

MULTI-CRITERIA PERFORMANCE ASSESSMENT OF BEVERAGE COMPANIES INTEGRATING FINANCIAL AND ESG INDICATORS: A HYBRID ANALYTICAL FRAMEWORK

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ABSTRACT

This research introduces a hybrid Multi-Criteria Decision-Making (MCDM) framework for assessing the multidimensional performance of beverage companies listed on the London Stock Exchange, integrating financial metrics with Environmental, Social, and Governance (ESG) indicators. The suggested approach combines two advanced objective weighting techniques—CRISUS and MAXC—with the CRADIS ranking algorithm, forming a robust and transparent decision-support structure. A total of 15 performance indicators spanning four dimensions (environmental, social, governance, and financial) were assessed for eight firms employing 2022 Refinitiv Eikon data. The framework captures the intrinsic structure of performance data, enabling reproducible and data-driven prioritization of criteria. Empirical findings reveal that innovation, closing price, and community engagement are the most influential drivers of performance, with Diageo ranking highest and Daniel Thwaites lowest. Robustness and sensitivity analyses confirm the model's internal consistency and resistance to rank reversal, validating its reliability under varying parametric conditions. This research contributes to the MCDM literature by introducing a replicable, stakeholder-oriented, and sector-specific evaluation framework tailored to ESG-sensitive industries. The integration of financial and non-financial indicators within a unified structure enhances strategic relevance and supports evidence-based decision-making. Overall, the developed model provides actionable insights for executives, investors, and policy-makers seeking to assess corporate sustainability and competitiveness in complex decision environments.

Keywords: Open Sustainable Innovation, Port Ecosystem, Digitalisation, Maritime Ports, Innovation Strategies, Stakeholders

1. INTRODUCTION

In recent years, corporate performance assessment has undergone a profound transformation, driven by rising stakeholder expectations, regulatory pressure, and the growing recognition that long-term firm value cannot be captured solely through traditional financial indicators (Işık, 2023). In this evolving context, Environmental, Social, and Governance (ESG) dimensions have become integral components of corporate evaluation frameworks, reflecting firms' environmental responsibility, social engagement, and governance quality alongside their economic

outcomes (Çetenak et al., 2022; Shabir et al., 2025).

The integration of financial and ESG indicators has therefore emerged as a strategic necessity rather than a normative preference. Investors increasingly rely on ESG-adjusted performance metrics to manage risk and identify sustainable value creation opportunities, while corporate executives use these indicators to guide strategic planning, innovation investments, and stakeholder communication. From a regulatory and policy perspective, multidimensional performance assessment supports transparency, accountability, and evidence-based policy design. Consequently, the ability to evaluate corporate performance in a comprehensive and structured manner holds substantial relevance for managers, investors, regulators, and researchers alike (Ünlü & Yalçın, 2023; Ünlü and Çıtak, 2025).

However, evaluating corporate performance across heterogeneous dimensions presents a complex analytical challenge. Financial indicators such as profitability and market valuation are quantitative and market-driven, whereas ESG indicators often capture qualitative, long-term, and stakeholder-oriented aspects of firm behavior (İç et al., 2022; Türegün, 2022; Lukin et al., 2022). These criteria differ in scale, direction, and relative importance, and they frequently involve trade-offs—for instance, between short-term financial performance and long-term environmental sustainability. As a result, aggregating such diverse indicators into a single, coherent performance measure cannot be achieved through conventional unidimensional evaluation techniques.

In this regard, Multi-Criteria Decision-Making (MCDM) methodologies offer a theoretically rigorous and practically effective solution. MCDM techniques enable the systematic integration of heterogeneous criteria, support transparent weighting procedures, and generate interpretable rankings of decision alternatives. In particular, hybrid MCDM frameworks—combining multiple weighting and ranking algorithms—have gained prominence due to their ability to enhance robustness, reduce methodological bias, and improve the explanatory power of performance evaluation outcomes.

Despite the rapid expansion of MCDM-based performance studies, several gaps remain in the existing literature. First, many studies continue to prioritize financial indicators, treating ESG dimensions as supplementary rather than integral components of performance assessment. Second, a considerable portion of the literature relies on a single weighting or ranking method, which may limit robustness and sensitivity to data structure. Third, sector-specific applications that explicitly account for sustainability-sensitive industries remain relatively scarce, particularly in developed capital markets.

Against this backdrop, the present study proposes a novel hybrid MCDM framework for evaluating the multidimensional performance of beverage companies listed on the London Stock Exchange. The beverage industry represents an especially relevant empirical context due to its intensive use of natural resources, complex supply chains, strong regulatory exposure, and increasing emphasis on sustainability-oriented innovation (Anderson and Baumberg, 2006; Chen et al., 2023; Bennett and James, 2017). Firms operating in this sector face growing pressure to balance financial performance with environmental responsibility, social engagement, and transparent governance practices, making them suitable candidates for ESG-integrated performance assessment (Porter & Heppelmann, 2014; Zhou et al., 2024).

The proposed framework integrates two advanced objective weighting techniques—CRISUS (CRiterion Importance based on SUM of Squares) and MAXC (MAXimum of Criterion)—with the CRADIS (Compromise Ranking of Alternatives from Distance to the Ideal Solution) ranking method. By relying exclusively on data-driven weighting procedures, the model minimizes subjectivity and ensures that criterion importance reflects the intrinsic structure of the dataset. The integration of these objective weights into the CRADIS ranking process further enhances

transparency, consistency, and resistance to rank reversal.

Accordingly, this study addresses the following research questions:

- (i) How can financial and ESG indicators be jointly assessed within a unified multidimensional performance framework?
- (ii) Which performance criteria exert the greatest influence on firm rankings in sustainability-sensitive industries?
- (iii) How does a hybrid MCDM framework contribute to the robustness and interpretability of corporate performance evaluation?

The main contributions of this research are threefold. First, it introduces a novel hybrid MCDM framework that combines CRISUS, MAXC, and CRADIS—an integration not previously explored in the literature. Second, by employing objective weighting methods, the proposed model enhances methodological rigor and reproducibility while reducing expert-induced bias. Third, the empirical application to the beverage sector provides sector-specific insights into the relative importance of innovation, market valuation, and community engagement in shaping multidimensional corporate performance.

2. LITERATURE REVIEW AND RESEARCH GAP ANALYSIS

In recent decades, MCDM methodologies have become a widely adopted analytical tool for evaluating firm performance across multiple dimensions. Their increasing popularity stems from the ability to integrate heterogeneous indicators—financial, operational, environmental, and social—within a single, coherent decision framework. In sustainability-oriented research, MCDM approaches are particularly valuable, as they explicitly capture trade-offs between economic performance and long-term ESG objectives.

Existing studies demonstrate substantial methodological diversity in both weighting and ranking procedures. Objective weighting techniques such as CRISUS, ITARA, MSD, MPSI, LOP-COW, and LODECI have been employed to derive criterion importance from intrinsic data structures, while subjective and semi-subjective approaches including AHP, BWM, FUCOM, DEMATEL, and ANP incorporate expert judgment into the evaluation process. On the ranking side, algorithms such as TOPSIS, VIKOR, MARCOS, RAM, COBRA, RAWEC, and CRADIS have been widely used to generate performance hierarchies across firms and sectors.

Recent empirical applications reveal that MCDM-based performance assessment has been extensively applied in banking, insurance, energy, manufacturing, retail, and technology industries. For instance, [Adalar and Işık \(2025\)](#) employed the CRISUS–RAM framework to evaluate sustainability performance in the food and beverage sector, while [Deng et al. \(2025\)](#) integrated DEMATEL and ANP with VIKOR to assess pharmaceutical firms' sustainable performance. Similarly, [Katrancı et al. \(2025\)](#) and [Akbulut and Aydın \(2024\)](#) focused on financial performance evaluation using objective weighting schemes combined with advanced ranking methods. These studies collectively confirm the analytical strength and flexibility of MCDM techniques in handling multidimensional performance problems.

As summarized in Table 1, recent contributions illustrate the breadth of methodological approaches and sectoral applications, ranging from food and beverage firms to banks, insurers, and tourism companies. The table highlights both the diversity of weighting techniques (e.g., CRISUS, LODECI, ITARA, fuzzy methods) and the variety of ranking procedures (e.g., RAM, VIKOR, MARCOS, COBRA, CRADIS), underscoring the adaptability of MCDM frameworks to different industry contexts.

Despite these methodological advances, several limitations persist in the existing literature. First, a significant proportion of studies remain predominantly finance-oriented, with ESG indi-

cators either excluded or treated as secondary variables. This limits the ability of performance models to fully reflect sustainability-driven competitive dynamics. Second, many studies rely on a single weighting or ranking method, which may reduce robustness and increase sensitivity to methodological assumptions. Hybrid frameworks that combine multiple objective weighting techniques with reference-point-based ranking methods remain relatively underexplored.

Third, sector-specific applications that explicitly address ESG-sensitive industries are still limited, particularly in developed capital markets. While sustainability performance has been widely examined in banking and energy sectors, industries such as beverages—characterized by resource-intensive production processes, environmental externalities, and strong social visibility—have received comparatively less attention. Moreover, studies focusing on firms listed on the London Stock Exchange within an integrated financial–ESG evaluation framework are scarce.

Another notable gap concerns methodological integration. Although CRISUS and MAXC have individually demonstrated strong performance in objective weighting, their combined use within a single decision framework has not yet been systematically investigated. Likewise, the integration of such objective weights into the CRADIS ranking method—known for its resistance to rank reversal and transparent distance-based logic—remains largely absent from prior research. Addressing this gap has the potential to enhance both the robustness and interpretability of performance evaluation outcomes.

In response to these limitations, the present study contributes to the literature by proposing a novel hybrid MCDM framework that jointly assesses financial and ESG indicators using CRISUS–MAXC weighting and CRADIS ranking. By applying the model to beverage companies listed on the London Stock Exchange, the study not only advances methodological integration but also provides sector-specific insights into sustainability-driven performance dynamics. This positioning enables a direct transition from the literature to the methodological framework introduced in the subsequent section.

Table 1. Multidimensional firm performance assessments via MCDM approaches

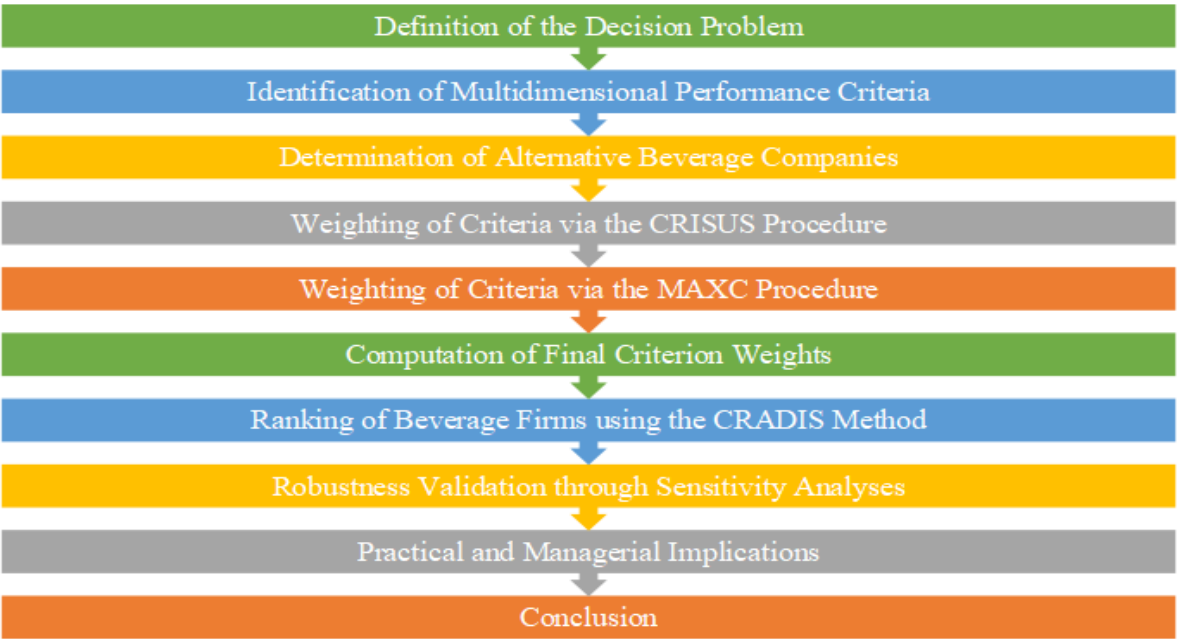
Study	Firms	Weighting methodology	Ranking procedure	Scope
Adalar and Işık (2025)	BIST-listed food and beverage firms	CRISUS	RAM	Multidimensional sustainability performance measurement
Deng et al. (2025)	Pharmaceutical firms	DEMATEL and ANP	VIKOR	Sustainable performance analysis
Katrançcı et al. (2025)	Companies listed in the BIST 100 index	ITARA	COBRA	Financial performance assessment
Işık and Adalar (2025)	Non-life insurers	Intuitionistic fuzzy method	Intuitionistic fuzzy CRADIS	Sustainability performance evaluation
Çilek and Şeyranlıoğlu (2025)	Reinsurance firms	LODECI	CRADIS and AROMAN	Measuring the financial performance
Akbulut (2025)	Insurance firms	Grey PSI	Grey MARCOS	Corporate financial performance measurement
Akbulut and Aydın (2024)	Commercial banks	MSD and MPSI	RAWEC	Multidimensional performance measurement
İç et al. (2022)	Retail and wholesale firms	AHP	VIKOR	Financial performance modeling
Türegün (2022)	Tourism firms	Entropy	TOPSIS and VIKOR	Financial performance analysis
Işık et al. (2025a)	Commercial bank	Fuzzy LBWA and Fuzzy LMAW	MARCOS	Multidimensional performance evaluation
Işık (2025b)	Islamic banks	Spherical fuzzy SPC and SWARA	Spherical fuzzy AROMAN	Efficiency, productivity and sustainability performance assessment
Işık et al. (2025c)	Insurance firms	Pythagorean Fuzzy AHP	MAIRCA	Performance assessment

Source: Author's own construction

3. METHODOLOGY

This research evaluates the sustainability performance of beverage companies listed on the London Stock Exchange through an integrated MCDM framework. The analytical procedure combines three complementary methods—CRISUS, MAXC, and CRADIS—to ensure methodological diversity and robustness of decision outcomes. CRISUS, a six-step objective weighting technique, derives criterion importance using the sum of squares operator and variance-based calculations, thereby mitigating distortions caused by scale differences and extreme values. MAXC, also a six-step procedure, determines relative weights by calculating expected distances from maximum criterion values, offering statistically sensitive and fully data-driven results. Both approaches eliminate subjectivity by relying exclusively on the intrinsic structure of the dataset. Their outputs are subsequently integrated through a linear operator to generate the final criterion weights, consolidating the strengths of distinct objective approaches into a balanced and reliable weighting scheme. In the final stage, CRADIS, an eight-step ranking algorithm, evaluates alternatives according to their proximity to both ideal and anti-ideal solutions, reducing the risk of rank reversal and ensuring transparent, comparable, and analytically robust rankings. Figure 1 illustrates the methodological flow, while the detailed computational steps and mathematical formulations of all three methods are provided in **Appendix A**, thereby preserving reproducibility and maintaining readability in the main text.

Figure 1. Methodological Framework



Source: Author’s own construction

4. EMPIRICAL CASE STUDY ON MULTI-DIMENSIONAL PERFORMANCE EVALUATION

This section presents the empirical application of the suggested MCDM framework, designed to assess the multidimensional performance of beverage companies listed on the London Stock Exchange. The case study aims to demonstrate how integrated decision models can capture complex performance dynamics across financial, environmental, social, and governance dimensions.

4. 1. PROBLEM DEFINITION

Evaluating corporate performance in today’s multidimensional business landscape requires more than conventional financial metrics. Firms are increasingly assessed across a spectrum of

indicators that reflect not only profitability but also environmental stewardship, social responsibility, and governance quality. This complexity necessitates a structured MCDM approach capable of integrating diverse performance dimensions into a coherent analytical framework. The present work addresses the problem of ranking beverage companies listed on the London Stock Exchange based on their overall performance across four key dimensions: Environmental, Social, Governance, and Financial. A total of 15 evaluation criteria were identified to represent these dimensions, each contributing to a comprehensive understanding of firm behavior and strategic positioning. To ensure methodological rigor and objectivity, the study employs a hybrid MCDM framework that integrates the CRISUS, MAXC and CRADIS techniques. The CRISUS and MAXC procedure is utilized to determine objective weights for each criterion. Following the weighting stage, the CRADIS algorithm is applied to rank the decision alternatives. This formulation enables a transparent and analytically sound evaluation of corporate performance, offering valuable insights for investors, analysts, and decision-makers seeking to compare firms in a multidimensional context.

4. 2. DEFINITION OF ALTERNATIVES

The decision alternatives in this study consist of publicly traded beverage companies operating in the UK market. A total of 8 firms were selected based on their continuous listing status, data availability, and sectoral relevance. Each firm represents a distinct decision unit subject to comparative performance assessment. The selection ensures diversity in operational scale, market positioning, and sustainability orientation, allowing for a robust evaluation across heterogeneous profiles. The firms included as decision alternatives in the current study are listed in Table 2.

Table 2. Firm Alternatives

Firm	Code	Description
Diageo	A1	A global leader in alcoholic beverages headquartered in London, Diageo owns iconic brands such as Guinness, Johnnie Walker, and Smirnoff. The company operates across more than 180 countries and emphasizes sustainability and innovation in its production processes.
Coca Cola	A2	Coca-Cola is a multinational beverage corporation with a strong presence in the UK through Coca-Cola Europacific Partners. It offers a wide portfolio including Coca-Cola, Fanta, and Sprite, and is known for its extensive distribution network and local production capabilities.
Britvic	A3	Britvic is a UK-based soft drink manufacturer offering brands such as Robinsons, Tango, and J2O. It also produces PepsiCo beverages under license. Following its merger with Carlsberg UK, Britvic operates under the Carlsberg Britvic name, enhancing its market reach.
Barr-Ag Ltd	A4	A.G. Barr is a Scottish beverage company best known for IRN-BRU. It also owns Rubicon and Funkin brands. The firm has diversified into cocktail mixers and oat-based drink, maintaining a strong regional identity and expanding its product categories.
C&C Group	A5	Headquartered in Dublin, C&C Group specializes in cider and beer, with brands like Bulmers, Magners, and Tennent's. It is a major distributor to the hospitality sector in the UK and Ireland, and has invested in digital transformation and sustainability.
Fever-Tree Drink	A6	Fever-Tree is a premium mixer brand offering tonic water, ginger ale, and soda products. Founded in 2005, it has a global footprint in over 75 countries and is recognized for its high-quality ingredients and strong positioning in both retail and hospitality channels.
Nichols	A7	Nichols plc is the producer of Vimto, a popular fruit-flavored soft drink. The company also operates in frozen beverage systems and exports to over 60 countries. Its portfolio includes SLUSH PUPPiE and Levi Roots drink, reflecting a diverse market strategy.
Daniel Thwaites	A8	Established in 1807, Daniel Thwaites is a traditional brewery and hospitality company based in England. It operates pubs, hotels, and spas across Northern England, combining heritage brewing with modern accommodation services.

Source: Author's own construction

4. 3. DEFINITION OF EVALUATION CRITERIA

To capture performance in a multidimensional structure, 15 evaluation criteria were identified and grouped under four major dimensions: Environmental, Social, Governance, and Financial. These criteria were selected through a synthesis of prior MCDM literature, ESG reporting standards, and expert consultation. Table 3 presents the full list of criteria, along with their codes, thematic categories, and optimization objectives. The data related to performance indicators for the year 2022 were obtained from the Refinitiv Eikon database.

4. 3. 1. ENVIRONMENTAL PERFORMANCE INDICATORS

This group captures the ecological dimension of corporate performance, reflecting a firm's commitment to sustainability and resource efficiency. In MCDM applications, environmental indicators are essential for evaluating long-term risk exposure, regulatory compliance, and stakeholder trust (da Cunha et al., 2025; Işık et al., 2025d).

E1 – Resource Use: It assesses the efficiency of natural resource utilization, including energy, water, and raw materials. Higher scores indicate more sustainable operations with minimal resource waste.

E2 – Emissions: It measures the level of environmental pollutants, particularly greenhouse gas emissions. Lower emission levels are interpreted as higher environmental performance.

E3 – Environmental Innovation: It evaluates the firm's capacity for environmental innovation, such as investment in green technologies and sustainable product development.

4. 3. 2. SOCIAL PERFORMANCE INDICATORS

Social indicators reflect a firm's impact on employees, communities, and consumers. In MCDM models, this group helps assess corporate responsibility, ethical conduct, and stakeholder engagement (Hoang et al., 2024; Reig-Mullor et al., 2022; Aydın, 2025).

S1 – Workforce: It measures employee-related policies, including workplace safety, training, diversity, and satisfaction.

S2 – Human Rights: It assesses the firm's adherence to ethical labor practices, anti-discrimination policies, and respect for individual rights.

S3 – Community: It captures the firm's involvement in local development, philanthropy, and social outreach initiatives.

S4 – Product Responsibility: It evaluates product safety, consumer protection, and ethical marketing practices.

4. 3. 3. GOVERNANCE PERFORMANCE INDICATORS

Governance indicators examine the structural and procedural aspects of corporate leadership. In MCDM frameworks, this group is used to evaluate transparency, accountability, and strategic oversight (Işık ve Adalar, 2025; Lombardi Netto et al., 2026).

G1 – Management: It assesses the effectiveness of the board of directors, strategic decision-making, and governance transparency.

G2 – Shareholders: It measures the protection of shareholder rights, dividend policies, and investor relations.

G3 – Corporate Social Responsibility (CSR): It evaluates voluntary CSR initiatives, including sustainability programs and ethical commitments beyond regulatory requirements.

4. 3. 4. FINANCIAL PERFORMANCE INDICATORS

Financial indicators represent the economic dimension of corporate performance. In MCDM applications, they are critical for evaluating profitability, market valuation, and risk exposure (Ramírez-Orellana et al., 2023; Görçün et al., 2025; Işık et al., 2025a).

F1 – Return on Assets: It indicates how efficiently a firm uses its assets to generate earnings.

F2 – Return on Equity: It measures profitability relative to shareholder equity, reflecting capital utilization.

F3 – Closing Price: It represents the market valuation of the firm's shares at the end of a trading period.

F4 – Market-to-Book Ratio: It compares market value to book value, signaling investor expectations and growth potential.

F5 – Beta: It captures the firm's sensitivity to market volatility. Unlike other criteria, beta is a non-benefit indicator—lower values are preferred as they imply greater stability.

Table 3. Performance indicators

Dimension	Assessment Criteria	Code	Objective
Environmental Performance Indicators	Resource Use	E1	Benefit (Maximum)
	Emissions	E2	Benefit (Maximum)
	Innovation	E3	Benefit (Maximum)
Social Performance Indicators	Workforce	S1	Benefit (Maximum)
	Human Rights	S2	Benefit (Maximum)
	Community	S3	Benefit (Maximum)
	Product Responsibility	S4	Benefit (Maximum)
Governance Performance Indicators	Management	G1	Benefit (Maximum)
	Shareholders	G2	Benefit (Maximum)
	Corporate Social Responsibility	G3	Benefit (Maximum)
Financial Performance Indicators	Return on Assets	F1	Benefit (Maximum)
	Return on Equity	F2	Benefit (Maximum)
	Closing Price	F3	Benefit (Maximum)
	Market-to-Book Ratio	F4	Benefit (Maximum)
	Beta	F5	Non Benefit (Minimum)

Source: Author's own construction

5. FINDINGS

This section systematically reports the empirical findings obtained through the implementation of the integrated decision-making model proposed within the scope of this study

5. 1. FINDINGS BASED ON THE CRISUS PROCEDURE

The evaluation process for the beverage firms examined within the scope of the analysis commenced with the weighting of the selected performance indicators using the CRISUS procedure. In the initial stage of the CRISUS-based weighting approach, the decision matrix comprising the alternatives and evaluation criteria was constructed in accordance with Equation (1) and is presented in Table 4. The values displayed in this table represent the firms' annual average performance data for the year 2021.

Table 4. Decision Matrix

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
A1	96.39	94.66	1.58	98.61	89.88	93.06	96.57	77.06	46.47	98.31	2.56	2.75	3892.5	11.64	0.67
A2	75.77	98.54	1.58	99.54	89.88	89.35	92.65	91.81	61.50	87.04	2.37	1.83	2513	3.51	1.55
A3	93.30	90.78	2.60	73.61	89.88	74.54	62.75	61.12	43.12	75.32	2.30	2.16	884.5	5.63	0.93
A4	23.20	14.08	0.00	41.20	23.81	4.63	62.75	92.10	64.46	55.77	2.28	1.37	487	2.23	0.56
A5	80.93	55.83	0.23	20.83	46.43	50.46	36.76	60.53	92.11	39.58	0.97	0.01	245.4	3.58	1.35
A6	31.44	40.29	0.23	35.65	26.79	4.63	4.90	39.01	83.35	17.37	3.07	1.73	2721	11.26	1.22
A7	20.10	19.90	0.00	22.69	4.17	4.63	4.90	43.77	15.23	55.77	0.01	0.01	1300	5.16	0.59
A8	6.70	15.05	0.00	9.72	23.81	7.87	4.90	11.50	16.65	0.00	1.41	0.70	99.0	0.27	0.73

Source: Author's own construction

The primary normalization of the values in the decision matrix was performed using Equation (2), and the resulting normalized data are presented in Table 5.

Table 5. First Normalized Decision Matrix

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
A1	0.54	0.53	0.46	0.58	0.53	0.59	0.59	0.42	0.28	0.56	0.43	0.60	0.69	0.62	0.77
A2	0.42	0.55	0.46	0.58	0.53	0.57	0.56	0.50	0.37	0.49	0.40	0.40	0.45	0.19	0.46
A3	0.52	0.50	0.75	0.43	0.53	0.47	0.38	0.33	0.26	0.43	0.39	0.47	0.16	0.30	0.68
A4	0.13	0.08	0.00	0.24	0.14	0.03	0.38	0.50	0.39	0.32	0.39	0.30	0.09	0.12	0.80
A5	0.45	0.31	0.07	0.12	0.28	0.32	0.22	0.33	0.55	0.22	0.16	0.00	0.04	0.19	0.53
A6	0.18	0.22	0.07	0.21	0.16	0.03	0.03	0.21	0.50	0.10	0.52	0.38	0.48	0.60	0.57
A7	0.11	0.11	0.00	0.13	0.02	0.03	0.03	0.24	0.09	0.32	0.00	0.00	0.23	0.28	0.79
A8	0.04	0.08	0.00	0.06	0.14	0.05	0.03	0.06	0.10	0.00	0.24	0.15	0.02	0.01	0.75

Source: Author's own construction

The second normalization of the decision matrix was conducted by utilizing Equation (4), and the resulting normalized values are presented in Table 6.

Table 6. Secondary Normalized Decision Matrix

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
A1	0.23	0.22	0.25	0.25	0.23	0.28	0.26	0.16	0.11	0.23	0.17	0.26	0.32	0.27	0.14
A2	0.18	0.23	0.25	0.25	0.23	0.27	0.25	0.19	0.15	0.20	0.16	0.17	0.21	0.08	0.09
A3	0.22	0.21	0.42	0.18	0.23	0.23	0.17	0.13	0.10	0.18	0.15	0.20	0.07	0.13	0.13
A4	0.05	0.03	0.00	0.10	0.06	0.01	0.17	0.19	0.15	0.13	0.15	0.13	0.04	0.05	0.15
A5	0.19	0.13	0.04	0.05	0.12	0.15	0.10	0.13	0.22	0.09	0.06	0.00	0.02	0.08	0.10
A6	0.07	0.09	0.04	0.09	0.07	0.01	0.01	0.08	0.20	0.04	0.20	0.16	0.22	0.26	0.11
A7	0.05	0.05	0.00	0.06	0.01	0.01	0.01	0.09	0.04	0.13	0.00	0.00	0.11	0.12	0.15
A8	0.02	0.04	0.00	0.02	0.06	0.02	0.01	0.02	0.04	0.00	0.09	0.07	0.01	0.01	0.14

Source: Author's own construction

Following the second normalization process, the sum of squares () for each evaluation criterion, the standard deviation values () derived from the first normalized matrix, and the final objective weight scores () for each criterion were calculated using Equations (5) and (6), respectively. The results of these computations are systematically reported in Table 7.

Table 7. Results of CRISUS Procedure

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
ρ_j	0.18	0.18	0.30	0.18	0.18	0.23	0.20	0.15	0.16	0.17	0.16	0.19	0.21	0.19	0.13
σ_j	0.20	0.20	0.29	0.21	0.21	0.26	0.23	0.15	0.17	0.19	0.17	0.22	0.24	0.22	0.13
$\rho_j \cdot \sigma_j$	0.04	0.04	0.09	0.04	0.04	0.06	0.05	0.02	0.03	0.03	0.03	0.04	0.05	0.04	0.02
w_j	0.060	0.060	0.147	0.063	0.064	0.097	0.079	0.037	0.044	0.054	0.044	0.068	0.087	0.068	0.028
Rank	10	9	1	8	7	2	4	14	13	11	12	5	3	6	15

Source: Author's own construction

5. 2. FINDINGS BASED ON THE MAXC PROCEDURE

In this section of the study, the importance weights of the multidimensional performance criteria were calculated based on the MAXC procedure. Accordingly, the decision matrix was first constructed using Equation (1), as presented in Table 4. All values within the matrix were normalized via Equation (7). Subsequently, the maximum values for each criterion were determined using Equation (8). The computational results derived from these steps are presented in Table 8.

Table 8. Normalized Decision Matrix

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
A1	0.23	0.22	0.25	0.25	0.23	0.28	0.26	0.16	0.11	0.23	0.17	0.26	0.32	0.27	0.09
A2	0.18	0.23	0.25	0.25	0.23	0.27	0.25	0.19	0.15	0.20	0.16	0.17	0.21	0.08	0.20
A3	0.22	0.21	0.42	0.18	0.23	0.23	0.17	0.13	0.10	0.18	0.15	0.20	0.07	0.13	0.12
A4	0.05	0.03	0.00	0.10	0.06	0.01	0.17	0.19	0.15	0.13	0.15	0.13	0.04	0.05	0.07
A5	0.19	0.13	0.04	0.05	0.12	0.15	0.10	0.13	0.22	0.09	0.06	0.00	0.02	0.08	0.18
A6	0.07	0.09	0.04	0.09	0.07	0.01	0.01	0.08	0.20	0.04	0.20	0.16	0.22	0.26	0.16
A7	0.05	0.05	0.00	0.06	0.01	0.01	0.01	0.09	0.04	0.13	0.00	0.00	0.11	0.12	0.08
A8	0.02	0.04	0.00	0.02	0.06	0.02	0.01	0.02	0.04	0.00	0.09	0.07	0.01	0.01	0.10
Max.	0.23	0.23	0.42	0.25	0.23	0.28	0.26	0.19	0.22	0.23	0.20	0.26	0.32	0.27	0.20

Source: Author's own construction

Table 9 presents the distance matrix, calculated based on the deviations from the maximum values using Equation (9).

Table 9. Distance Matrix from Maximum Values

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
A1	0.00	0.01	0.16	0.00	0.00	0.00	0.00	0.03	0.11	0.00	0.03	0.00	0.00	0.00	0.12
A2	0.05	0.00	0.16	0.00	0.00	0.01	0.01	0.00	0.07	0.03	0.05	0.09	0.11	0.19	0.00
A3	0.01	0.02	0.00	0.06	0.00	0.06	0.09	0.06	0.12	0.05	0.05	0.06	0.25	0.14	0.08
A4	0.17	0.20	0.42	0.15	0.17	0.27	0.09	0.00	0.07	0.10	0.05	0.13	0.28	0.22	0.13
A5	0.04	0.10	0.38	0.20	0.11	0.13	0.16	0.07	0.00	0.14	0.14	0.26	0.30	0.19	0.03
A6	0.15	0.14	0.38	0.16	0.16	0.27	0.25	0.11	0.02	0.19	0.00	0.10	0.10	0.01	0.04
A7	0.18	0.18	0.42	0.19	0.22	0.27	0.25	0.10	0.18	0.10	0.20	0.26	0.21	0.15	0.13
A8	0.21	0.19	0.42	0.22	0.17	0.26	0.25	0.17	0.18	0.23	0.11	0.19	0.31	0.26	0.11

Source: Author's own construction

In the final stage of the MAXC procedure, the expected distance values () corresponding to each performance criterion were first calculated using Equation (10). Subsequently, the objective importance weights () of the performance indicators were determined through Equation (11). The

results obtained from these computations are systematically reported in Table 10.

Table 10. Results of MAXC Procedure

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
E_j	0.100	0.105	0.292	0.123	0.103	0.158	0.139	0.068	0.093	0.104	0.080	0.136	0.196	0.144	0.079
w_j	0.052	0.055	0.152	0.064	0.054	0.082	0.072	0.036	0.048	0.054	0.042	0.071	0.102	0.075	0.041
Rank	11	8	1	7	10	3	5	15	12	9	13	6	2	4	14

Source: Author's own construction

5. 3. FINDINGS RELATED TO THE FINAL WEIGHTING PROCEDURE

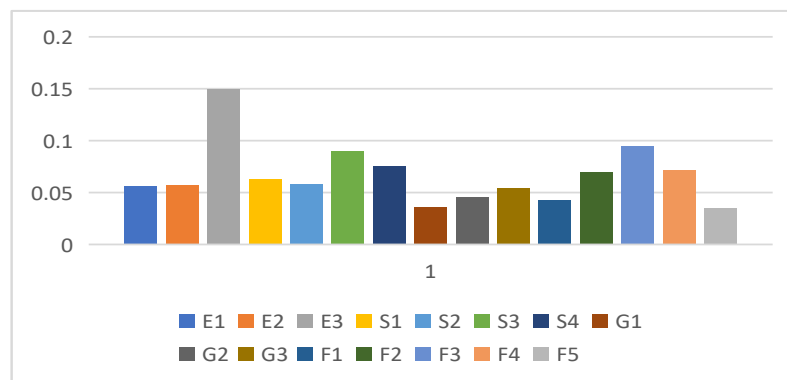
The weighting coefficients derived from the CRISUS and MAXC procedures for multidimensional firm performance indicators were integrated through the aggregation operator presented in Equation (12), thereby yielding the final weight values for each evaluation criterion. The final weight scores computed for the criteria are reported in Table 11 and Figure 2. Based on the final weighting results presented in Table 11, the three most influential criteria shaping the firms' multidimensional performance are E3 (Environmental Innovation), F3 (Closing Price), and S3 (Community Engagement), indicating that technological sustainability, market valuation, and societal contribution play a decisive role in overall corporate evaluation.

Table 11. Results of Final Weighting Procedure

	$w_j^{(CRISUS)}$	$w_j^{(MAXC)}$	$w_j^{(FINAL)}$	Rank
E1	0.0598	0.0523	0.0560	10
E2	0.0598	0.0546	0.0572	9
E3	0.1472	0.1521	0.1496	1
S1	0.0625	0.0640	0.0633	7
S2	0.0636	0.0536	0.0586	8
S3	0.0974	0.0823	0.0898	3
S4	0.0791	0.0724	0.0757	4
G1	0.0373	0.0355	0.0364	14
G2	0.0437	0.0484	0.0461	12
G3	0.0537	0.0543	0.0540	11
F1	0.0440	0.0417	0.0428	13
F2	0.0683	0.0707	0.0695	6
F3	0.0872	0.1020	0.0946	2
F4	0.0679	0.0751	0.0715	5
F5	0.0284	0.0412	0.0348	15

Source: Author's own construction

Figure 2. Weight coefficients of ESG indicators



Source: Author's own construction

5. 4. FINDINGS BASED ON THE CRADIS PROCEDURE

To assess the multidimensional performance of the beverage firms, the final weights assigned to the selected evaluation indicators were incorporated into the CRADIS procedure to compute the performance scores for the year 2021. In the initial stage of the CRADIS method, the decision matrix was constructed based on Equation (1) and reported in Table 4. This matrix was subsequently normalized according to Equations (13) and (14), and the resulting normalized values are presented in Table 12.

Table 12. Normalized Decision Matrix

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
A1	1.00	0.96	0.61	0.99	1.00	1.00	1.00	0.84	0.50	1.00	0.83	1.00	1.00	1.00	0.84
A2	0.79	1.00	0.61	1.00	1.00	0.96	0.96	1.00	0.67	0.89	0.77	0.67	0.65	0.30	0.36
A3	0.97	0.92	1.00	0.74	1.00	0.80	0.65	0.66	0.47	0.77	0.75	0.78	0.23	0.48	0.60
A4	0.24	0.14	0.00	0.41	0.26	0.05	0.65	1.00	0.70	0.57	0.74	0.50	0.13	0.19	1.00
A5	0.84	0.57	0.09	0.21	0.52	0.54	0.38	0.66	1.00	0.40	0.32	0.00	0.06	0.31	0.41
A6	0.33	0.41	0.09	0.36	0.30	0.05	0.05	0.42	0.90	0.18	1.00	0.63	0.70	0.97	0.46
A7	0.21	0.20	0.00	0.23	0.05	0.05	0.05	0.48	0.17	0.57	0.00	0.00	0.33	0.44	0.95
A8	0.07	0.15	0.00	0.10	0.26	0.08	0.05	0.12	0.18	0.00	0.46	0.25	0.03	0.02	0.77

Source: Author's own construction

The values corresponding to the weighted normalized decision matrix, as presented in Table 13, were obtained using Equation (15).

Table 13. Weighted Normalized Decision Matrix

	E1	E2	E3	S1	S2	S3	S4	G1	G2	G3	F1	F2	F3	F4	F5
A1	0.06	0.05	0.09	0.06	0.06	0.09	0.08	0.03	0.02	0.05	0.04	0.07	0.09	0.07	0.03
A2	0.04	0.06	0.09	0.06	0.06	0.09	0.07	0.04	0.03	0.05	0.03	0.05	0.06	0.02	0.01
A3	0.05	0.05	0.15	0.05	0.06	0.07	0.05	0.02	0.02	0.04	0.03	0.05	0.02	0.03	0.02
A4	0.01	0.01	0.00	0.03	0.02	0.00	0.05	0.04	0.03	0.03	0.03	0.03	0.01	0.01	0.03
A5	0.05	0.03	0.01	0.01	0.03	0.05	0.03	0.02	0.05	0.02	0.01	0.00	0.01	0.02	0.01
A6	0.02	0.02	0.01	0.02	0.02	0.00	0.00	0.02	0.04	0.01	0.04	0.04	0.07	0.07	0.02
A7	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.01	0.03	0.00	0.00	0.03	0.03	0.03
A8	0.00	0.01	0.00	0.01	0.02	0.01	0.00	0.00	0.01	0.00	0.02	0.02	0.00	0.00	0.03

Source: Author's own construction

At this stage, the ideal and anti-ideal solution points, along with the respective deviations from these reference points for each multidimensional performance indicator, were determined using Equations (16) through (19). Subsequently, Equations (20) to (23) were applied to compute the deviation degrees and benefit function values for each decision alternative. In the final step of the CRADIS procedure, the performance score for each alternative was obtained by applying Equation (24). The results derived from these computations are comprehensively presented in Table 14 and Figure 3.

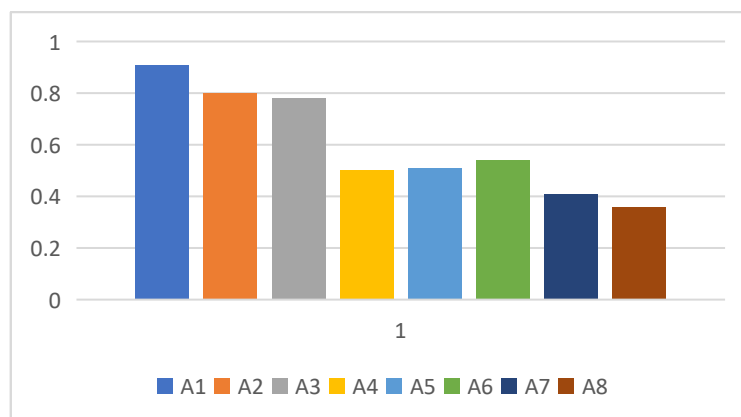
Table 14. Results of CRADIS Procedure

	S_i^+	K_i^+	S_i^-	K_i^-	Q_i	Rank
A1	1.35	0.92	0.90	0.90	0.91	1
A2	1.48	0.84	0.76	0.76	0.80	2
A3	1.51	0.82	0.73	0.73	0.78	3
A4	1.90	0.65	0.34	0.34	0.50	6
A5	1.88	0.66	0.36	0.36	0.51	5
A6	1.84	0.68	0.41	0.41	0.54	4
A7	2.04	0.61	0.20	0.20	0.41	7
A8	2.12	0.59	0.13	0.13	0.36	8
	1.24		1.00			

Source: Author's own construction

According to the results of the CRADIS procedure presented in Table 14, the firm with the highest multidimensional performance score for the year 2021 is Diageo. Conversely, the firm identified with the lowest overall performance during the same period is A8 (Daniel Thwaites).

Figure 3. Ranking results based on CRADIS method



Source: Author's own construction

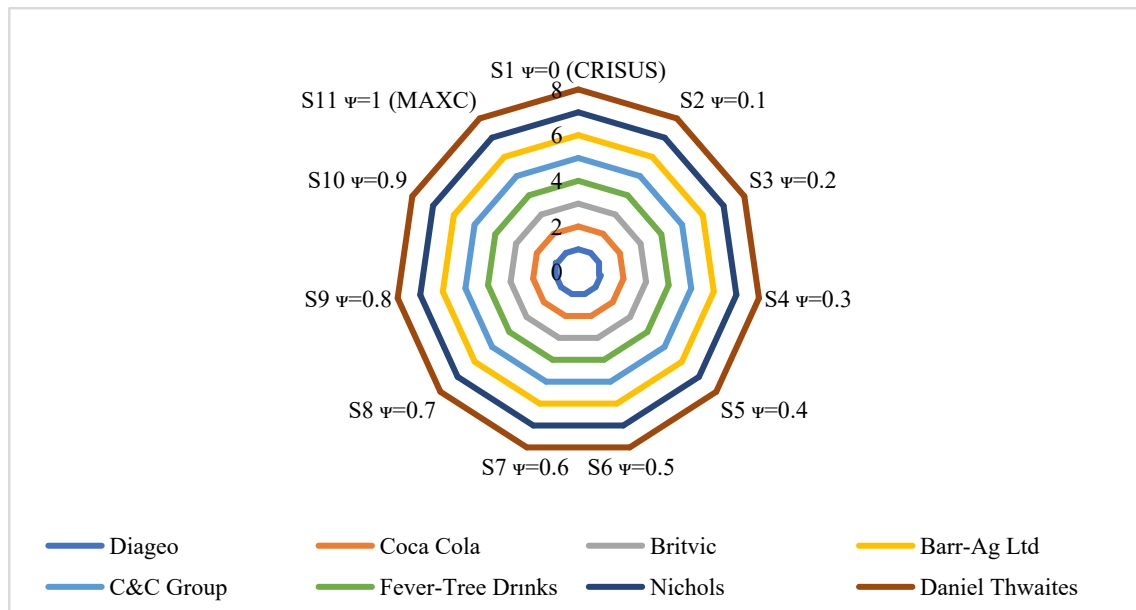
6. ROBUSTNESS AND SENSITIVITY ANALYSES

In order to ensure the methodological validity and reliability of the proposed decision-making framework for assessing the multidimensional performance of firms, it is essential to conduct comprehensive robustness and sensitivity evaluations. Accordingly, this section presents a two-stage sensitivity analysis aimed at validating the soundness of the developed model within the context of the current case study. In the first stage, the potential influence of variations in the ψ parameter on the final ranking results was investigated. In the second stage, a rank reversal analysis was performed to assess the extent to which the ranking outcomes remain stable under parametric perturbations, thereby providing empirical evidence on the robustness of the proposed integrated approach.

6.1. ANALYSIS OF THE IMPACT OF VARIATIONS IN THE Ψ PARAMETER ON RANKING OUTCOMES

In the context of the proposed decision-making framework, a sensitivity analysis was conducted to examine the impact of variations in the ψ parameter-considered a critical component-on the ranking of alternatives. Although the current study adopts a ψ value of 0.5 in accordance with prior literature, it is important to note that this parameter can assume different values within the closed interval $[0, 1]$. Therefore, to investigate whether such changes influence the stability of the ranking results, ψ was systematically varied using ten distinct integer-based scenarios across the defined interval. The findings of this analysis are presented in Figure 4. As observed, the variation in ψ does not lead to any changes in the relative rankings of the alternatives. This result highlights the robustness and internal consistency of the proposed framework, further affirming its methodological reliability under different integration conditions.

Figure 4. Re-Ranking of Alternatives Under Varying Values of the ψ

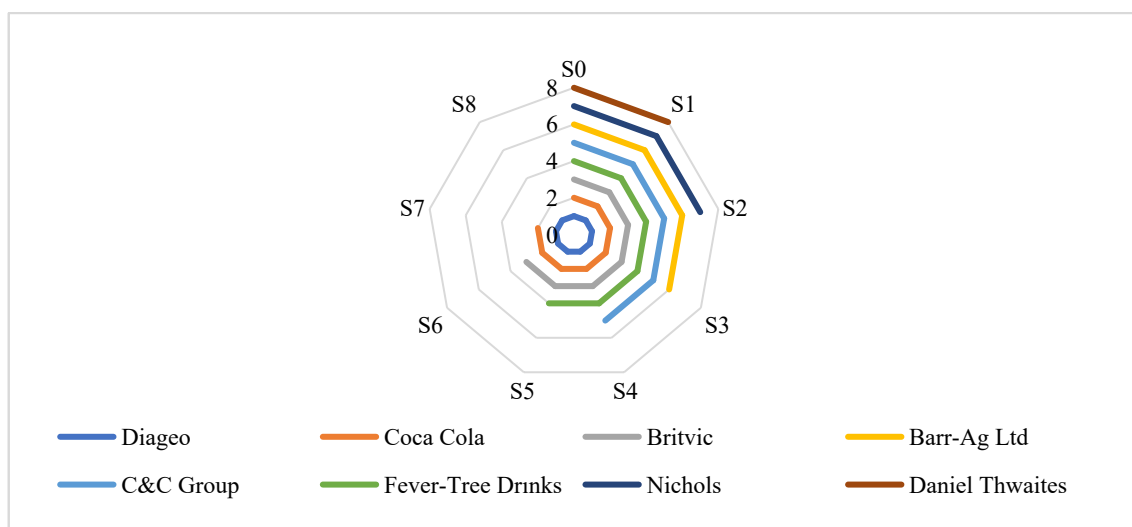


Source: Author's own construction

6. 2. INVESTIGATION OF THE RANK REVERSAL PHENOMENON

To address the issue of inconsistency, which is frequently debated within the decision-making literature, this work investigates the impact of the rank reversal phenomenon on the ranking outcomes produced by the proposed model. In this context, in each scenario, the worst-performing alternative was sequentially removed from the analysis until only the best-performing alternative remained, following the procedures suggested by Akbulut (2024). The results obtained from eight different scenarios are presented in Figure 5. As shown in Figure 5, the rank reversal phenomenon does not induce any changes in the final ranking of alternatives, thereby confirming the robustness and reliability of the proposed decision-making framework.

Figure 5. Re-Ranking of Alternatives Under Various Scenario Configurations



Source: Author's own construction

7. DISCUSSION AND MANAGERIAL IMPLICATIONS

This study introduces a multidimensional performance assessment framework that integrates financial and non-financial ESG variables. By combining CRISUS and MAXC for objective weighting with CRADIS for ranking, the model provides a transparent and replicable tool for evaluating beverage companies listed on the London Stock Exchange.

The findings from weighting model highlight Innovation (E3) as the most influential criterion, underscoring its central role in shaping competitiveness. In practice, this indicates that firms in the beverage sector must go beyond product diversification and invest in process innovation, digital transformation, and sustainable production technologies. Managers should therefore prioritize R&D, foster collaborative innovation ecosystems, and embed sustainability into product development to secure long-term resilience.

The second most important factor, Closing Price (F3), reflects investor confidence and market valuation. This finding emphasizes the need for financial transparency, consistent communication, and strategic investor relations. For publicly traded firms, aligning operational decisions with shareholder expectations while maintaining agility is critical to sustaining market trust and long-term value creation.

Community Investment (S3) ranks third, demonstrating that stakeholder engagement and social responsibility are not peripheral but integral to performance. Firms that actively invest in local development, environmental stewardship, and socially impactful initiatives strengthen reputational capital and secure stakeholder loyalty. This reinforces the view that ESG frameworks function not only as ethical commitments but as strategic levers for competitiveness.

The CRADIS-based rankings confirm that Diageo, Coca-Cola, and Britvic lead the sector, reflecting balanced excellence across financial and ESG dimensions. In contrast, Daniel Thwaites lags due to weaker ESG performance, illustrating the strategic risks of underinvestment in sustainability. These findings provide managers with actionable insights: leaders should benchmark against top performers to identify blind spots, while lagging firms must recalibrate strategies to strengthen ESG integration.

Beyond firm-level implications, the framework offers guidance for policy-makers and regulators. The prioritization of innovation and community investment suggests that incentive structures—such as R&D tax credits, mandatory ESG disclosures, and regional development partnerships—should be designed to reward firms that embed sustainability into their core strategies. Such alignment between public policy and multidimensional performance indicators can foster a more resilient and inclusive beverage sector.

For investors, the results highlight the growing importance of intangible assets and strategic agility. Long-term value creation is increasingly anchored in innovation capacity, transparent governance, and proactive community engagement. Institutional investors should therefore integrate ESG-aligned filters and forward-looking metrics into their evaluation frameworks, ensuring portfolio resilience and alignment with sustainable growth trajectories.

Taken together, these findings redefine success in the beverage industry as a multidimensional construct that transcends traditional financial measures. Firms that simultaneously enhance innovation, sustain market valuation, and deliver tangible social value are best positioned to achieve superior outcomes and long-term stakeholder trust.

8. CONCLUSION

The existing paper introduces a novel hybrid decision support framework to assess the multidimensional sustainability performance of beverage firms listed on the London Stock Exchange, integrating both financial and non-financial ESG criteria. Objective criterion weights are derived through the CRISUS and MAXC procedures, aggregated via a linear operator to ensure impartiality and consistency. Firm alternatives are then ranked based on the CRADIS technique.

The results highlight that indicators such as innovation capacity, closing price, and community investment are key determinants of sectoral performance, underscoring the growing importance of intangible assets and stakeholder-driven value creation. According to the CRADIS-based ranking, Diageo achieved the highest overall performance, while Daniel Thwaites ranked lowest, demonstrating the effectiveness of the hybrid MCDM approach in capturing corporate performance disparities across financial and ESG dimensions.

Despite its contributions, the study has several limitations. First, the analysis is restricted to the beverage industry, limiting generalizability. Future research should extend the framework to other sectors such as energy, banking, insurance, and technology. Second, the evaluation relies on publicly available indicators from a single year, constraining the ability to capture temporal dynamics. Longitudinal datasets would allow tracking performance trajectories and assessing ranking stability. Third, while the model integrates CRISUS, MAXC, and CRADIS to ensure methodological rigor, future studies could explore hybrid weighting approaches combining objective and subjective inputs (e.g., LBWA, RANCOM, FullEX, SIWEC) and incorporate fuzzy or grey-based techniques to better handle uncertainty.

By addressing these limitations, subsequent research can broaden the scope and enhance the analytical power of hybrid MCDM frameworks. Practically, the proposed framework offers managers, investors, and policymakers a transparent tool to support sustainability-oriented strategic decision-making and assess competitive positioning across industries.

REFERENCES

- Adalar, İ. & Işık, Ö. (2025). CRiterion Importance Based on SUM of Squares (CRISUS): A Novel Objective Weighting Method and Its Implementation in Multidimensional Sustainability Performance Measurement. *Economic Computation and Economic Cybernetics Studies and Research*, 59, 205-221. <https://doi.org/10.24818/18423264/59.2.25.13>
- Akbulut, O. Y. (2024). Assessing the environmental sustainability performance of the banking sector: A novel integrated grey Multi-Criteria Decision-Making (MCDM) approach. *Int J. Knowl. Innov Stud*, 2(4), 239-258. <https://doi.org/10.56578/ijkis020404>
- Akbulut, O. Y. (2025). Analysis of the corporate financial performance based on grey PSI and grey MARCOS model in Turkish insurance sector. *Knowledge and Decision Systems with Applications*, 1, 57-69. <https://doi.org/10.59543/kadsa.v1i.13623>
- Akbulut, O. Y., & Aydın, Y. (2024). A hybrid multidimensional performance measurement model using the MSD-MPSI-RAWEC model for Turkish Banks. *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty*, 11(3), 1157-1183. <https://doi.org/10.30798/makuiibf.1464469>
- Anderson, P. and Baumberg, B. (2006). Alcohol in Europe: A public health perspective. *European Addiction Research*, 12(2), 75-80. <https://www.ias.org.uk/wp-content/uploads/2020/09/rp03062006.pdf>
- Aydın, Y. (2025). A Hybrid Multi-Criteria Decision-Making Model for Performance Assessment in the Banking Industry. *Knowledge and Decision Systems with Applications*, 1, 234-256. <https://doi.org/10.59543/kadsa.v1i.14725>
- Bennett, M., and James, P. (2017). *The Green Bottom Line: Environmental Accounting for Management*. Routledge, Taylor and Francis Group, USA. <https://doi.org/10.4324/9781351283328>
- Çetenak, E. H., Ersoy, E., & Işık, Ö. (2022). ESG (Çevresel, Sosyal ve Kurumsal Yönetim) Skorunun Firma Performansına Etkisi: Türk Bankacılık Sektörü Örneği. *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, (63), 75-82. <https://doi.org/10.18070/erciyesiibd.1212587>
- Chen, S., Song, Y., & Gao, P. (2023). Environmental, social, and governance (ESG) performance and financial outcomes: Analyzing the impact of ESG on financial performance. *Journal of environmental management*, 345, 118829. <https://doi.org/10.1016/j.jenvman.2023.118829>
- Çilek, A., & Şeyranlıoğlu, O. (2025). Measuring the financial performance of reinsurance companies in Türkiye with LODECI, CRADIS and AROMAN MCDM methods. *International Journal of Business and Economic Studies*, 7(1), 1-18. <https://doi.org/10.54821/uiecd.1587675>
- da Cunha, Í. G. F., Policarpo, R. V. S., de Oliveira, P. C. S., Zanon, L. G., & do Nascimento Rebelatto, D. A. (2025). Exploring ESG Indicators and the Sustainable Development Goals: A Fuzzy Multi-Criteria Approach to Cause-and-Effect Analysis. *Business Strategy & Development*, 8(3), e70155. <https://doi.org/10.1002/bsd2.70155>
- Demir, E. (2025). An innovative decision support model for the financial performance assessment: A Study of BIST cement firms. *Knowledge and Decision Systems with Applications*, 1, 125-144. <https://doi.org/10.59543/kadsa.v1i.14021>
- Deng, D., Zhang, J., Wang, J., & Zong, X. (2025). Sustainable performance evaluation of pharmaceutical companies: sustainable balanced scorecard and hybrid MCDM approach. *Frontiers in Public Health*, 12. <https://doi.org/10.3389/fpubh.2024.1495156>
- Dündar, S. (2025). Performance evaluation of G7 countries in terms of patent applications. *Black Sea Journal of Engineering and Science*, 8(3), 11-12. <https://doi.org/10.34248/bsengineering.1605982>
- Gligorić, Z., Görçün, Ö. F., Gligorić, M., Pamucar, D., Simic, V., & Küçükönder, H. (2024). Evaluating the deep learning software tools for large-scale enterprises using a novel TODIFFA-MCDM framework. *Journal of King Saud University-Computer and Information Sciences*, 36(5), 102079. <https://doi.org/10.1016/j.jksuci.2024.102079>
- Görçün, Ö. F., Shabir, M., Çalık, A., & Işık, Ö. (2025). Evaluation of the Financial Performance of the Textile and Apparel Industry in interval type-2 fuzzy environment. *Applied Soft Computing*, 113830. <https://doi.org/10.1016/j.asoc.2025.113830>

- Hoang, P. D., Nguyen, L. T., & Tran, B. Q. (2024). Assessing environmental, social and governance (ESG) performance of global electronics industry: an integrated MCDM approach-based spherical fuzzy sets. *Cogent Engineering*, 11(1), 2297509. <https://doi.org/10.1080/23311916.2023.2297509>
- İç, Y. T., Çelik, B., Kavak, S., & Baki, B. (2022). An integrated AHP-modified VIKOR model for financial performance modeling in retail and wholesale trade companies. *Decision Analytics Journal*, 3, 100077. <https://doi.org/10.1016/j.dajour.2022.100077>
- Işık, Ö. (2023). ESG activities and financial performance in banking industry. *International Journal of Insurance and Finance*, 3(2), 53-64. <https://doi.org/10.52898/ijif.2023.10>
- Işık, Ö., & Adalar, İ. (2025). A multi-criteria sustainability performance assessment based on the extended CRADIS method under intuitionistic fuzzy environment: a case study of Turkish non-life insurers. *Neural Computing and Applications*, 37(5), 3317-3342. <https://doi.org/10.1007/s00521-024-10803-0>
- Işık, Ö., Shabir, M., Demir, G., Puška, A., & Pamucar, D. (2025a). A hybrid framework for assessing Pakistani commercial bank performance using multi-criteria decision-making. *Financial Innovation*, 11(1), 38. <https://doi.org/10.1186/s40854-024-00728-x>
- Işık, Ö., Adalar, İ., & Shabir, M. (2025b). Measuring efficiency, productivity and sustainability performance for Islamic banks: a fuzzy expert-based multi-criteria decision support model using spherical fuzzy information. *International Journal of Islamic and Middle Eastern Finance and Management*. <https://doi.org/10.1108/IMEFM-09-2024-0477>
- Işık, Ö., Çalık, A., & Shabir, M. (2025c). A consolidated MCDM framework for overall performance assessment of listed insurance companies based on ranking strategies. *Computational Economics*, 65(1), 271-312. <https://doi.org/10.1007/s10614-024-10578-5>
- Işık, Ö., Zolfani, S. H., Shabir, M., & Šaparauskas, J. (2025d). A grey-based hybrid decision support framework for assessing the Environmental, Social, and Governance (ESG) sustainable performance: a case study of BIST-listed banks. *Technological and Economic Development of Economy*, 31(4), 1237-1273. <https://doi.org/10.3846/tede.2025.24359>
- Katrancı, A., Kundakcı, N., & Pamucar, D. (2025). Financial performance evaluation of firms in BIST 100 index with ITARA and COBRA methods. *Financial Innovation*, 11(1), 34. <https://doi.org/10.1186/s40854-024-00704-5>
- Lombardi Netto, A., Salomon, V. A., & Ortiz-Barrios, M. A. (2026). An environmental, social, and governance (ESG) model for multiple criteria analysis of investments. *International Transactions in Operational Research*, 33(1), 489-506. <https://doi.org/10.1111/itor.70026>
- Lukin, E., Krajnović, A., & Bosna, J. (2022). Sustainability strategies and achieving SDGs: A comparative analysis of leading companies in the automotive industry. *Sustainability*, 14(7), 4000. <https://doi.org/10.3390/su14074000>
- Nijkamp, P., & Van Delft, A. (1977). Multi-criteria analysis and regional decision-making Studies in Applied Regional Science. Springer New York, NY, USA. <https://link.springer.com/book/9789020706895>
- Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, 92(11), 64-88. <https://hbr.org/2014/11/how-smart-connected-products-are-transforming-competition>
- Puška, A., & Stojanović, I. (2022). Fuzzy multi-criteria analyses on green supplier selection in an agri-food company. *J. Intell. Manag. Decis*, 1(1), 2-16. <https://doi.org/10.56578/jimd010102>
- Puška, A., Stević, Ž., & Pamučar, D. (2022). Evaluation and selection of healthcare waste incinerators using extended sustainability criteria and multi-criteria analysis methods. *Environment, Development and Sustainability*, 1-31. <https://doi.org/10.1007/s10668-021-01902-2>
- Ramírez-Orellana, A., Martínez-Victoria, M., García-Amate, A., & Rojo-Ramírez, A. A. (2023). Is the corporate financial strategy in the oil and gas sector affected by ESG dimensions? *Resources Policy*, 81, 103303. <https://doi.org/10.1016/j.resourpol.2023.103303>

- Rao, R.V., Patel, B.K. (2010). A subjective and objective integrated multiple attribute decision-making method for material selection. *Materials & Design*, 31(10), 4738-4747. <https://doi.org/10.1016/j.matdes.2010.05.014>
- Reig-Mullor, J., Garcia-Bernabeu, A., Pla-Santamaria, D., & Vercher-Ferrandiz, M. (2022). Evaluating ESG corporate performance using a new neutrosophic AHP-TOPSIS based approach. *Technological and Economic Development of Economy*, 28(5), 1242-1266. <https://doi.org/10.3846/tede.2022.17004>
- Shabir, M., Ping, J., Işık, Ö., & Razzaq, K. (2025). Impact of corporate social responsibility on bank performance in emerging markets. *International Journal of Emerging Markets*, 20(8), 3607-3636. <https://doi.org/10.1108/IJOEM-02-2023-0208>
- Shannon, C.E. (1948). A mathematical theory of communication. *The Bell system technical journal*, 27(3), 379-423. <https://doi.org/10.1002/j.1538-7305.1948.tb01338.x>
- Türegün, N. (2022). Financial performance evaluation by multi-criteria decision-making techniques. *Heliyon*, 8(5). <https://doi.org/10.1016/j.heliyon.2022.e09361>
- Ünlü, U., & Çıtak, Ö. (2025). Assessing Corporate Sustainability in Turkish Banks: WASPAS and ARAS Approaches in the Covid-19 and the Post-Covid-19 Era. *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 10(2), 758-780. <https://doi.org/10.30784/epfad.1678030>
- Ünlü, U., & Yalçın, N. (2023). A financial performance evaluation of commercial banks traded on Borsa Istanbul with a multi-dimensional perspective. *International Journal of Trade and Global Markets*, 17(2), 151-171. <https://doi.org/10.1504/IJTGM.2023.130734>
- Zhou, C., Wang, K., Liu, R., Shu, A. and Wang, D. (2024). Impact of ESG ratings on Chinese market performance during the COVID-19 crisis. *Journal of Accounting Literature*, Vol. ahead-of-print No. ahead-of-print. <https://doi.org/10.1108/JAL-05-2024-0095>

Appendix A. Computational Steps of CRISUS, MAXC, and CRADIS

CRISUS PROCEDURE

The CRISUS procedure is a newly proposed objective weighting algorithm developed by Adalar and Işık (2025) for the purpose of estimating the objective significance coefficients of evaluation criteria within the context of complex decision-making problems. This method is theoretically grounded in the fundamental principles of the Statistical Variance (SV) technique proposed by Rao and Patel (2010) and the Entropy approach introduced by Shannon (1948). What distinguishes the CRISUS procedure from traditional objective weighting methods is its two-stage normalization mechanism, which is built upon the sum of squares operator. This unique structure enhances the reliability and sensitivity of the calculated weights, while mitigating the potential distortions caused by scale differences or extreme values in the dataset. The computational framework of the CRISUS procedure consists of the following six sequential steps, as illustrated below (Adalar and Işık, 2025):

Step 1. Construct the decision matrix that encapsulates the set of alternatives and evaluation criteria, as formulated in Equation (1).

$$\tilde{X} = \begin{pmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{pmatrix} \quad (1)$$

Step 2. The initial normalization process is performed based on the Euclidean distance-based total norm, a technique originally introduced into the decision-making literature by Nijkamp and Van Delft (1977). In this stage, benefit-oriented evaluation criteria are normalized using Equation (2), while cost-oriented criteria are handled through the transformation defined in Equation (3).

$$x_{ij} = \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^m \tilde{x}_{ij}^2}} \quad (2)$$

$$x_{ij} = 1 - \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^m \tilde{x}_{ij}^2}} \quad (3)$$

Step 3. The second normalization procedure is carried out using Equation (4), irrespective of the qualitative nature of the criteria.

$$s_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (4)$$

Step 4. The sum of squares for each criterion is computed using Equation (5).

$$\rho_j = \sum_{i=1}^m s_{ij}^2 \quad (5)$$

Step 5. Following the first normalization procedure, the standard deviation values (σ_j , $j = 1, 2, \dots, n$) corresponding to each criterion are calculated.

Step 6. In the final stage of the proposed decision-making procedure, the objective weight values of the criteria are computed using Equation (6).

$$w_j = \frac{\sigma_j \rho_j}{\sum_{j=1}^n \sigma_j \rho_j} \quad (6)$$

Considering the computed weight values, the criterion with the highest score is interpreted as

having a more pronounced influence on overall performance, thereby exerting greater impact in the evaluation process.

MAXC PROCEDURE

The MAXC procedure, introduced to the decision-making literature by [Gligorić et al. \(2024\)](#), represents a relatively recent objective weighting methodology. Designed to quantify the significance of each performance indicator in the decision-making process, this algorithm evaluates the cumulative influence of criteria on overall performance. Notably, the MAXC approach has garnered increasing attention due to its ability to generate statistically sensitive and objective results, particularly when applied to large-scale datasets. The implementation of the MAXC weighting procedure comprises the following six steps ([Gligorić et al., 2024](#); [Dündar, 2025](#)).

Step 1. The decision matrix is constructed in accordance with Equation (1).

Step 2. The normalization of the decision matrix is carried out using Equation (7).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (7)$$

Step 3. The maximum values of the criteria in the normalized matrix are obtained using Equation (8).

$$r_{ij}(\max) = \max (r_{ij}) \quad (8)$$

Step 4. The distance between the maximum value of each performance criterion and its corresponding normalized values is determined using Equation (9)

$$d_{ij} = r_{ij}(\max) - r_{ij} \quad (9)$$

Step 5. The expected distance values corresponding to each criterion are calculated using Equation (10).

$$E_j = \frac{\sum_{i=1}^m d_{ij}}{m} \quad (10)$$

Step 6. In the final step of the MAXC procedure, the objective weight scores for each performance criterion are computed using Equation (11).

$$w_j = \frac{E_j}{\sum_{i=1}^m E_j} \quad (11)$$

As a result of the computations, the criterion with the highest weight is considered the most influential in determining overall performance.

INTEGRATED WEIGHTING PROCEDURE

In order to calculate the final weights for each criterion, the weight coefficients obtained from the CRISUS and MAXC procedures were integrated using the aggregation operator presented in Equation (12). This integration enables the consolidation of importance scores derived from distinct weighting methodologies, thereby ensuring a more balanced, reliable, and comprehensive weighting scheme in the decision-making process. In Equation (12), the weight values obtained from the CRISUS and MAXC procedures are denoted by $w_j^{(CRISUS)}$ and $w_j^{(MAXC)}$, respectively.

$$w_j^{(FINAL)} = \Psi w_j^{(CRISUS)} + (1 - \Psi) w_j^{(MAXC)} \quad (12)$$

The parameter Ψ in the corresponding equation assumes values within the [0–1] interval and represents a constant coefficient employed in the integration of weights. In line with the rel-

evant literature, this parameter is conventionally set to 0.5 during the computational process.

CRADIS PROCEDURE

The CRADIS procedure, introduced into the MCDM literature by Puška et al. (2022), is employed for ranking decision alternatives based on benefit functions and their proximity to ideal and anti-ideal solutions. The fundamental premise of the method lies in evaluating the alternatives by considering their deviation levels from both the optimal (ideal) and suboptimal (anti-ideal) solutions (Puška & Stojanović, 2022). From this perspective, the CRADIS method represents a novel conceptual contribution to the MCDM literature, offering an alternative viewpoint for ranking problems. The procedural implementation of the CRADIS method consists of eight systematic steps (Puška et al., 2021; Demir, 2025).

Step 1. The initial decision matrix is constructed as presented in Equation (1).

Step 2. In the second stage, normalization is performed by considering the benefit and cost characteristics of the criteria in the decision matrix. Specifically, Equation (13) is applied for benefit-type criteria, whereas Equation (14) is employed for cost-type criteria.

$$n_{ij} = \frac{x_{ij}}{mak_{ij}} \quad (13)$$

$$n_{ij} = \frac{min_{ij}}{x_{ij}} \quad (14)$$

Step 3. The weighted normalized matrix values are computed in accordance with Equation (15).

$$v_{ij} = n_{ij} \times w_j \quad (15)$$

Step 4. The ideal solution points are determined by the maximum values in the weighted normalized matrix, while the anti-ideal solution points correspond to the minimum v_{ij} values in the same matrix. The computation of the ideal and anti-ideal values is conducted using Equation (16) and Equation (17), respectively.

$$t_i = max v_{ij} \quad (16)$$

$$t_{ai} = min v_{ij} \quad (17)$$

Step 5. The deviation values from the ideal and anti-ideal solution points are calculated using Equation (18) and Equation (19), respectively.

$$d^+ = t_i - v_{ij} \quad (18)$$

$$d^- = v_{ij} - t_{ai} \quad (19)$$

Step 6. The degrees of deviation of the decision alternatives from the ideal and anti-ideal solutions are computed using Equation (20) and Equation (21), respectively.

$$s_i^+ = \sum_{j=1}^n d^+ \quad (20)$$

$$s_i^- = \sum_{j=1}^n d^- \quad (21)$$

Step 7. In order to identify the deviations of each decision alternative from the optimum solutions, benefit functions are calculated for each alternative. These computations are carried out using Equation (22) and Equation (23).

$$K_i^+ = \frac{s_0^+}{s_i^+} \quad (22)$$

$$K_i^- = \frac{s_i^-}{s_0^-} \quad (23)$$

In the context of the equations, s_0^+ represents the optimum alternative with the shortest distance from the ideal solution, while s_0^- denotes the optimal alternative with the greatest distance from the anti-ideal solution.

Step 8. In the final stage of the method, the overall performance scores for each decision alternative, as well as their corresponding rankings, are obtained using Equation (24).

$$Q_i = \frac{K_i^+ + K_i^-}{2} \quad (24)$$

Where the decision alternative with the highest performance score is considered the most successful.