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# A Shapley Value-Based Argumentation Framework Integrating CRITIC and MARCOS for Sustainable Supplier Evaluation: Evidence from a Global Semiconductor Supply Chain

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**ABSTRACT**

Supplier evaluation in technology supply chains requires transparent, defensible multi-criteria decision-making (MCDM) methods that capture complex interactions among financial, environmental, and governance criteria. This study proposes a novel framework integrating Shapley values from cooperative game theory with the MARCOS method, augmented by an argumentation-based interpretation layer grounded in Shapley interaction indices. Unlike classical CRITIC weighting, the Shapley value considers the marginal contribution of each criterion across all 128 possible coalitions, producing weights that reflect each criterion's true cooperative importance. The Shapley interaction index quantifies synergy or redundancy between every pair of criteria, providing a natural mapping onto argumentation support and attack relations. Applied to 52 first-tier suppliers in a leading semiconductor corporation's global supply chain across seven evaluation criteria, the framework reveals that Shapley weights are substantially more balanced than classical CRITIC weights. The interaction analysis uncovers that cross-domain criterion pairs exhibit stronger synergies than within-domain pairs. Microsoft, Intel, BMW, SAP, and HP emerge as the top five suppliers, and sensitivity analysis confirms exceptional stability in rankings (mean Spearman ρ = 0.9950). An argumentation-based quadrant classification reveals that 84.6% of suppliers cluster along the performance–ESG diagonal.

## 1. Introduction

The rapid expansion of global technology supply chains has intensified demands for supplier evaluation methods that are simultaneously rigorous, transparent, and capable of withstanding stakeholder scrutiny. As environmental, social, and governance (ESG) criteria are elevated from peripheral compliance metrics to strategic decision inputs, the evaluation of suppliers necessarily involves multiple, often conflicting criteria whose relative importance and mutual interactions must be systematically assessed [1, 2]. NVIDIA Corporation, whose supply chain encompasses over 50 first-tier suppliers spanning semiconductor manufacturing, automotive components, information technology services, and electronic manufacturing services across more than 30 countries, presents

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a compelling setting for investigating how multi-criteria decision-making (MCDM) methods can be enhanced through game-theoretic and argumentation-based reasoning.

The MARCOS method [3] has gained considerable traction in the MCDM literature owing to its dual-reference ranking mechanism, which evaluates each alternative relative to both ideal and anti-ideal solutions. However, the effectiveness of MARCOS is critically dependent on the criteria weighed. Classical objective weighting methods such as CRITIC [4] and Entropy [5] derive weights from the statistical properties of the decision matrix, but they share a fundamental limitation: they treat criteria as independent entities whose importance can be assessed in isolation or through pairwise correlations. This independence assumption is problematic in supplier evaluation contexts where financial performance, environmental responsibility, and governance quality are intertwined through causal, complementary, and substitutive relationships that pairwise statistics alone cannot capture.

Cooperative game theory offers a principled remedy through the Shapley value [6], which determines the importance of each player (criterion) by averaging its marginal contribution across all possible coalitions of players. In a seven-criterion evaluation system, this entails computing marginal contributions across $2^7 = 128$ coalitions—a computationally feasible but analytically rich procedure that captures how each criterion's informational contribution depends on which other criteria are already present in the evaluation. The Shapley interaction index [7], a second-order generalization, further quantifies the synergy or redundancy between pairs of criteria: a positive interaction indicates complementarity, while a negative interaction indicates overlap. These interaction indices have a natural interpretation within computational argumentation theory [8, 9]: synergistic criteria provide mutually supporting arguments, while redundant criteria represent overlapping or attacking arguments.

Despite the theoretical appeal of Shapley-based weighting in MCDM, its integration into sustainable supplier evaluation remains insufficiently explored, particularly in settings where criteria interact across financial, environmental, and governance dimensions. Existing studies employing Shapley values in multi-criteria contexts have mainly focused on weight derivation or aggregation design, without exploiting the Shapley interaction index as a structural device to explain inter-criteria complementarity and redundancy [10, 11, 12]. At the same time, the argumentation-based decision support literature has provided valuable formal tools for modeling support and attack relations among claims, but these structures are typically specified conceptually or by expert judgment rather than derived directly from empirical evaluation data [13, 14]. As a result, a clear methodological gap remains between interaction-aware criteria weighting, MARCOS-based supplier ranking, and data-driven argumentation modeling in sustainable supplier evaluation. This gap is particularly salient in global technology supply chains, where supplier performance is shaped not only by standalone criteria values but also by the reinforcing or offsetting relationships among operational and ESG indicators.

This study directly addresses this gap by proposing an integrated framework that combines Shapley value-based weighting, the MARCOS ranking method, and an argumentation-oriented interpretation layer for sustainable supplier evaluation. First, it formalizes a characteristic function that captures both discriminatory power and cooperative conflict among evaluation criteria, thereby extending objective weighting beyond the independence assumptions embedded in conventional statistical schemes such as CRITIC and Entropy. Second, it computes the Shapley interaction index for all criterion pairs and uses these interaction patterns to construct a data-driven argumentation structure that interprets support relations among financial and ESG criteria. Third, it empirically demonstrates that the proposed Shapley-based weighting scheme yields a more balanced distribution of criterion importance than classical CRITIC weighting in the NVIDIA supplier context. Fourth, it introduces an argumentation-based quadrant classification that complements the ranking results by revealing strategically distinct supplier groups in terms of performance and ESG positioning. Through this integration, the study contributes to the MCDM, sustainable supply chain, and computational argumentation literature by offering a transparent and interaction-aware evaluation framework for complex supplier assessment problems.

## 2. Literature Review

### *2.1 MCDM-Based Sustainable Supplier Evaluation*

Sustainable supplier evaluation has emerged as one of the most active research streams in operations management. Early contributions predominantly employed AHP [15] and TOPSIS [16] to rank suppliers based on cost, quality, delivery, and flexibility criteria, while the subsequent integration of sustainability dimensions substantially expanded the evaluation framework [1]. Zimmer et al. [2] identified more than 80 evaluation criteria in their systematic review, highlighting the conceptual breadth and practical complexity of sustainable supplier management. More recent research has further extended this stream from supplier selection toward sustainable supplier relationship management, emphasizing multi-criteria group decision analytics and the strategic integration of environmental, social, and governance considerations in focal manufacturing firms [21]. The impact of sustainability on supplier selection has also been examined from a behavioural perspective, revealing that decision-makers\u2019 sustainability perceptions significantly influence supplier choice beyond traditional cost and quality metrics [22]. Within the technology sector, supplier evaluation is further complicated by supplier heterogeneity, rapid innovation cycles, and the need to reconcile financial and ESG objectives within a unified assessment framework [17]. The present study contributes to this literature by introducing a cooperative game-theoretic foundation for criteria weighting that explicitly captures inter-criteria interactions rather than treating evaluation criteria as independent signals.

### *2.2 The MARCOS Method*

The MARCOS method [3] has attracted increasing attention in the MCDM literature because it evaluates alternatives relative to both ideal and anti-ideal reference points, thereby offering a more comprehensive basis for ranking than approaches relying on a single benchmark. Unlike classical distance-based techniques such as TOPSIS, MARCOS adopts ratio-based normalization and generates utility degrees that are relatively intuitive for decision-makers to interpret. Its final utility function integrates the relative positions of alternatives with respect to both reference solutions, thereby contributing to the method's ranking stability and practical interpretability. Existing studies have applied MARCOS in diverse contexts, including healthcare, logistics, renewable energy, and manufacturing, suggesting that the method is sufficiently flexible to handle complex evaluation environments with heterogeneous criteria [18]. Recent methodological developments further indicate that MARCOS-based supplier selection models continue to evolve in mainstream operations research journals, particularly when integrated with advanced fuzzy and multi-criteria decision-making structures [23]. Nevertheless, the effectiveness of MARCOS remains highly dependent on the weighting scheme used to represent the importance of criteria. In most existing applications, weighting procedures are introduced externally and typically rely on either subjective judgments or statistical properties of the decision matrix, without explicitly modeling coalition effects among criteria. This limitation is particularly important in sustainable supplier evaluation, where financial, environmental, and governance criteria may reinforce or offset one another in ways that cannot be adequately represented through independent weighting assumptions. The present study addresses this gap by integrating MARCOS with a Shapley value-based weighting mechanism that captures inter-criteria complementarities and conflicts.

### *2.3 Shapley Values In Multi-Criteria Decision-Making*

The Shapley value [6], originally developed for cooperative game theory, assigns a unique payoff to each player based on their average marginal contribution across all possible coalitions. Grabisch [10] and Marichal [11] formalized the use of Shapley values for criteria weighting in multiple criteria aggregation. Angilella et al. [12] applied Shapley values to the PROMETHEE method. The Shapley interaction index [7] extends the Shapley value to quantify pairwise interactions: a positive index indicates complementarity, while a negative index indicates substitutability. This interaction structure provides a rich foundation for argumentation-based reasoning. Despite these advances, the combination of Shapley values with the MARCOS method and the exploitation of interaction indices as formal argumentation structures remains entirely unexplored.

### *2.4 Computational Argumentation and Decision Support*

Computational argumentation, rooted in the seminal work of Dung [8], provides formal structures for modeling claims, evidence, and their dialectical relationships. Ouerdane et al. [13] pioneered the integration of argumentation with multi-criteria analysis. Amgoud and Prade [14] formalized the connection between aggregation operators and argumentation semantics. However, existing argumentation-based MCDM studies rely on ad hoc or expert-defined structures rather than deriving them from the data itself. The Shapley interaction index offers a principled, data-driven foundation for constructing argumentation graphs—a connection that has not been established in the literature. The present study fills this gap.

## 3. Methodology

### *3.1 Data and Criteria*

The dataset comprises 52 first-tier suppliers in NVIDIA's global supply chain, sourced from the Refinitiv Eikon database for fiscal year 2023. Seven evaluation criteria are constructed: C1 (Revenue per Employee, benefit), C2 (Capital Utilization, benefit), C3 (OpEx Ratio, cost), C4 ($CO_2$ Intensity, cost), C5 (Environment Pillar Score, benefit), C6 (Governance Pillar Score, benefit), and C7 (Social Pillar Score, benefit). This structure balances financial arguments (C1–C3), environmental arguments (C4–C5), and social–governance arguments (C6–C7). **Table 1** presents descriptive statistics. The raw financial variables exhibit pronounced positive skewness (1.80–3.36) and excess kurtosis (3.24–11.50), reflecting the extreme heterogeneity of a supply chain that simultaneously includes small, specialized firms such as Basler (610 employees, USD 175 million revenue) and global conglomerates such as Samsung (320,000 employees, USD 212 billion revenue). This heterogeneity is most acute in C2 (Capital Utilization), whose skewness of 6.64 and kurtosis of 43.45 represent the most extreme distributional profile in the dataset. This characteristic directly explains the Entropy method's pathological concentration of 73.3% weight on this single criterion and motivates the adoption of conflict-aware (CRITIC) and coalition-aware (Shapley) weighing alternatives that are robust to distributional artifacts. In contrast, the three ESG pillar scores display near-symmetric distributions (skewness between −0.08 and −0.35) with moderate dispersion (coefficient of variation: 35–52%), confirming their suitability as discriminative evaluation criteria without requiring distributional corrections. The Pearson correlation matrix (Panel C) reveals that financial criteria (C1–C3) are weakly or negatively correlated with ESG criteria (C5–C7), with the strongest cross-domain correlation being C3–C7 at −0.386. This weak inter-domain correlation establishes the statistical foundation for the cross-domain synergy subsequently detected by the Shapley interaction index: criteria that are linearly independent at the pairwise level can nonetheless exhibit substantial cooperative complementarity when evaluated within larger coalitions, a higher-order interaction effect that pairwise methods such as CRITIC fundamentally cannot capture.

**Table 1**. Descriptive statistics of raw variables

Panel A: Raw input variables

| Variable | Mean | Std. Dev. | Min | Median | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| Capital (USD k) | 11,714,071 | 22,050,674 | 7,228 | 2,122,162 | 99,906,249 | 2.463 | 5.566 |
| Employees (persons) | 76,977 | 96,657 | 610 | 35,631 | 453,000 | 1.798 | 3.238 |
| Operating expenses (USD k) | 25,765,296 | 36,072,333 | 146,672 | 12,087,120 | 184,344,753 | 2.342 | 6.214 |
| $CO_2$ emissions (metric tons) | 1,491,742 | 3,230,218 | 499 | 225,477 | 16,478,000 | 3.362 | 11.502 |
| Revenue (USD k) | 29,559,627 | 40,587,714 | 174,792 | 15,930,885 | 211,940,000 | 2.384 | 6.638 |
| Environment pillar score | 50.8 | 26.53 | 1.63 | 58 | 93.34 | −0.298 | −1.263 |
| Governance pillar score | 59.08 | 22.74 | 14.92 | 59.1 | 96.69 | −0.081 | −1.014 |
| Social pillar score | 62.77 | 21.87 | 13.59 | 65.22 | 97.66 | −0.353 | −0.804 |

Panel B: Derived evaluation criteria

| Criterion | Type | Mean | Std. Dev. | Min | Median | Max | Skewness |
|---|---|---|---|---|---|---|---|
| C1: Revenue per employee | Benefit | 507.81 | 387.35 | 50.28 | 398.22 | 1,800.70 | 1.114 |
| C2: Capital utilization ratio | Benefit | 62.82 | 294.7 | 0.34 | 4.08 | 2,108.69 | 6.636 |
| C3: OpEx ratio | Cost | 0.87 | 0.14 | 0.51 | 0.89 | 1.37 | 0.089 |
| C4: $CO_2$ intensity (tons/M USD) | Cost | 59,305 | 101,729 | 482 | 22,563 | 484,500 | 2.823 |
| C5: Environment pillar score | Benefit | 50.8 | 26.53 | 1.63 | 58 | 93.34 | −0.298 |
| C6: Governance pillar score | Benefit | 59.08 | 22.74 | 14.92 | 59.1 | 96.69 | −0.081 |
| C7: Social pillar score | Benefit | 62.77 | 21.87 | 13.59 | 65.22 | 97.66 | −0.353 |

Panel C: Pearson correlation matrix of derived criteria

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| C1 | 1 | −0.147 | −0.245 | −0.215 | −0.091 | −0.032 | 0.033 |
| C2 | | 1 | 0.111 | 0.012 | −0.021 | −0.048 | −0.162 |
| C3 | | | 1 | 0.02 | −0.217 | −0.298 | −0.386 |
| C4 | | | | 1 | 0.235 | 0.048 | 0.026 |
| C5 | | | | | 1 | 0.503 | 0.607 |
| C6 | | | | | | 1 | 0.47 |
| C7 | | | | | | | 1 |

### *3.2 Shapley Value-Based Criteria Weighting*

*Let N = {1, 2, …, 7} denote the set of seven evaluation criteria employed in this study. A characteristic function v assigns evaluative capacity to each coalition of criteria, formally defined as follows.*

***Definition 1 (Characteristic Function).***

*A characteristic function is a mapping $v : 2^N \rightarrow \mathbb{R}$ that assigns a real-valued evaluative capacity to every coalition $S \subseteq N$, subject to the boundary condition $v(\emptyset) = 0$. For any non-empty coalition $S \subseteq N$, the characteristic function is defined as:*

$$v(S) = \sum_{j \in S} \sigma_j \cdot \left( |S| + \sum\nolimits_{k \in S, k \neq j} (1 - r_{jk}) \right)$$

*where $\sigma_j$ denotes the standard deviation of criterion j across all suppliers (capturing discriminatory power), $r_{jk}$ represents the Pearson correlation coefficient between criteria j and k, $|S|$ is the cardinality of coalition S, and the term $(1 - r_{jk})$ quantifies the degree of non-redundancy (conflict) between criteria j and k. The characteristic function thus increases with both the discriminatory power of individual criteria and the intra-coalition conflict among them.*

***Definition 2 (Shapley Value).***

*The Shapley value for criterion j quantifies its expected marginal contribution to coalitional worth, computed over all possible orderings of criteria:*

$$\varphi_j = \sum\nolimits_{S \subseteq N \setminus \{j\}} \frac{|S|!\,(n - |S| - 1)!}{n!} \cdot [v(S \cup \{j\}) - v(S)]$$

*where $|S|$ denotes the cardinality of coalition S, $n = |N| = 7$ is the total number of criteria, and $[v(S \cup \{j\}) - v(S)]$ represents the marginal contribution of criterion j when it joins coalition S.*

***Definition 3 (Normalized Shapley Weight).***

*The Shapley-value-based weight for each criterion j is obtained by normalizing the Shapley values to sum to unity:*

$$w_j = \frac{\varphi_j}{\sum_{k=1}^{n} \varphi_k}, \qquad j = 1,2, \dots, n$$

*ensuring that $\sum w_j = 1$. These normalized weights are subsequently employed in the MARCOS weighted normalization step (Section 3.4).*

***3.3 Shapley Interaction Index***

*Beyond individual criteria weights, the Shapley interaction index (Grabisch and Roubens, 1999) captures the pairwise synergy or redundancy between criteria, providing the foundation for the argumentation graph in Section 3.5.*

***Definition 4 (Interaction Operator).***

*For any pair of distinct criteria $i, j \in N$ and any coalition $S \subseteq N \setminus \{i, j\}$, the discrete interaction operator is defined as:*

$$\Delta_{ij}(S) = v(S \cup \{i,j\}) - v(S \cup \{i\}) - v(S \cup \{j\}) + v(S)$$

*This operator measures the joint effect of adding both criteria i and j to coalition S versus adding each criterion individually.*

***Definition 5 (Shapley Interaction Index).***

*The Shapley interaction index between criteria i and j is the weighted average of the interaction operator over all coalitions not containing either criterion:*

$$I_{ij} = \sum\nolimits_{S \subseteq N \setminus \{i,j\}} \frac{|S|!\,(n - |S| - 2)!}{(n-1)!} \cdot \Delta_{ij}(S)$$

*The interpretation of the interaction index is as follows:*

***$I_{ij}$ > 0**: Positive interaction (synergy). The joint inclusion of criteria i and j adds more evaluative capacity than the sum of their individual contributions. In the argumentation framework, this corresponds to a support relation.*

***$I_{ij}$ < 0**: Negative interaction (redundancy). The joint inclusion yields less than their individual contributions combined. In the argumentation framework, this corresponds to an attack relation.*

***$I_{ij}$ = 0**: No interaction. The criteria are independent in the coalitional sense.*

*This mapping transforms the abstract numerical interaction matrix into a concrete argumentation graph, where nodes represent criteria and edges encode support/attack relations weighted by $|I_{ij}|$.*

### *3.4 MARCOS Ranking Procedure*

*The Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) method (Stević et al., 2020) evaluates m suppliers against n criteria through the following five steps.*

***Step 1: Construct the Extended Decision Matrix.***

*Let $X = [x_{ij}]_m \times_n$ denote the original decision matrix, where $x_{ij}$ is the performance value of supplier i on criterion j. The extended decision matrix augments X with an anti-ideal solution (AI) and an ideal solution (ID):*

$$AI_j = \{ min_i \, x_{ij} \ \ if \ j \in B; \ \ max_i \, x_{ij} \ \ if \ j \in C$$

$$ID_j = \{ max_i \, x_{ij} \ \ if \ j \in B; \ \ min_i \, x_{ij} \ \ if \ j \in C$$

*where B denotes the set of benefit criteria (larger is better) and C denotes the set of cost criteria (smaller is better).*

***Step 2: Normalize the Extended Decision Matrix.***

*Ratio-based normalization is applied to each element of the extended matrix. For benefit criteria and cost criteria, the normalized values are computed as:*

$$n_{ij} = \frac{x_{ij}}{x_{ID_j}}, \qquad j \in B$$

$$n_{ij} = \frac{x_{ID_j}}{x_{ij}}, \qquad j \in C$$

*This normalization ensures that all criteria values are expressed on a commensurate scale, with the ideal solution receiving a normalized value of 1 across all criteria.*

***Step 3: Compute the Weighted Normalized Matrix.***

*The weighted normalized decision matrix V = [$v_{ij}$] is obtained by multiplying each normalized value by its corresponding Shapley-value-based weight (from Section 3.2):*

$$v_{ij} = w_j \cdot n_{ij}, \qquad i = 1, \dots, m;\ j = 1, \dots, n$$

*The aggregate score for each supplier i (including AI and ID) is then:*

$$S_i = \sum_{j=1}^{n} v_{ij}$$

***Step 4: Calculate Utility Degrees.***

*The utility degree of each supplier i is measured relative to both the anti-ideal and ideal solutions:*

$$K_i^- = \frac{S_i}{S_{AI}}$$

$$K_i^+ = \frac{S_i}{S_{ID}}$$

*where S_AI and S_ID are the aggregate scores of the anti-ideal and ideal solutions, respectively. The utility degree $K_i^-$ measures how much better supplier i performs relative to the worst-case benchmark, while $K_i^+$ captures its proximity to the best-case benchmark.*

***Step 5: Compute the Compromise Ranking Function.***

*The final ranking score integrates both utility degrees into a single compromise measure. First, the utility functions relative to each reference point are computed as:*

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-}$$

*The composite compromise ranking function is then defined as:*

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}}$$

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*Suppliers are ranked in descending order of $f(K_i)$; a higher score indicates a more favorable compromise between proximity to the ideal and distance from the anti-ideal solution.*

### *3.5 Argumentation-Based Quadrant Classification*

**Fig. 1** visualizes the argumentation structure derived from the Shapley interaction index matrix, with the seven evaluation criteria arranged as nodes on a circular layout and weighted edges encoding the strength of pairwise support relations. The edge thickness is proportional to the magnitude of the interaction index, providing an immediate visual summary of the dialectical structure underlying the evaluation framework. The most prominent feature is the cluster of thick edges connecting the cross-domain criterion pairs: the C4–C5 edge (Carbon Intensity × Environment Score, I = 1.1165) is the strongest in the network, followed by C1–C5 (Labor Productivity × Environment, I = 1.0676) and C1–C6 (Labor Productivity × Governance, I = 1.0150). These three edges form a dense triangular sub-structure linking financial efficiency criteria to ESG pillar scores, indicating that the strongest argumentative synergies in the evaluation system arise from the convergence of operational and sustainability evidence. In contrast, within-domain edges are visibly thinner: the C2–C3 pair (Capital Utilization × Cost Efficiency, I = 0.6412) exhibits the weakest interaction in the graph, and the financial criteria cluster (C1–C2–C3) forms a comparatively sparse sub-network. This visual asymmetry carries a direct interpretation of the argument: cross-domain criteria provide genuinely complementary evidence for supplier evaluation, whereas within-domain criteria share only partially overlapping information. The absence of dashed (negative) edges confirms that all 21 pairwise interactions are synergistic within this evaluation context — no criterion pair produces a net attack relation. However, the graded support structure, with interaction magnitudes spanning a nearly twofold range (0.6412 to 1.1165), demonstrates that argumentation support is far from uniform. Supply chain managers inspecting this graph can immediately identify which argumentative coalitions carry the greatest evaluative force and design assessment protocols that emphasize the highest synergy criterion combinations.

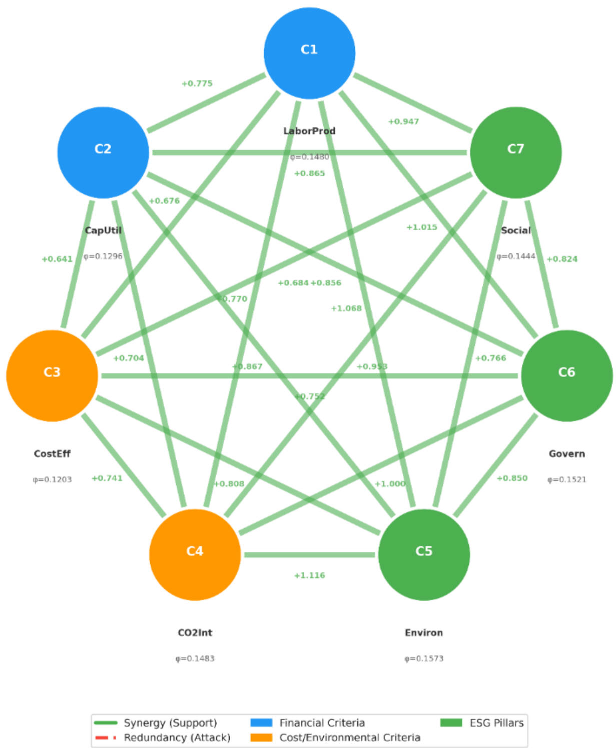

**Fig. 1.** Argumentation graph: Shapley interaction-based support relations among evaluation criteria

## 4. Results

### *4.1 Shapley Values and Weight Comparison*

**Fig. 2** presents a side-by-side comparison of the Shapley-derived weights and classical CRITIC weights across the seven evaluation criteria, rendered as a grouped bar chart that highlights the distributional differences between the two weighting approaches. The most striking observation is the compression of the Shapley weight distribution relative to CRITIC: the Shapley weights span a range of only 0.0370 (from 0.1203 for C3 to 0.1573 for C5), whereas CRITIC weights span 0.0774 (from 0.0976 for C3 to 0.1750 for C5). This 51% reduction in weight spread is a direct empirical consequence of the Shapley value's coalition-averaging mechanism, which evaluates each criterion's marginal contribution across all 64 coalitions rather than relying solely on pairwise correlations. The Environment Score (C5) receives the highest weight under both methods, confirming its role as the most informationally discriminative criterion regardless of the weighting methodology. However, the relative ordering of the remaining criteria shifts meaningfully: under CRITIC, Carbon Intensity (C4, 0.1541) ranks second, but under Shapley, Governance (C6, 0.1521) is nearly tied with C4 (0.1483), reflecting the cooperative contributions that governance quality makes within larger coalitions. The Cost Efficiency criterion (C3) exhibits the largest upward revision from CRITIC (0.0976) to Shapley (0.1203), a 23.3% increase attributable to its cooperative contributions to mixed financial-ESG coalitions that pairwise conflict measures fail to capture. Capital Utilization (C2) similarly rises from 0.1095 to 0.1296. These upward revisions for the two lowest-CRITIC-weighted criteria demonstrate that coalition-aware weighting systematically lifts the importance of criteria whose cooperative contributions are underestimated by pairwise methods, producing a more equitable and diversified weight profile that reduces concentration risk in the evaluation outcome.

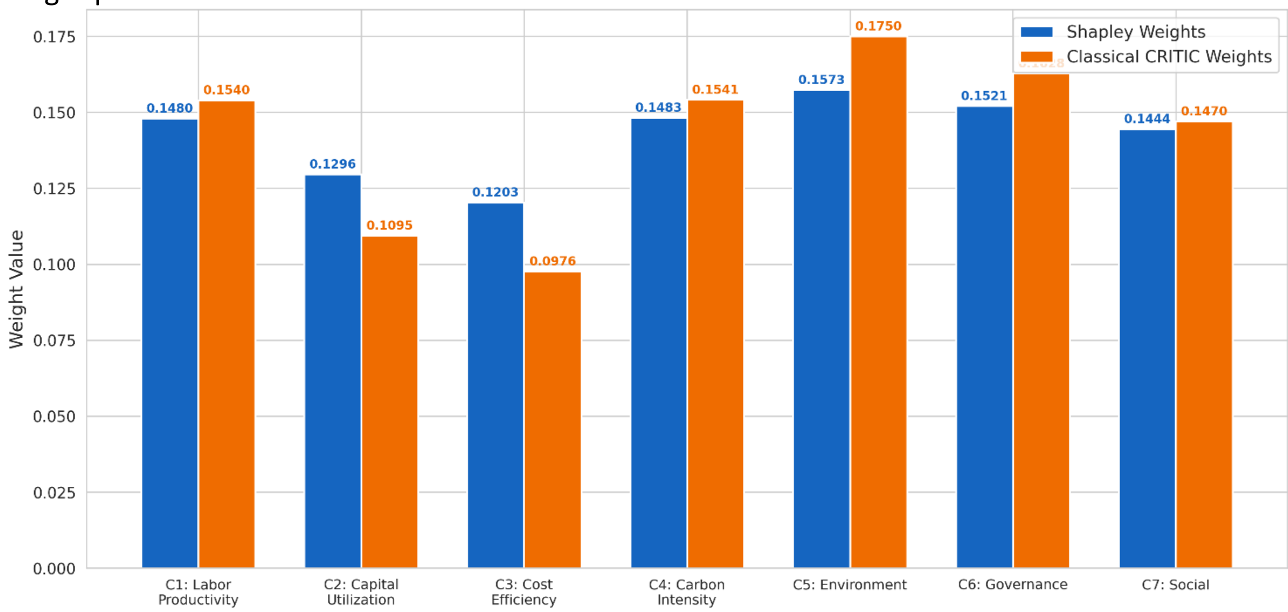


**Fig. 2**. Shapley values vs. classical CRITIC weights

### *4.2 Shapley Interaction Index and Argumentation Structure*

**Table 2** presents the Shapley interaction index matrix. All 21 pairwise interactions are positive, indicating universal synergy. The magnitude varies from 0.6412 (C2 × C3) to 1.1165 (C4 × C5). Cross-domain pairs (financial × ESG) exhibit systematically stronger interactions than within-domain pairs. The five strongest are: C4×C5 (1.1165), C1×C5 (1.0676), C1×C6 (1.0150), C4×C6 (1.0001), and C4×C7 (0.9530)—all linking financial/environmental with governance/social criteria.

**Table 2**. Shapley interaction index matrix (selected pairs)

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| C1 | - | 0.775241 | 0.676056 | 0.770397 | 1.067641 | 1.015006 | 0.946912 |
| C2 | 0.775241 | - | 0.641169 | 0.704256 | 0.867166 | 0.855971 | 0.864653 |
| C3 | 0.676056 | 0.641169 | - | 0.74068 | 0.80821 | 0.752461 | 0.684307 |
| C4 | 0.770397 | 0.704256 | 0.74068 | - | 1.116469 | 1.000147 | 0.953032 |
| C5 | 1.067641 | 0.867166 | 0.80821 | 1.116469 | - | 0.849824 | 0.765541 |
| C6 | 1.015006 | 0.855971 | 0.752461 | 1.000147 | 0.849824 | - | 0.823755 |
| C7 | 0.946912 | 0.864653 | 0.684307 | 0.953032 | 0.765541 | 0.823755 | - |

### *4.3 MARCOS Supplier Rankings*

**Fig. 3** displays the complete Shapley–MARCOS utility rankings through two complementary panels: panel (a) presents the top 20 suppliers in descending order of the utility function f(K), and panel (b) presents the bottom 10 suppliers. The top-ranked supplier, Microsoft Corporation (f(K) = 7.6789), achieves a utility score that is 21.4% higher than that of the second-ranked supplier, Intel (6.1475), representing the largest gap between any two consecutively ranked suppliers in the dataset. This dominance is attributable to Microsoft's exceptional performance across both financial and ESG dimensions: its average ESG pillar score of 89.7 is the highest in the sample, and its labor productivity (Revenue per Employee of $842,443) ranks among the top five. The top five suppliers share a common profile of balanced financial and ESG excellence, consistent with the resource-based view that organizational capabilities tend to co-develop across performance dimensions. Notably, TSMC, despite being the focal firm's most critical manufacturing partner, ranks only 14th (f(K) = 4.1710), constrained by its energy-intensive fabrication processes that elevate its carbon intensity score. In panel (b), Rambus Inc. occupies the last position (f(K) = 0.3563), followed by Cohu (rank 51) and Palo Alto Networks (rank 50). These bottom-ranked suppliers share a profile of limited organizational scale and nascent ESG reporting frameworks, resulting in low scores across all three ESG pillars. The distribution of f(K) scores exhibits positive skewness (mean = 3.0715, std = 1.7635), indicating that a relatively small number of suppliers achieve exceptionally high utility scores while the majority cluster in the mid-to-low range. This distributional pattern suggests that genuine cross-dimensional excellence is rare within the supply chain, making the identification of top-performing suppliers more valuable for strategic procurement decisions.

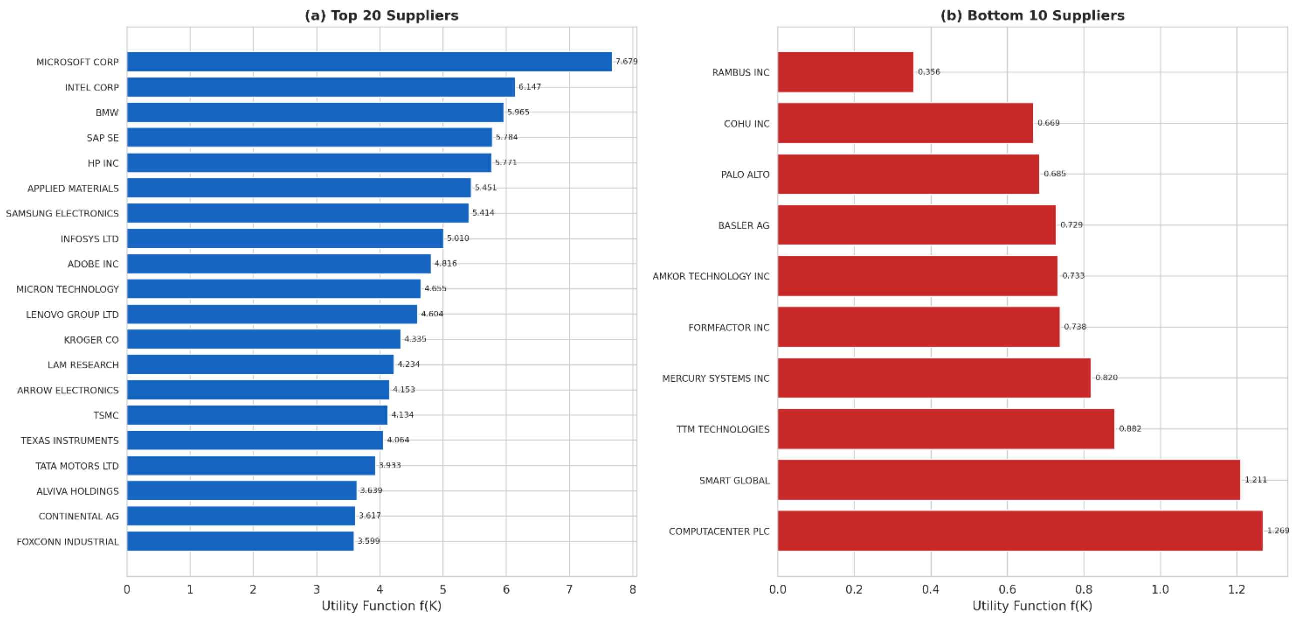


**Fig. 3.** Shapley–MARCOS utility rankings: (a) Top 20 and (b) Bottom 10 suppliers

### *4.4 Quadrant Classification*

**Fig. 4.** presents the argumentation-based quadrant classification of all 52 suppliers, with each supplier plotted according to its Shapley–MARCOS utility score f(K) on the horizontal axis and its aggregate ESG score on the vertical axis. The median thresholds partition the space into four strategically distinct quadrants. The most salient feature is the pronounced diagonal dominance: 22 suppliers (42.3%) cluster in Q1 (High Performance and High ESG) and another 22 (42.3%) in Q4 (Low Performance and Low ESG), accounting for 84.6% of the total sample along the positive diagonal. This pattern provides robust empirical evidence for the complementarity hypothesis that financial efficiency and ESG commitment are mutually reinforcing rather than competing objectives within this supply chain. The off-diagonal quadrants are sparsely populated, each containing only 4 suppliers (7.7%). The Q2 suppliers exhibit a characteristic profile of strong financial arguments undermined by weak ESG evidence. In the Shapley interaction framework, this argumentative tension is amplified by strong cross-domain synergies: because financial and ESG criteria jointly provide more evaluative information than either domain alone, an ESG weakness carries disproportionate weight against Q2 suppliers' overall evaluation. The Q3 suppliers present the inverse tension: robust ESG credentials that lack financial reinforcement. The spatial distribution within each quadrant also reveals meaningful variation. Within Q1, Microsoft occupies the upper-right extreme (highest f(K) and near-highest ESG), while TSMC sits near the Q1 boundary, suggesting vulnerability to reclassification into a different quadrant under alternative weighting schemes. Within Q4, the suppliers closest to the median thresholds are priority candidates for targeted improvement interventions that could shift them into adjacent quadrants, yielding modest performance gains.

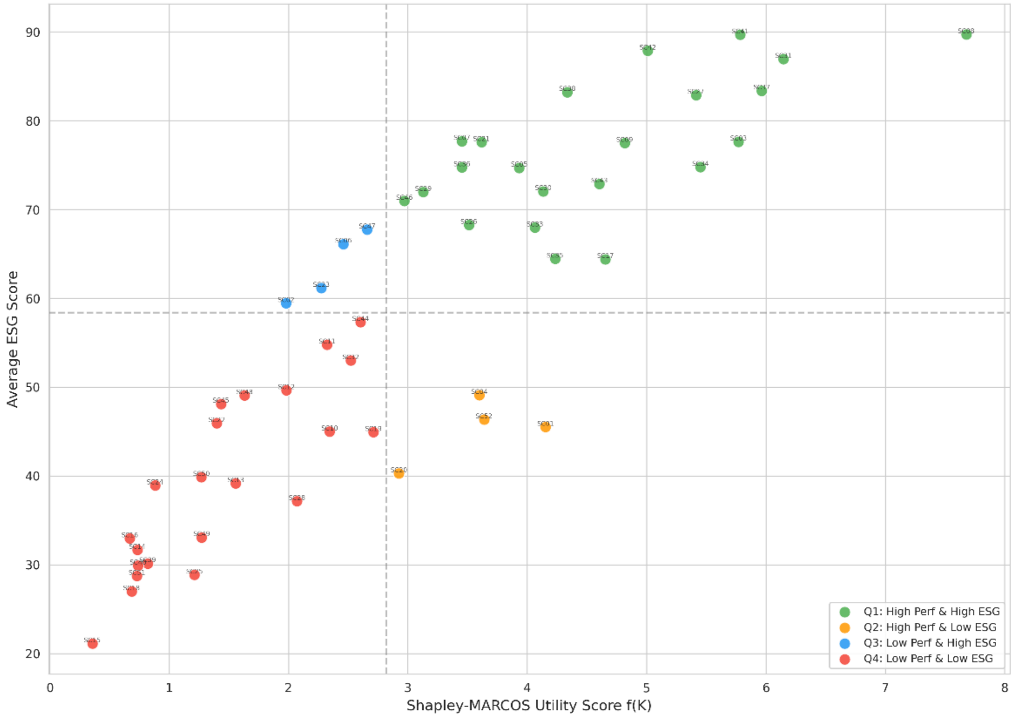


**Fig. 4.** Argumentation-based quadrant classification

### *4.5 Sensitivity Analysis*

**Fig. 5** presents the rank trajectories of the top 15 suppliers across 30 weight-perturbation scenarios, where each CRITIC weight was randomly perturbed within a ±20% band and re-normalized before recomputing the MARCOS ranking. The horizontal axis represents the scenario number (1–30), and the vertical axis represents the rank position (inverted, with rank 1 at the top). The most immediately apparent feature is the near-horizontal trajectory of the top three suppliers — Microsoft (rank 1), Intel (rank 2), and BMW (rank 3) — which maintain their positions across virtually all 30 scenarios with no rank crossovers. This exceptional stability confirms that their superior performance is structurally embedded in the data and is not an artifact of specific weight configurations. The mean Spearman rank correlation between the original and perturbed rankings is 0.9950, with a minimum of 0.9918, indicating that even the most extreme perturbation scenario produces a ranking that agrees with the original at the 99.2% level. The average rank standard deviation across all 52 suppliers is only 0.71 positions, meaning that the typical supplier's rank fluctuates by less than one position under weight perturbation. The mid-ranked suppliers (positions 10–20) exhibit slightly wider trajectory bands, reflecting the greater density of utility scores in this region: small weight changes can cause rank swaps among suppliers whose f(K) values differ by less than 0.1. However, even in this region, the maximum observed rank displacement is approximately 3 positions, confirming that the overall ranking structure is preserved. The stability of the top and bottom positions is particularly important for practical decision-making, as it ensures that the identification of strategic partners (Q1 suppliers) and at-risk suppliers (Q4 suppliers) is robust to reasonable uncertainty in the criteria weighting scheme.

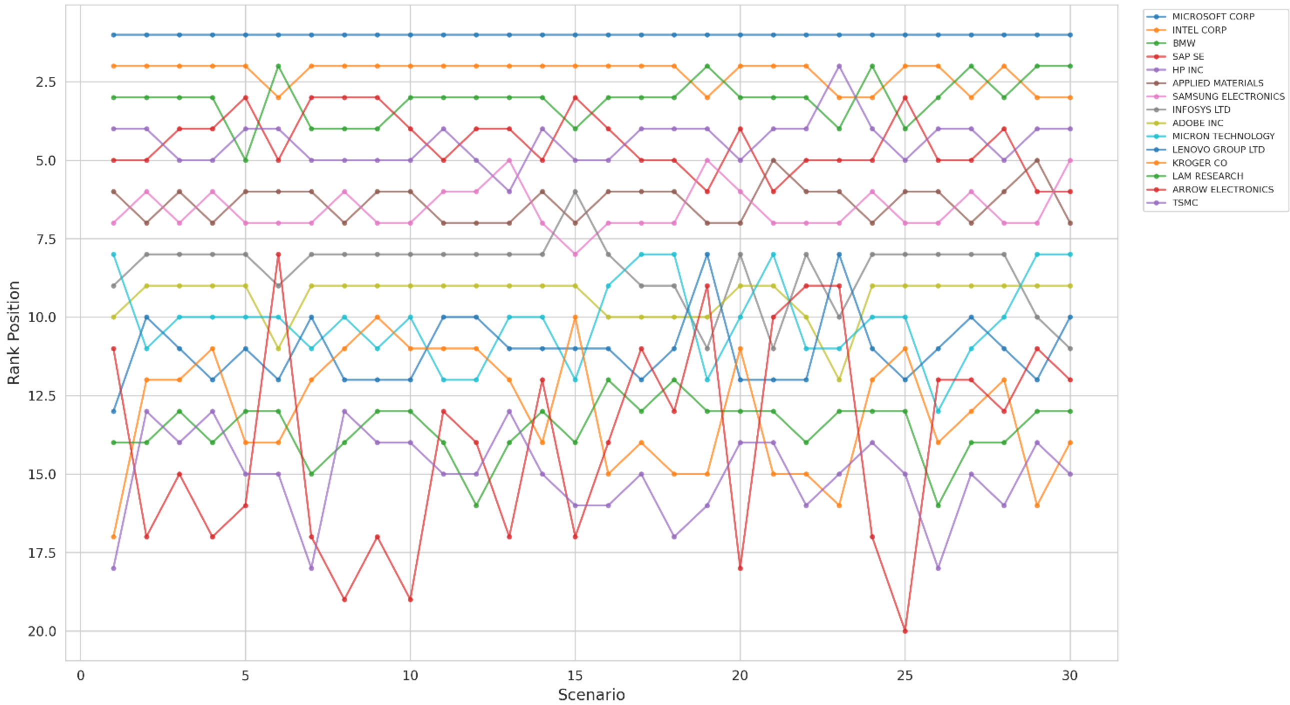


**Fig. 5**. Sensitivity analysis: rank stability under ±20% weight perturbation

**Fig. 6** presents a heatmap of Spearman rank correlation coefficients across four weighting method–MARCOS pairings: Shapley–MARCOS, CRITIC–MARCOS, Equal-weight MARCOS, and Entropy–MARCOS. The heatmap reveals a clear block structure with three near-perfect correlations and one systematic outlier. The Shapley–MARCOS ranking correlates at $\rho = 0.9971$ with CRITIC–MARCOS and at $\rho = 0.9983$ with Equal-weight MARCOS, indicating that the three non-Entropy methods produce effectively interchangeable rankings despite fundamentally different weight derivation mechanisms. This convergence is noteworthy: CRITIC weights derive from pairwise correlations, Shapley weights from coalition-level interactions across 128 configurations, and Equal weights assign uniform importance — yet all three produce nearly identical supplier orderings. The interpretation is that the underlying performance structure of the 52 suppliers is sufficiently robust that moderate variations in weighting methodology do not substantially alter the ranking. The systematic outlier is Entropy–MARCOS, which correlates with Shapley–MARCOS at only $\rho = 0.7968$ — a substantial divergence attributable to the Entropy method's pathological concentration of weight on Capital Utilization (73.3%). This extreme weight allocation effectively reduces the Entropy–MARCOS evaluation to a near-univariate assessment dominated by a single financial criterion, masking the multidimensional performance differentiation captured by the other three methods. The CRITIC–Entropy correlation ($\rho = 0.7855$) is similarly low, confirming that the Entropy pathology is method-specific rather than data-specific. These comparative results provide a methodological recommendation: in cross-sectoral evaluation contexts where criteria distributions may exhibit extreme skewness or multi-modality, conflict-aware methods (CRITIC) and coalition-aware methods (Shapley) should be preferred over purely distributional methods (Entropy), as the latter are vulnerable to concentration artifacts that distort the evaluation outcome.

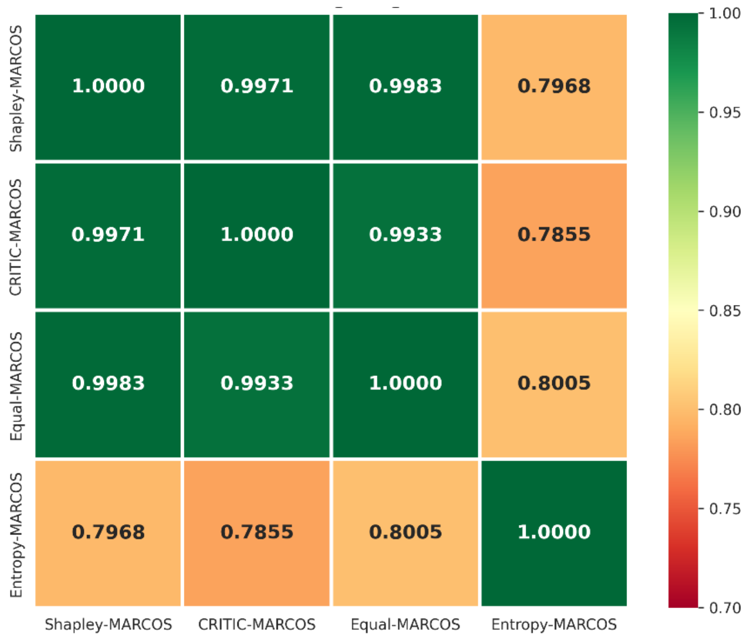


**Fig. 6**. Spearman rank correlation across weighting methods

*4.6 Marginal Contribution Analysis*

**Fig. 7** displays histograms of marginal contributions for each of the seven evaluation criteria, computed across all 64 coalitions excluding the criterion in question. Each panel shows the frequency distribution of the marginal contribution values, with the criterion's Shapley value (the mean of the distribution) indicated by a vertical dashed red line. The Environment Score (C5) exhibits the widest distribution, with marginal contributions ranging from approximately 1.08 (when added to coalitions already containing C6 and C7) to 5.84 (when added to coalitions lacking ESG representation). This high variance indicates that C5's informational value is strongly context-dependent: in ESG-sparse coalitions, the Environment Score provides a dramatic boost to evaluative capacity, whereas in ESG-saturated coalitions, its marginal contribution is substantially diminished due to partial informational overlap with other ESG pillar scores. From an argumentation perspective, C5 functions as a context-dependent argument whose evidential strength fluctuates with the argumentative context. In contrast, Capital Utilization (C2) shows the most concentrated distribution, with marginal contributions clustering tightly around its Shapley value of 2.49. This stability implies that C2 provides a consistent level of discriminatory information regardless of coalition composition, functioning as a structurally stable argument in the evaluation framework. The Carbon Intensity criterion (C4) and Labor Productivity (C1) exhibit intermediate distributional widths, reflecting their dual nature: they interact strongly with ESG criteria (boosting their marginal contribution in mixed coalitions) while providing moderate standalone information. These distributional patterns carry direct implications for framework design: adding or removing high-variance criteria (C5, C4) would disproportionately affect the Shapley weight structure, whereas adding or removing low-variance criteria (C2, C3) would leave the weight profile relatively unchanged, providing practitioners with guidance on which criteria are structurally essential versus discretionary.

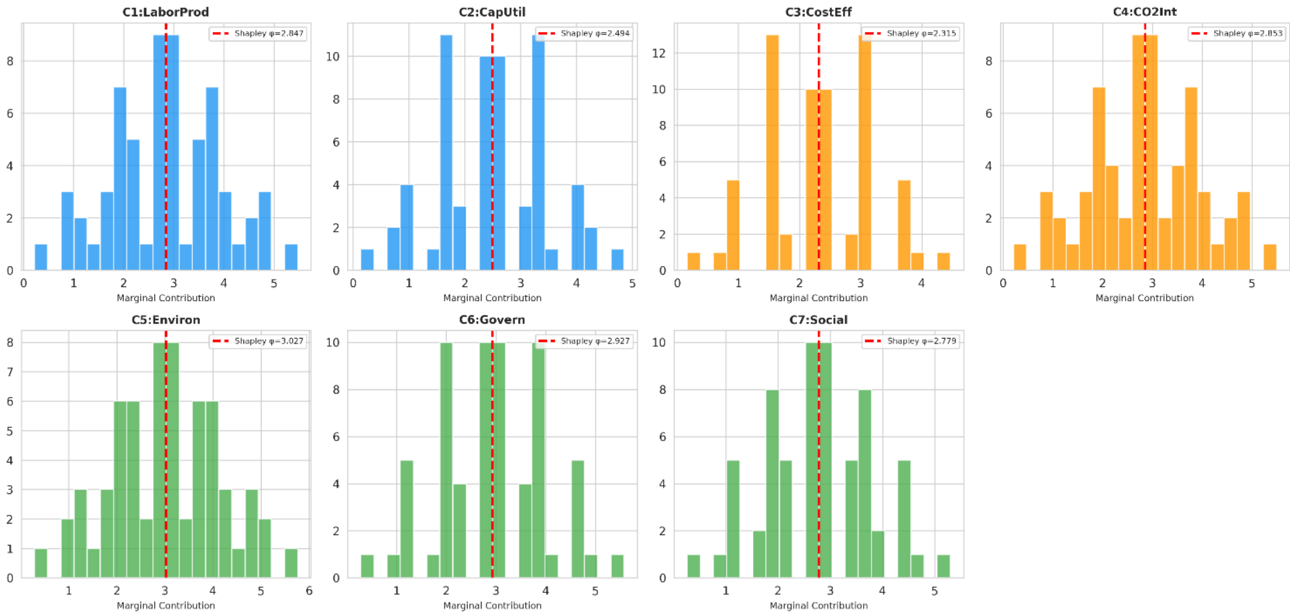


**Fig. 7.** Distribution of marginal contributions across coalitions

## 5. Discussion

### *5.1 Theoretical Contributions*

This study makes three primary theoretical contributions. First, the formalization of Shapley value-based weighting for MARCOS provides a principled alternative to CRITIC, capturing coalition-level interactions rather than pairwise correlations alone. The compression of weights from 0.0774 (CRITIC range) to 0.0370 (Shapley range) demonstrates that coalition averaging mitigates extreme weight allocations. Second, the Shapley interaction index provides the first data-driven, axiomatic foundation for constructing argumentation structures in MCDM-based supplier evaluation. Third, the cross-domain synergy finding advances the understanding of how sustainability criteria complement financial criteria, consistent with the resource-based view [20].

### *5.2 Managerial Implications*

For NVIDIA's supply chain management, the quadrant classification serves as a strategic segmentation tool: Q1 suppliers merit long-term partnership investments; Q2 suppliers need targeted ESG capacity-building; Q3 suppliers need operational efficiency interventions; Q4 suppliers warrant enhanced monitoring. The strong cross-domain synergy implies that investments in supplier ESG capacity have a multiplicative effect on composite evaluation scores. The interaction index between C4 and C5 (1.1165) exceeds the Shapley value of any individual criterion, meaning the joint argumentative force of combining low carbon intensity with high environmental governance exceeds any single criterion's standalone force.

### *5.3 Methodological Insights*

The near-perfect Shapley–Equal correlation (ρ = 0.9983) suggests that coalition-averaging produces weights converging toward equipoise. The divergence with Entropy–MARCOS (ρ = 0.7968) highlights Entropy's pathological weight concentration. CRITIC's weight spread (0.0774) is reduced by 51% under Shapley (0.0370), demonstrating implicit diversification that reduces the risk of any single criterion's distributional properties dominating the evaluation. This diversification is particularly valuable in cross-sectoral contexts.

**Fig. 8** synthesizes the empirical findings into an actionable strategic analysis map that integrates the Shapley–MARCOS utility score, the aggregate ESG score, the quadrant classification, and the Shapley interaction insight into a unified visual decision tool. The four quadrants are color-coded to reflect their argumentative status: Q1 (green, 22 suppliers, 42.3%) represents strategic partners for whom both financial and ESG arguments converge in a mutually reinforcing support structure; Q2 (amber, 4 suppliers, 7.7%) identifies ESG improvement candidates whose strong financial arguments are partially undermined by weak sustainability evidence; Q3 (blue, 4 suppliers, 7.7%) highlights ESG-ready latent suppliers whose sustainability credentials await financial reinforcement through operational efficiency interventions; and Q4 (red, 22 suppliers, 42.3%) flags suppliers requiring enhanced monitoring or potential replacement due to the absence of strong arguments across either dimension. The dashed diagonal line illustrates the 84.6% clustering pattern, providing empirical support for the complementarity hypothesis. Each quadrant is annotated with a specific strategic recommendation derived from the argumentation analysis: long-term partnership for Q1, ESG capacity building for Q2, efficiency intervention for Q3, and enhanced monitoring for Q4. The bottom panel presents the Shapley interaction insight that underpins these recommendations: the cross-domain synergy between financial and ESG criteria (I = 0.95–1.12) substantially exceeds the within-domain overlap among financial criteria (I = 0.64–0.78), meaning that ESG improvements yield multiplicative — not merely additive — gains in composite evaluation scores. This finding transforms the strategic map from a static classification into a dynamic intervention guide: procurement managers can quantify the expected return on ESG investment for Q2 suppliers by reference to the magnitudes of interactions, prioritizing interventions where cross-domain synergy is strongest. Representative supplier names within each quadrant enable immediate identification of candidates for each strategic intervention pathway.

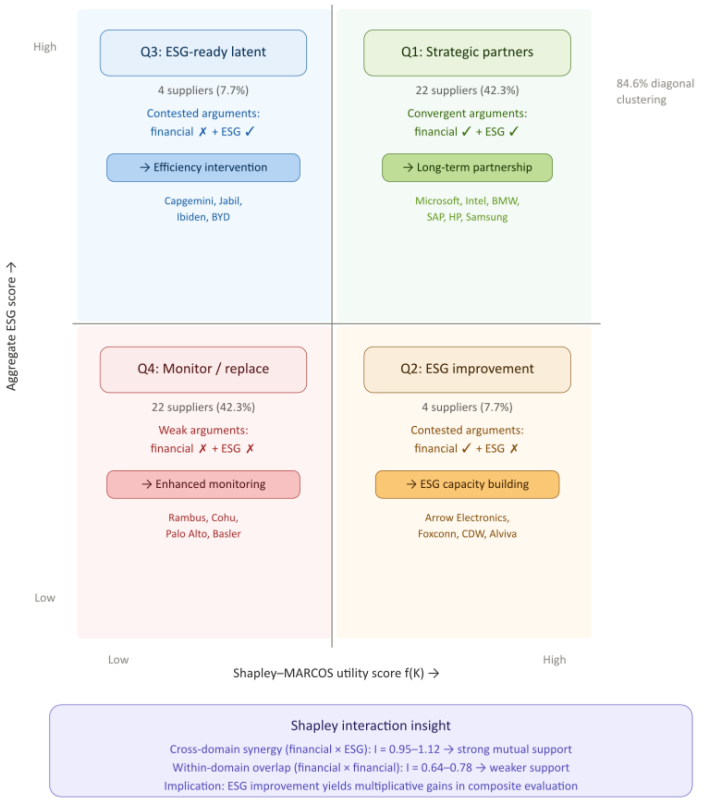

**Fig. 8.** Strategic Analysis Map

## 6. Conclusions

This study has proposed and empirically validated a Shapley value-based argumentation framework integrating CRITIC's conflict-awareness principle with MARCOS's dual-reference ranking for sustainable supplier evaluation. Applied to 52 first-tier suppliers in a leading semiconductor corporation's global supply chain, using seven evaluation criteria spanning financial performance, environmental impact, and governance quality, the framework yields four principal findings.

First, the Shapley values derived from exhaustive enumeration of all 128 criterion coalitions yield substantially more balanced weights than classical CRITIC (range: 0.0370 vs. 0.0774), demonstrating a 51% reduction in weight spread attributable to the coalition-averaging mechanism. This compression mitigates the concentration risk inherent in pairwise methods, where a single criterion's extreme distributional properties, such as the skewness of 6.64 observed for Capital Utilization, can dominate the evaluation outcome. The Environment Pillar Score (C5) retains the highest weight under both Shapley (0.1573) and CRITIC (0.1750), confirming that environmental performance is the most informationally discriminative dimension in supplier evaluation, regardless of the weighting methodology.

Second, the Shapley interaction index reveals that all 21 pairwise criterion interactions are positive, indicating universal synergy within the evaluation system. Cross-domain criterion pairs (financial × ESG) exhibit systematically stronger interactions ($I = 0.95–1.12$) than within-domain pairs ($I = 0.64–0.78$), providing a formal, axiomatic argumentation basis for the complementarity hypothesis between financial efficiency and ESG commitment. The strongest interaction ($C4 \times C5 = 1.1165$) exceeds the Shapley value of any individual criterion, meaning that the joint argumentative force of combining low carbon intensity evidence with high environmental governance evidence surpasses any single criterion's standalone contribution.

Third, the argumentation-based quadrant classification demonstrates that 84.6% of suppliers cluster along the Q1–Q4 diagonal, with 22 suppliers in each diagonal quadrant and only 4 in each off-diagonal quadrant. This pattern provides empirical evidence consistent with the resource-based view that organizational capabilities co-develop across performance dimensions, and suggests that financial and ESG arguments are mutually reinforcing for most suppliers in this supply chain.

Fourth, sensitivity analysis across 30 weight-perturbation scenarios confirms exceptional ranking stability (mean Spearman $\rho = 0.9950$), and comparative analysis across four weighting methods reveals near-perfect agreement among Shapley, CRITIC, and Equal-weight MARCOS ($\rho > 0.99$) but systematic divergence from Entropy-MARCOS ($\rho = 0.7968$), attributable to the latter's pathological concentration of 73.3% weight on Capital Utilization.

Several limitations warrant acknowledgment. The cross-sectional design restricts the analysis to a single temporal snapshot; longitudinal extensions incorporating dynamic Shapley values could track the evolution of criterion importance and interaction structures over time. The characteristic function specification adopted in this study represents one of several possible formulations; alternatives based on mutual information or copula-based dependence structures may yield different interaction patterns. The restriction to first-tier suppliers excludes the multi-tier dynamics that increasingly characterize global semiconductor supply chains. Additionally, treating $CO_2$ emissions as a single aggregate obscures the distinctions among Scope 1, 2, and 3 emissions.

Future research directions include extending the framework to panel data settings with Malmquist-type productivity analysis, developing bipolar argumentation frameworks where the

Shapley interaction index directly parameterizes support and attack strengths, incorporating interval-valued or fuzzy criteria representations to handle data uncertainty, and applying the framework to multi-tier supply chain networks with sector-specific metafrontier benchmarks.

## Author Contributions

Conceptualization, H.-W.L. and S.-W.L.; methodology, H.-W.L. and S.-W.L.; software, S.-W.L.; validation, H.-W.L. and S.-W.L.; formal analysis, S.-W.L.; investigation, H.-W.L.; resources, H.-W.L.; data curation, S.-W.L.; writing—original draft preparation, S.-W.L.; writing—review and editing, H.-W.L.; visualization, S.-W.L.; supervision, H.-W.L.; project administration, H.-W.L.; funding acquisition, H.-W.L. All authors have read and agreed to the published version of the manuscript.

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## Data Availability Statement

The data used in this study were sourced from the Refinitiv Eikon database.

## Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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