4.800	4.200	8.400	4.000	5.200	7.400	4.600	5.200
R <sub>10</sub>	8.000	8.200	5.200	6.400	7.200	4.200	4.800	3.800	4.200	7.400	4.000	4.200	5.200	4.600	4.200
R <sub>11</sub>	4.000	4.200	4.000	3.000	4.200	3.400	5.600	4.600	3.000	4.000	2.600	3.000	3.000	2.200	2.800
R <sub>12</sub>	8.000	8.200	5.200	6.400	7.200	4.200	4.800	3.800	4.200	7.400	4.000	4.200	5.200	4.600	4.200
R <sub>13</sub>	2.800	3.000	3.000	3.400	3.000	4.400	4.600	4.600	4.000	3.000	4.400	4.600	4.600	4.400	4.400

The decision matrix was normalized by applying Eq. (2) to the beneficial criteria and Eq. (3) to the non-beneficial criteria. The normalized matrix is presented in Table 5.

**Table 5**  
 Normalized Matrix

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
R <sub>1</sub>	0.0474	0.0459	0.0585	0.0575	0.0632	0.0794	0.0916	0.0874	0.0839	0.0640	0.0820	0.0775	0.0716	0.0877	0.0796
R <sub>2</sub>	0.0741	0.0699	0.0745	0.0732	0.0752	0.0794	0.0726	0.0677	0.0789	0.0662	0.0724	0.0775	0.0716	0.0703	0.0711
R <sub>3</sub>	0.0536	0.0639	0.0615	0.0605	0.0654	0.0794	0.0689	0.1029	0.0673	0.0565	0.0790	0.0775	0.0716	0.0736	0.0796
R <sub>4</sub>	0.1002	0.0979	0.0918	0.0989	0.0959	0.0878	0.0778	0.0796	0.0789	0.0924	0.0820	0.0890	0.0926	0.0877	0.0915
R <sub>5</sub>	0.0825	0.0813	0.0964	0.0833	0.0752	0.0721	0.0838	0.0677	0.0814	0.0857	0.0820	0.0775	0.0823	0.0825	0.0796
R <sub>6</sub>	0.0825	0.0813	0.0722	0.0709	0.0752	0.0721	0.0838	0.0774	0.0789	0.0857	0.0650	0.0628	0.0716	0.0592	0.0645
R <sub>7</sub>	0.0661	0.0735	0.0722	0.0709	0.0752	0.0771	0.0778	0.0677	0.0789	0.0662	0.0820	0.0775	0.0716	0.0825	0.0796
R <sub>8</sub>	0.0896	0.0880	0.0829	0.0815	0.0832	0.0747	0.0778	0.0796	0.0789	0.0857	0.0650	0.0749	0.0716	0.0631	0.0645
R <sub>9</sub>	0.1012	0.0979	0.0993	0.1052	0.0959	0.0878	0.0778	0.0796	0.0789	0.0982	0.0820	0.0890	0.0999	0.0877	0.0915
R <sub>10</sub>	0.0958	0.0938	0.0829	0.0917	0.0900	0.0747	0.0708	0.0677	0.0789	0.0924	0.0820	0.0775	0.0823	0.0877	0.0796
R <sub>11</sub>	0.0638	0.0639	0.0697	0.0543	0.0654	0.0637	0.0778	0.0774	0.0604	0.0640	0.0565	0.0593	0.0548	0.0453	0.0571
R <sub>12</sub>	0.0958	0.0938	0.0829	0.0917	0.0900	0.0747	0.0708	0.0677	0.0789	0.0924	0.0820	0.0775	0.0823	0.0877	0.0796
R <sub>13</sub>	0.0474	0.0490	0.0552	0.0605	0.0501	0.0771	0.0689	0.0774	0.0762	0.0507	0.0877	0.0824	0.0762	0.0851	0.0822

At this stage, the standard deviation values for each indicator were first calculated. Subsequently, using these values, the G matrix was derived within the scope of Eq. (4). Finally, the weights of each performance indicator were calculated by means of Eq. (5). The results obtained as a result of these calculations are reported in Table 6.

**Table 6**  
 Findings of LOGSTA Approach

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
$\sigma_j$	0.0197	0.0177	0.0140	0.0166	0.0138	0.0064	0.0067	0.0101	0.0062	0.0160	0.0092	0.0084	0.0112	0.0137	0.0101
$g_j$	0.0006	0.0005	0.0004	0.0005	0.0004	0.0002	0.0002	0.0003	0.0002	0.0005	0.0003	0.0003	0.0003	0.0004	0.0003
$w_j$	0.1087	0.0979	0.0779	0.0920	0.0768	0.0357	0.0373	0.0565	0.0348	0.0887	0.0515	0.0467	0.0627	0.0764	0.0564
Rank	1	2	5	3	6	14	13	9	15	4	11	12	8	7	10

#### 4.2 Findings Related to the SPC Approach

In the second phase of the assessment process, the weights of the ESG risk metrics were calculated based on the SPC approach. In this context, the initial matrix was first created in accordance with Eq. (1). Subsequently, the symmetry points of the criteria were identified by employing Eq. (6) on the initial matrix. In the third stage of the SPC procedure, the absolute distance matrix for the performance criteria was derived through Eq. (7). The findings obtained from these calculations are shown in Table 7.

**Table 7**  
 Symmetry Points and Absolute Distance Matrix

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
SPC <sub>j</sub>	5.9000	5.9000	5.1000	5.7000	5.6000	4.4000	6.1000	5.7000	3.8000	5.7000	3.5000	4.1000	5.2000	3.4000	4.0000
R <sub>1</sub>	3.1000	3.1000	1.9000	2.5000	1.6000	0.2000	1.5000	0.1000	0.8000	1.7000	0.5000	0.1000	1.0000	1.2000	0.2000
R <sub>2</sub>	0.9000	1.1000	0.7000	1.3000	0.4000	0.2000	1.1000	1.9000	0.4000	1.5000	0.1000	0.1000	1.0000	0.0000	0.4000
R <sub>3</sub>	2.7000	1.7000	1.7000	2.3000	1.4000	0.2000	1.5000	1.9000	0.4000	2.3000	0.3000	0.1000	1.0000	0.2000	0.2000
R <sub>4</sub>	2.9000	3.1000	1.1000	1.7000	2.6000	1.0000	0.5000	0.9000	0.4000	1.7000	0.5000	1.1000	1.2000	1.2000	1.2000
R <sub>5</sub>	0.1000	0.3000	1.7000	0.3000	0.4000	0.4000	0.3000	1.9000	0.6000	0.7000	0.5000	0.1000	0.0000	0.8000	0.2000
R <sub>6</sub>	0.1000	0.3000	0.9000	1.5000	0.4000	0.4000	0.3000	1.1000	0.4000	0.7000	0.5000	0.9000	1.0000	0.6000	0.8000
R <sub>7</sub>	1.7000	0.7000	0.9000	1.5000	0.4000	0.0000	0.5000	1.9000	0.4000	1.5000	0.5000	0.1000	1.0000	0.8000	0.2000
R <sub>8</sub>	1.1000	1.3000	0.1000	0.5000	0.6000	0.2000	0.5000	0.9000	0.4000	0.7000	0.5000	0.1000	1.0000	0.4000	0.8000
R <sub>9</sub>	3.1000	3.1000	2.1000	2.7000	2.6000	1.0000	0.5000	0.9000	0.4000	2.7000	0.5000	1.1000	2.2000	1.2000	1.2000
R <sub>10</sub>	2.1000	2.3000	0.1000	0.7000	1.6000	0.2000	1.3000	1.9000	0.4000	1.7000	0.5000	0.1000	0.0000	1.2000	0.2000
R <sub>11</sub>	1.9000	1.7000	1.1000	2.7000	1.4000	1.0000	0.5000	1.1000	0.8000	1.7000	0.9000	1.1000	2.2000	1.2000	1.2000
R <sub>12</sub>	2.1000	2.3000	0.1000	0.7000	1.6000	0.2000	1.3000	1.9000	0.4000	1.7000	0.5000	0.1000	0.0000	1.2000	0.2000
R <sub>13</sub>	3.1000	2.9000	2.1000	2.3000	2.6000	0.0000	1.5000	1.1000	0.2000	2.7000	0.9000	0.5000	0.6000	1.0000	0.4000

The symmetric modulus matrix derived using Eq. (8) is presented in Table 8.

**Table 8**  
 Symmetric Modulus Matrix

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
R <sub>1</sub>	0.3831	0.3830	0.2535	0.3619	0.2604	0.0836	0.1738	0.3543	0.1099	0.3901	0.1516	0.1007	0.2234	0.2489	0.1538
R <sub>2</sub>	0.5986	0.4377	0.3281	0.4683	0.3223	0.0836	0.1890	0.1771	0.1357	0.4819	0.1356	0.1007	0.2234	0.2350	0.1319
R <sub>3</sub>	0.2177	0.2043	0.1799	0.2152	0.1651	0.0712	0.1552	0.2804	0.1099	0.2214	0.1288	0.0814	0.1466	0.1839	0.1065
R <sub>4</sub>	0.3192	0.2965	0.1640	0.2949	0.2604	0.0962	0.1358	0.3543	0.1049	0.2560	0.1288	0.1007	0.1805	0.2015	0.1319
R <sub>5</sub>	0.3192	0.2965	0.2656	0.3791	0.2604	0.0962	0.1358	0.2926	0.1099	0.2560	0.1718	0.1322	0.2234	0.3022	0.1731
R <sub>6</sub>	0.4560	0.3536	0.2656	0.3791	0.2604	0.0874	0.1552	0.3543	0.1099	0.3901	0.1288	0.1007	0.2234	0.2015	0.1319
R <sub>7</sub>	0.2736	0.2553	0.2145	0.3062	0.2184	0.0916	0.1552	0.2804	0.1099	0.2560	0.1718	0.1058	0.2234	0.2821	0.1731
R <sub>8</sub>	0.2128	0.2043	0.1549	0.1896	0.1651	0.0712	0.1552	0.2804	0.1099	0.1951	0.1288	0.0814	0.1268	0.1839	0.1065
R <sub>9</sub>	0.2394	0.2242	0.2145	0.2488	0.1880	0.0916	0.1811	0.3543	0.1099	0.2214	0.1288	0.1007	0.1805	0.1839	0.1319
R <sub>10</sub>	0.4788	0.4377	0.2788	0.5308	0.3223	0.1131	0.1552	0.2926	0.1538	0.4096	0.1982	0.1410	0.3128	0.3846	0.1978
R <sub>11</sub>	0.2394	0.2242	0.2145	0.2488	0.1880	0.0916	0.1811	0.3543	0.1099	0.2214	0.1288	0.1007	0.1805	0.1839	0.1319
R <sub>12</sub>	0.6841	0.6128	0.3718	0.4683	0.4513	0.0874	0.1890	0.2926	0.1154	0.5462	0.1171	0.0920	0.2040	0.1923	0.1259
R <sub>13</sub>	0.6841	0.6566	0.3486	0.4976	0.3385	0.0836	0.1144	0.2404	0.1003	0.4096	0.1288	0.1007	0.2234	0.1839	0.1319

In the final phase of the SPC method, the vector matrix related to the ESG risk criteria was first derived via Eq. (9). Subsequently, the criterion weights for each metric were determined by means of Eq. (10). The results obtained are reported in Table 9.

**Table 9**  
 Results of SPC Approach

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
Q <sub>j</sub>	0.3928	0.3528	0.2503	0.3530	0.2616	0.0883	0.1597	0.3006	0.1146	0.3273	0.1422	0.1030	0.2056	0.2283	0.1406
w <sub>j</sub>	0.1148	0.1031	0.0732	0.1032	0.0765	0.0258	0.0467	0.0879	0.0335	0.0957	0.0416	0.0301	0.0601	0.0667	0.0411
Rank	1	3	7	2	6	15	10	5	13	4	11	14	9	8	12

### 4.3 Findings Concerning the Final Weighting Approach

The criterion weights calculated under the LOGSTA and SPC approaches were integrated within the framework of Eq. (11), and the final weights of each performance indicator were thereby determined. These weights are reported in Table 10.

**Table 10**  
 Final Weights of the Criteria

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
w <sub>j</sub> <sup>LOGSTA</sup>	0.1087	0.0979	0.0779	0.0920	0.0768	0.0357	0.0373	0.0565	0.0348	0.0887	0.0515	0.0467	0.0627	0.0764	0.0564
w <sub>j</sub> <sup>SPC</sup>	0.1148	0.1031	0.0732	0.1032	0.0765	0.0258	0.0467	0.0879	0.0335	0.0957	0.0416	0.0301	0.0601	0.0667	0.0411
w <sub>j</sub> <sup>(final)</sup>	0.1118	0.1005	0.0755	0.0976	0.0766	0.0308	0.0420	0.0722	0.0342	0.0922	0.0465	0.0384	0.0614	0.0716	0.0488
Rank	1	2	6	3	5	15	12	7	14	4	11	13	9	8	10

The final weight results displayed in Table 10 clearly show that the ESG risk structure of manufacturing firms is concentrated primarily in environmental dimension. According to the final weights, the top three criteria are Carbon Emission Risk (E<sub>1</sub>), Energy Consumption and Efficiency Risk (E<sub>2</sub>), and Environmental Compliance Risk (E<sub>4</sub>). This pattern suggests that risks related to environmental obligations, as well as resource and energy use, have stronger discriminating power within the manufacturing industry. On other hand, three lowest-ranked criteria are Human Capital Risk (S<sub>4</sub>), Product Responsibility Risk (S<sub>1</sub>), and Corruption and Ethical Misconduct Risk (G<sub>2</sub>). This result indicates that these indicators exhibit relatively lower variation across the firms included in analysis.

### 4.4 Findings Regarding the MUNRA Approach

In the final stage of the assessment process, the final criterion weights were integrated into the MUNRA approach in order to determine the relative performance rankings of the manufacturing firms. To do so, the analysis first used the initial decision matrix constructed according to Eq. (1) and reported in Table 4. This matrix was then subjected to the multiple-normalization framework required by MUNRA. Specifically, Eqs. (12)–(13) were applied for linear normalization, Eqs. (14)–(15) for vector normalization, and Eqs. (16)–(17) for nonlinear normalization. The normalized matrices derived from these procedures are presented in Tables 11–13, respectively.

**Table 11**  
 Linear Normalization Matrix

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
R <sub>1</sub>	1.0000	1.0000	0.9375	0.9375	0.7500	0.7391	0.6053	0.6786	0.6522	0.7500	0.6500	0.7143	0.7143	0.4783	0.6667
R <sub>2</sub>	0.5600	0.5833	0.6818	0.6818	0.5769	0.7391	0.9200	1.0000	0.7143	0.7143	0.7647	0.7143	0.7143	0.6471	0.7778
R <sub>3</sub>	0.8750	0.6667	0.8824	0.8824	0.7143	0.7391	1.0000	0.5000	0.8824	0.8824	0.6842	0.7143	0.7143	0.6111	0.6667
R <sub>4</sub>	0.3182	0.3111	0.4839	0.4054	0.3659	0.6296	0.8214	0.7917	0.7143	0.4054	0.6500	0.5769	0.4688	0.4783	0.5385
R <sub>5</sub>	0.4667	0.4516	0.4412	0.5556	0.5769	0.8500	0.7188	1.0000	0.6818	0.4688	0.6500	0.7143	0.5769	0.5238	0.6667
R <sub>6</sub>	0.4667	0.4516	0.7143	0.7143	0.5769	0.8500	0.7188	0.8261	0.7143	0.4688	0.8667	0.9375	0.7143	0.7857	0.8750
R <sub>7</sub>	0.6667	0.5385	0.7143	0.7143	0.5769	0.7727	0.8214	1.0000	0.7143	0.7143	0.6500	0.7143	0.7143	0.5238	0.6667
R <sub>8</sub>	0.4000	0.3889	0.5769	0.5769	0.4839	0.8095	0.8214	0.7917	0.7143	0.4688	0.8667	0.7500	0.7143	0.7333	0.8750
R <sub>9</sub>	0.3111	0.3111	0.4167	0.3571	0.3659	0.6296	0.8214	0.7917	0.7143	0.3571	0.6500	0.5769	0.4054	0.4783	0.5385
R <sub>10</sub>	0.3500	0.3415	0.5769	0.4688	0.4167	0.8095	0.9583	1.0000	0.7143	0.4054	0.6500	0.7143	0.5769	0.4783	0.6667
R <sub>11</sub>	0.7000	0.6667	0.7500	1.0000	0.7143	1.0000	0.8214	0.8261	1.0000	0.7500	1.0000	1.0000	1.0000	1.0000	1.0000
R <sub>12</sub>	0.3500	0.3415	0.5769	0.4688	0.4167	0.8095	0.9583	1.0000	0.7143	0.4054	0.6500	0.7143	0.5769	0.4783	0.6667
R <sub>13</sub>	1.0000	0.9333	1.0000	0.8824	1.0000	0.7727	1.0000	0.8261	0.7500	1.0000	0.5909	0.6522	0.6522	0.5000	0.6364

**Table 12**  
 Vector Normalization Matrix

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
R <sub>1</sub>	0.8738	0.8781	0.8209	0.8314	0.8104	0.7131	0.6246	0.6734	0.6886	0.8105	0.7036	0.7254	0.7625	0.6800	0.7172
R <sub>2</sub>	0.7746	0.7910	0.7537	0.7682	0.7535	0.7131	0.7530	0.7783	0.7157	0.8010	0.7481	0.7254	0.7625	0.7635	0.7576
R <sub>3</sub>	0.8557	0.8171	0.8097	0.8209	0.8009	0.7131	0.7728	0.5567	0.7698	0.8389	0.7184	0.7254	0.7625	0.7496	0.7172
R <sub>4</sub>	0.6033	0.6081	0.6529	0.6102	0.6113	0.6632	0.7234	0.7200	0.7157	0.6494	0.7036	0.6600	0.6382	0.6800	0.6499
R <sub>5</sub>	0.7295	0.7300	0.6193	0.7156	0.7535	0.7505	0.6839	0.7783	0.7021	0.6968	0.7036	0.7254	0.7060	0.7078	0.7172
R <sub>6</sub>	0.7295	0.7300	0.7649	0.7788	0.7535	0.7505	0.6839	0.7317	0.7157	0.6968	0.7777	0.7908	0.7625	0.8052	0.7845
R <sub>7</sub>	0.8106	0.7736	0.7649	0.7788	0.7535	0.7255	0.7234	0.7783	0.7157	0.8010	0.7036	0.7254	0.7625	0.7078	0.7172
R <sub>8</sub>	0.6844	0.6865	0.7089	0.7261	0.7061	0.7380	0.7234	0.7200	0.7157	0.6968	0.7777	0.7385	0.7625	0.7913	0.7845
R <sub>9</sub>	0.5942	0.6081	0.5969	0.5576	0.6113	0.6632	0.7234	0.7200	0.7157	0.6021	0.7036	0.6600	0.5816	0.6800	0.6499
R <sub>10</sub>	0.6393	0.6429	0.7089	0.6629	0.6587	0.7380	0.7629	0.7783	0.7157	0.6494	0.7036	0.7254	0.7060	0.6800	0.7172
R <sub>11</sub>	0.8197	0.8171	0.7761	0.8420	0.8009	0.7879	0.7234	0.7317	0.7969	0.8105	0.8073	0.8039	0.8304	0.8470	0.8115
R <sub>12</sub>	0.6393	0.6429	0.7089	0.6629	0.6587	0.7380	0.7629	0.7783	0.7157	0.6494	0.7036	0.7254	0.7060	0.6800	0.7172
R <sub>13</sub>	0.8738	0.8694	0.8321	0.8209	0.8578	0.7255	0.7728	0.7317	0.7292	0.8579	0.6740	0.6993	0.7399	0.6939	0.7037

**Table 13**  
 Nonlinear Normalization Matrix

	E <sub>1</sub>	E <sub>2</sub>	E <sub>3</sub>	E <sub>4</sub>	E <sub>5</sub>	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>
R <sub>1</sub>	1.0000	1.0000	0.8240	0.8240	0.4219	0.4038	0.2217	0.3125	0.2774	0.4219	0.2746	0.3644	0.3644	0.1094	0.2963
R <sub>2</sub>	0.1756	0.1985	0.3170	0.3170	0.1920	0.4038	0.7787	1.0000	0.3644	0.3644	0.4472	0.3644	0.3644	0.2709	0.4705
R <sub>3</sub>	0.6699	0.2963	0.6870	0.6870	0.3644	0.4038	1.0000	0.1250	0.6870	0.6870	0.3203	0.3644	0.3644	0.2282	0.2963
R <sub>4</sub>	0.0322	0.0301	0.1133	0.0666	0.0490	0.2496	0.5543	0.4962	0.3644	0.0666	0.2746	0.1920	0.1030	0.1094	0.1561
R <sub>5</sub>	0.1016	0.0921	0.0859	0.1715	0.1920	0.6141	0.3713	1.0000	0.3170	0.1030	0.2746	0.3644	0.1920	0.1437	0.2963
R <sub>6</sub>	0.1016	0.0921	0.3644	0.3644	0.1920	0.6141	0.3713	0.5637	0.3644	0.1030	0.6510	0.8240	0.3644	0.4851	0.6699
R <sub>7</sub>	0.2963	0.1561	0.3644	0.3644	0.1920	0.4614	0.5543	1.0000	0.3644	0.3644	0.2746	0.3644	0.3644	0.1437	0.2963
R <sub>8</sub>	0.0640	0.0588	0.1920	0.1920	0.1133	0.5305	0.5543	0.4962	0.3644	0.1030	0.6510	0.4219	0.3644	0.3944	0.6699
R <sub>9</sub>	0.0301	0.0301	0.0723	0.0456	0.0490	0.2496	0.5543	0.4962	0.3644	0.0456	0.2746	0.1920	0.0666	0.1094	0.1561
R <sub>10</sub>	0.0429	0.0398	0.1920	0.1030	0.0723	0.5305	0.8801	1.0000	0.3644	0.0666	0.2746	0.3644	0.1920	0.1094	0.2963
R <sub>11</sub>	0.3430	0.2963	0.4219	1.0000	0.3644	1.0000	0.5543	0.5637	1.0000	0.4219	1.0000	1.0000	1.0000	1.0000	1.0000
R <sub>12</sub>	0.0429	0.0398	0.1920	0.1030	0.0723	0.5305	0.8801	1.0000	0.3644	0.0666	0.2746	0.3644	0.1920	0.1094	0.2963
R <sub>13</sub>	1.0000	0.8130	1.0000	0.6870	1.0000	0.4614	1.0000	0.5637	0.4219	1.0000	0.2063	0.2774	0.2774	0.1250	0.2577

The normalized values obtained from the multiple-normalization process were subjected to Eqs. (18)-(20), respectively, and the weighted aggregate scores for each alternative firm were calculated. In the final phase, the performance score of each firm was determined using Eq. (21), and the performance rankings were established on the basis of these scores. The findings obtained from these calculations are presented in Table 14.

**Table 14**  
 Findings of MUNRA Approach

	$r'_i$	$y'_i$	$p'_i$	$v_i$	Rank
R <sub>1</sub>	0.7889	0.7772	0.5513	0.7058	3
R <sub>2</sub>	0.6984	0.7648	0.3720	0.6117	5
R <sub>3</sub>	0.7640	0.7754	0.4838	0.6744	4
R <sub>4</sub>	0.4854	0.6490	0.1527	0.4290	12
R <sub>5</sub>	0.5874	0.7151	0.2488	0.5171	9
R <sub>6</sub>	0.6681	0.7490	0.3472	0.5881	7
R <sub>7</sub>	0.6887	0.7601	0.3562	0.6017	6
R <sub>8</sub>	0.6130	0.7240	0.2821	0.5397	8
R <sub>9</sub>	0.4665	0.6307	0.1432	0.4135	13
R <sub>10</sub>	0.5536	0.6876	0.2438	0.4950	10
R <sub>11</sub>	0.8491	0.8049	0.6599	0.7713	2
R <sub>12</sub>	0.5536	0.6876	0.2438	0.4950	10
R <sub>13</sub>	0.8465	0.7930	0.6750	0.7715	1

According to the MUNRA approach results presented in Table 14, the top three firms with the highest performance scores are R<sub>13</sub> (ULKER), R<sub>11</sub> (TUPRS), and R<sub>1</sub> (AEFES), respectively. This outcome demonstrates that these firms exhibit relatively stronger performance under the integrated assessment framework with respect to the chosen ESG risk indicators. In particular, the very close final utility scores of ULKER and TUPRS suggest that both firms display a high level of competitiveness within the overall assessment structure. The third-place position of AEFES likewise indicates that the firm belongs to the upper group in terms of its overall ESG risk profile. On the other hand, the bottom three firms are R<sub>9</sub> (OYAKC), R<sub>4</sub> (CIMSA), and R<sub>10</sub> (PETKM). This finding suggests that these firms show comparatively weaker performance within the integrated ESG risk assessment framework. The lower rankings of OYAKC and CIMSA may indicate that cement firms are more vulnerable in terms of environmental and operational risk metrics. Similarly, the position of PETKM in the lower group implies that ESG risk performance may remain more limited in sectors exposed to particularly intense environmental and energy-related pressures.

A sensitivity analysis was applied in this section to assess the robustness and reliability of the developed decision model. In this context, the ranking findings obtained from the integrated LOGSTA-SPC and MUNRA approach were compared with those derived from alternative ranking procedures widely utilized in the decision-making literature, including ALPAS, PIV, MARCOS, RAM, RAWEC, COPRAS, SAW, and WASPAS. The results of these comparisons are reported in Figure 2. The results reported in the figure show that the ranking generated by the developed model is highly consistent with those produced by the alternative MCDM ranking approaches and does not exhibit any substantial deviation. This result may be regarded as an important indication that the developed integrated model is capable of producing stable, consistent, and reliable results.

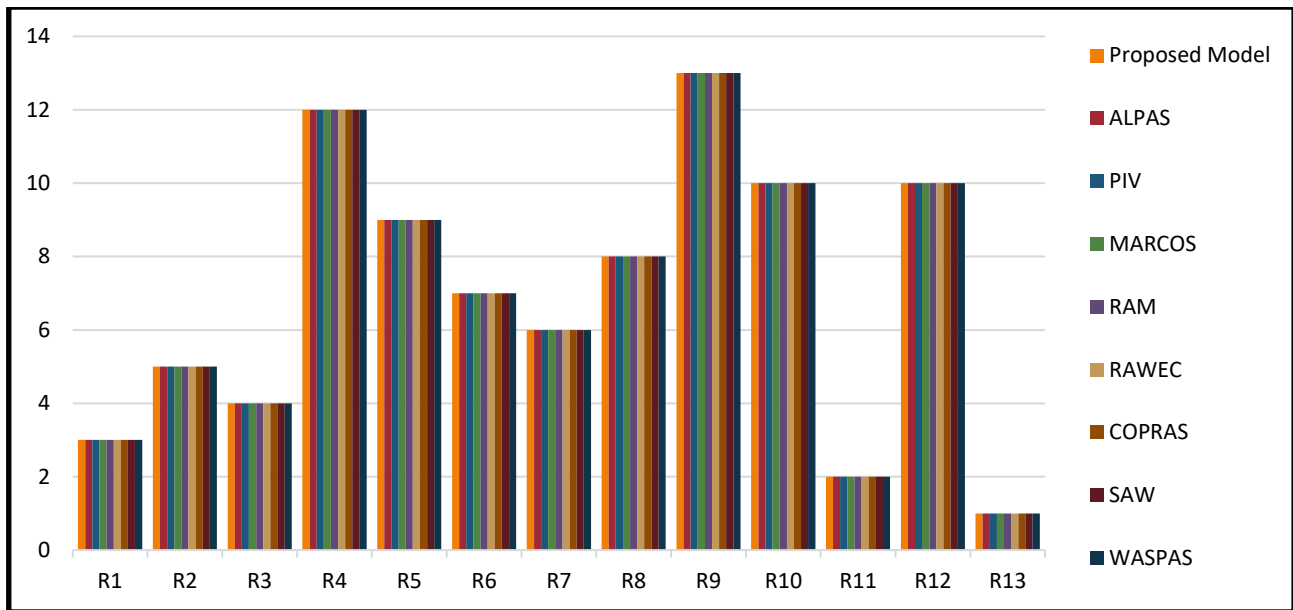


Fig. 2. Comparing the Proposed Model with Alternative Ranking Approaches

## 5. Conclusions

ESG risks are deemed ever more important in not only assessing the sustainability orientation of firms but also their long-term competitiveness, adaptive capacity, and strategic resilience. This is particularly true for manufacturing firms since environmental pressures, energy dependence, production-related responsibilities, and governance requirements intersect here in a very visible way. From this perspective, assessing ESG risks through a comprehensive and comparative framework has moved beyond being merely an academic exercise; it has become necessary to identify vulnerable areas, understand differences at the level of the firm, and support more resilient strategic choices. Therefore, an integrated decision-making framework that combines LOGSTA and SPC for weighting and MUNRA for ranking was developed in the present study. This framework was applied to 13 manufacturing companies listed in the BIST Sustainability-25 Index to systematically assess ESG risk structures.

The weighting results indicate that environmental factors primarily shape the ESG risk profiles of the sample firms. More specifically, Carbon Emission Risk, Energy Consumption and Efficiency Risk, and Environmental Compliance Risk have emerged as three most influential criteria. On the other hand, Human Capital Risk and Product Responsibility Risk have received lowest weights; Corruption and Ethical Misconduct Risk is also positioned among relatively less discriminating indicators. These results imply that within this sample strong differences among firms arise mainly from environmental and operational pressures. The prominence of Carbon Emission Risk is especially critical because it shows that carbon-related issues should no longer be treated as peripheral environmental concerns but should now be considered direct business risks with impacts on cost structure, regulatory exposure, corporate image, etc., affecting long-term competitiveness. The weight given to Energy Consumption and Efficiency Risk also indicates how important energy performance is when considering ESG risks for manufacturing companies. The strong position of Environmental Compliance Risk further confirms that compliance with environmental regulations remains a defining challenge for the sector. At the same time, the relatively low weights of some social and governance-related criteria should not be taken as an indication that these dimensions are unimportant. They

rather show that such criteria were less effective in distinguishing among the firms included in this particular sample. In other words, lower weight reflects weaker discriminatory power in the comparative framework and not conceptual insignificance. From this perspective, results imply that ESG-based differentiation in manufacturing is more strongly driven by environmental and operational vulnerabilities than by those social or governance indicators which have more limited variation across firms.

After the weighting stage, the MUNRA procedure was used to rank firms based on their ESG risk performance. Ülker, Tüpraş, and Anadolu Efes were identified as high performers while Oyak Çimento, Çimsa, and Petkim were found at the bottom end of the ranking. The good positions of Ülker and Tüpraş may reflect that these companies have been more successful in establishing relatively resilient ESG risk profiles possibly supported by stronger organizational capacity broader managerial resources as well as a more structured approach to risk governance. Anadolu Efes also seems to be managing such pressures in a better-balanced and integrated way with its larger corporate structure. When looking at the results for lower-ranked firms, they also point to how important sectoral conditions are. The positions of Oyak Cement and Çimsa, for example, seem closely tied to specific structural characteristics of the cement industry where carbon intensity, energy dependence, and environmental compliance pressures are especially strong. This indicates that ESG risk performance is influenced not only by managerial quality but also by the inherent risk profile of the sector in which a firm operates. A similar interpretation can be made for Petkim, whose lower ranking is broadly consistent with the environmental sensitivity and energy-intensive nature of the petrochemical industry. Taken together, these findings indicate that firms at the lower end of the ranking are likely operating under heavier ESG pressure and may have more limited room to offset sector-driven risk exposure through internal managerial practices alone.

The robustness of the proposed framework was examined by comparing the LOGSTA-SPC-MUNRA ranking results with those obtained from alternative MCDM methods. This comparison revealed a high degree of consistency across ranking structures and did not produce any major contradictions. Such a pattern supports the stability and reliability of the proposed model and suggests that the framework generates results that are not overly sensitive to method choice. Accordingly, the sensitivity analysis strengthens confidence in the analytical soundness of the integrated model and supports its use as a practical evaluation tool in ESG risk assessment.

The study also offers several implications. From a theoretical standpoint, the findings suggest that the relationship between ESG risks and firm performance cannot be captured adequately through narrow, one-dimensional, or purely disclosure-based indicators. The concentration of risk differentiation around environmental and operational dimensions indicates that ESG risk should be treated as a multidimensional and measurable analytical domain rather than as a loose extension of sustainability reporting. In this sense, the study contributes to the MCDM literature by demonstrating the usefulness of integrating LOGSTA, SPC, and MUNRA within a single analytical structure for ESG-oriented firm evaluation.

From a practical perspective, the findings show that firms should avoid approaching ESG risk as if it were a uniform and internally balanced construct. The dominant role of carbon emissions, energy consumption, and environmental compliance points to the need for a more focused allocation of managerial attention and organizational resources in these areas. The proposed model may therefore serve as a decision-support tool for identifying where ESG vulnerabilities are concentrated, comparing firms against their peers, and determining priority areas for strategic improvement. Its usefulness extends beyond reporting and may support internal monitoring, comparative benchmarking, and structured risk assessment processes.

The implications of the results also have significant managerial and policy implications. From a managerial point of view, ESG risk management in manufacturing industries is no more an ancillary issue to be addressed in a peripheral manner. Rather, it is an integral part that needs to be included in strategic management decisions because it is closely linked to industry competitiveness and survival. This calls for more attention to carbon management, energy efficiency, environmental compliance, and corporate governance in risk management practices in industries. From a policy and regulatory point of view, it may be noted that uniform ESG monitoring tools may not be effective in this context. More effective policy strategies would require industrial-specific evaluation systems that consider differences in industrial structure, environmental burden, and operation risk in ESG management. This calls for more nuanced incentives and effective regulatory mechanisms to facilitate compliance and transformation in industries.

In spite of these significant contributions, the study has some limitations. Firstly, the scope of the empirical study is restricted to 13 manufacturing firms included in the BIST Sustainability-25 Index. This might not be a comprehensive list to generalize the results. Secondly, the results heavily rely on the selection of ESG risk indicators. Different indicators and/or criteria for specific industries might lead to other possible results. Finally, the study is cross-sectional in nature and does not cover the dynamic nature of ESG risks. It is possible to address these issues in further studies by investigating a larger number of samples from different countries and industries, using other ESG indicators, and comparing the proposed method with other possible hybrid approaches to MCDM techniques.

### **Funding**

This research received no external funding.

### **Data Availability Statement**

The study did not report any data.

### **Conflicts of Interest**

The author declares no conflict of interest.

### **Acknowledgement**

This research was not funded by any grant.

### **AI-assisted Technologies**

In this study, the OpenAI ChatGPT tool was used to review language and improve grammatical accuracy. The author confirm that all content was carefully examined and validated to ensure its correctness and integrity.

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