# Sustainable supplier selection: A comparative study of VIKOR, TOPSIS, and alternative ranking methods

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**Abstract**

*Supplier selection has become an increasingly important issue in supply chain management, particularly in contexts where efficiency, sustainability, and competitiveness are essential for long-term success. To support decision-making in this complex environment, multi-criteria decision-making (MCDM) approaches provide a structured and objective way of evaluating suppliers across diverse performance dimensions. This study employs an integrated methodological framework that begins with data normalization and objective weight determination through entropy, followed by the application of established MCDM techniques to rank suppliers. By using quantitative data and a systematic evaluation procedure, the research ensures transparency and reduces subjectivity in the decision-making process. The results show that while there is overall consistency in identifying strong and weak supplier candidates, differences arise depending on the methodological perspective used. These variations highlight how different approaches emphasize distinct aspects of supplier performance, such as overall balance, relative distance, or outranking strength. Despite these differences, the convergence of findings strengthens confidence in the reliability of the evaluation process.*

**Research purpose:**
*This study aims to develop a robust decision-making framework for sustainable supplier selection in the electronics industry. By integrating entropy and interval entropy weighting with three prominent multi-criteria decision-making (MCDM) methods—TOPSIS, VIKOR, and ELECTRE—the research seeks to provide objective, transparent, and comprehensive evaluations of suppliers.*

**Research motivation:**
*Supplier selection has become increasingly complex under the growing demand for sustainability and resilience in global supply chains. Traditional methods relying solely on expert judgment often introduce subjectivity and bias. Therefore, there is a pressing need for data-driven, systematic approaches that capture both quantitative and qualitative performance indicators while also revealing the methodological sensitivity of MCDM techniques.*

**Research design, approach, and method:**
*A dataset of electronics suppliers was assessed using a two-step methodology. First, entropy and interval entropy were applied to determine objective weights for quantitative and qualitative criteria. Second, suppliers were ranked through TOPSIS, VIKOR, and ELECTRE, with Spearman correlation employed to analyze the consistency and divergence among results. This design ensures a balanced evaluation across distance-based, compromise-based, and outranking approaches.*

**Main findings:**
*The study reveals that the choice of method significantly affects supplier ranking outcomes. TOPSIS and ELECTRE demonstrate high consistency in identifying leading suppliers, whereas VIKOR highlights compromise alternatives that balance overall performance with risk considerations. The comparative analysis further indicates both convergence and divergence among the three methods, underscoring the importance of methodological pluralism in achieving reliable and transparent supplier selection.*

**Practical/managerial implications:**
*The study provides actionable insights for procurement managers by demonstrating the value of applying multiple MCDM methods in parallel. Decision-makers can leverage TOPSIS and ELECTRE for robust identification of best-in-class suppliers, while VIKOR offers compromise solutions that balance utility and risk. This multi-method framework enhances transparency, reduces reliance on subjective judgment, and supports more resilient and sustainable supplier decisions in the electronics sector.*

**Keywords**: sustainable sourcing, supplier evaluation,comparative, MCDM method


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## 1. INTRODUCTION

Since the concept of sustainability was introduced into supply chain management, both practitioners and researchers have shown increasing interest in Sustainable Supply Chain Management (SSCM). Various research papers have proposed definitions of SSCM. According to (SA, 2008), SSCM is the integration of supply chain management and sustainable development, where social and environmental issues across the entire chain must be considered to prevent sustainability-related risks. Similarly, Choi (2015) defines SSCM as the strategic integration of economic, environmental, and social dimensions into traditional supply chain activities—from raw material sourcing, production, and distribution, to consumption and end-of-life product management—with the aim of minimizing negative effects and maximizing long-term value for all stakeholders.

An essential component of SSCM is stakeholder management. SSCM does not only focus on the internal organization but also extends to the entire related ecosystem, including customers, suppliers, communities, regulatory bodies, NGOs, and even competitors (Cetinkaya, 2011). In particular, supplier management plays a pivotal role in implementing sustainable supply chain strategies, as suppliers are the first link that determines input quality, environmental impact, and labor conditions throughout the chain (Raj, 2017). Therefore, selecting suppliers and fostering long-term, transparent, and mutually beneficial partnerships is a core factor in realizing sustainability objectives.

According to VietnamCredit, electronics account for 17.8% of the country's industrial sector, with key products including components, telephones, computers, and office equipment, and the sector still achieved record-high turnover and contributed 30–40% of Vietnam's GDP in recent years (VietnamCredit, 2021). Recognizing this importance, the Vietnamese government has adopted the National Action Program on Sustainable Production and Consumption to 2030, which emphasizes greening distribution systems and developing environmentally friendly supply chains. At the same time, global market pressures have intensified: developed economies, particularly the European Union, have introduced increasingly stringent environmental regulations on imported electronics, such as the Restriction of Hazardous Substances (RoHS) directive and the forthcoming Digital Product Passports under the Ecodesign for Sustainable Products Regulation (ESPR), requiring firms to ensure environmental compliance throughout their supply chains (Guikema, 2022). Consequently, the selection of sustainable suppliers at the very first stage of the supply chain becomes a decisive factor for electronics manufacturers. Sustainable supplier selection not only mitigates environmental impacts through green production practices, pollution control, and efficient resource consumption, but also ensures compliance with tightening regulatory frameworks and growing societal expectations (Liu, 2019; Thomy Eko Saputro, 2024). Moreover, it enhances corporate competitiveness and reputation, while fostering long-term supply chain stability and resilience. In this sense, sustainable supplier management is not merely a matter of corporate responsibility but a strategic imperative for firms in high-tech sectors like electronics to secure enduring advantages in both domestic and global markets (Gomes, 2019)

While sustainable supplier management has attracted considerable attention, there are still limited studies that compare decision-making methods for selecting suppliers. Most existing research applies a single Multi-Criteria Decision Making (MCDM) method or proposes hybrid approaches, but few examine how different ranking methods perform in balancing sustainability and cost. Therefore, this study focuses on two main aspects. First, it identifies evaluation criteria that align with the Triple Bottom Line (TBL) framework, ensuring that economic, environmental, and social dimensions are included. Second, it compares several widely used MCDM ranking methods to evaluate their suitability for sustainable supplier selection. Based on these aims, two research questions are raised:

(1) What criteria should be considered in supplier evaluation under the need to balance sustainability and cost?

(2) Which MCDM ranking method is most suitable for ranking sustainable suppliers?

To answer these questions, the study follows a clear sequence. The first step is a literature review to identify relevant criteria. Next, the study reviews common MCDM approaches and selects three representative ranking methods for comparison. Finally, the methods are tested using a hypothetical dataset from Kaggle to validate the results. The contributions of this paper are twofold: it provides a structured set of criteria for sustainable supplier selection in the electronics industry, and it offers comparative insights into the effectiveness of different ranking-based MCDM methods.

The rest of the paper is organized as follows: **Section 2** reviews the literature and identifies research gaps; **Section 3** develops the methodology and applies a case study to compare the MCDM methods; **Section 4** discusses the results and implications; and **Section 5** concludes with contributions, limitations, and future research directions.

## 2. LITERATURE REVIEW

### 2.1 Sustainable supplier selection evaluation criteria

Supplier selection is one of the most critical decisions for any organization, as it directly affects profitability and the ability to maintain a competitive position. Traditionally, purchasing decisions were primarily based on economic factors. However, the increasing trend of outsourcing, stricter environmental policies, and growing social concerns are forcing firms to integrate the three pillars of sustainability—economic, environmental, and social—into their supply chain activities (Ghayebloo, 2015). As a first step in this direction, sustainable supplier selection (SSS) has become a complex decision-making process. Legal requirements for sustainability may sometimes conflict with organizational objectives, thereby increasing the complexity of SSS decisions. Most studies on sustainable supplier selection (SSS) adopt the Triple Bottom Line (TBL) framework, which integrates economic, environmental, and social dimensions. Within this framework, economic criteria typically include cost, quality, delivery reliability, and operational efficiency; environmental criteria focus on pollution control, $CO_2$ emissions, waste management, and green certifications; and social criteria cover labor conditions, health and safety, human rights, and community impact ( (Joseph, 2024; Ghosh, 2023; Avanish Singh Chauhan, 2020; Song, 2017). While economic considerations remain fundamental, the literature highlights a growing emphasis on balancing them with environmental and social aspects to ensure long-term sustainability.

Several studies have further explored these criteria in the electronics industry. For instance, (Medina Serrano, 2020) applied the TOPSIS method to the electronics sector in Germany and emphasized compliance with environmental regulations as a key criterion. Similarly, (Rahardjo, 2023) developed a hybrid DANP–VIKOR model for the electronics industry in Taiwan, showing that criteria are interdependent and highlighting the need to model the linkages among economic performance, environmental impact, and social responsibility. In another study, (Menon, 2022) employed AHP–TOPSIS in the electronics sector and extended the traditional TBL framework by including additional criteria such as human rights, workplace safety, and pollution control. Table 1 shows common criteria for sustainable supplier selection.

**Table 1**. Sustainable supplier selection criteria

| **TBL** | **Sub-criteria** | **Description** | **Author** |
|---|---|---|---|
| Economics | Cost per unit ($EC_1$) | The price paid to the supplier for each unit of product or material | (Memari, 2019; Erkan Celik, 2021; Joseph, 2024) |
| | Logistics cost ($EC_2$) | Contain custom and handling cost and transportation cost | (Joseph, 2024; Baki, 2021; Tong, 2022) |
| | Quality rating ($EC_3$) | Supplier's ability to provide products that meet technical specifications and quality standards | (Parkouhi, 2017) |
| | Historical performance ($EC_4$) | A composite, data-driven evaluation of a supplier's past record across key metrics such as quality, delivery, and cost, used to forecast future reliability and manage risk | (Baki, 2021; Cetinkaya, 2011) |
| | Return rate ($EC_5$) | The percentage of goods returned to the supplier due to defects, damages, or fulfillment errors, serving as a direct indicator of product quality and operational accuracy. | (Ghosh, 2023; Baki, 2021) |
| | Delivery time ($EC_6$) | The total elapsed time from the placement of an order to its final delivery, encompassing order processing, manufacturing lead time, and transit. | (Ghosh, 2023; Baki, 2021; Cetinkaya, 2011) |
| | On-time delivery ($EC_7$) | The ability to deliver products on time | (Ecer, 2025) |
| | Order fullfilment ($EC_8$) | The percentage of customer orders a supplier can ship completely and accurately from available stock, without backorders or substitutions. | (Wang, 2025; Kannan D, 2014) |
| | Contract duration ($EC_9$) | The specified, legally binding period of a supplier agreement, which strategically influences relationship stability, pricing structures, and operational flexibility. | (Baki, 2021; Chang, 2021; Erkan Celik, 2021) |
| | Compliance to contract ($EC_{10}$) | The supplier's measured adherence to all stipulated terms, conditions, performance metrics, and ethical standards outlined in | (Liu H. C., 2019; Kannan D, 2014) |

| | | | |
|---|---|---|---|
| | | the contractual agreement. | |
| | Risk level ($EC_{11}$) | The supplier's capacity to cope with risks in the supply chain | (Kannan D, 2014; Lo H. W., 2025) |
| | Total cost of ownership ($EC_{12}$) | The financial health and stability of the supplier to ensure their long-term business viability | (Ecer, 2025; Tong, 2022) |
| Environment | Carbon footprint ($EV_1$) | The total carbon emissions throughout the supplier's processes | (Wang, 2025) |
| | Water usage ($EV_2$) | The total amount of water consumed within a supplier's operations | (Lo H. W., 2023; Shen L, 2013) |
| | Sustainability certifications ($EV_3$) | Formal verification from an accredited third-party organization that a supplier's products, processes, or management systems comply with specific environmental and social standards. | (Thomy Eko Saputro, 2024) |
| Social | Labor right complince ($SO_1$) | The supplier's adherence to international and national laws and standards concerning human rights, working conditions, fair wages, and the prohibition of forced and child labor | (Yu C, 2019a; dos Santos B, 2019) |
| | Governance pratice ($SO_2$) | The formal framework of policies, processes, and ethical standards that guides a supplier's operations and stakeholder relationships, ensuring accountability, transparency, and risk management. | (Tong, 2022; Baki, 2021) |

**2.2 Sustainable suppliers weighting and ranking methods**

The weights of the criteria are the key factor that directly influences supplier rankings (Chang, 2021). Several studies emphasize that even small changes in the weights can lead to significant variations in the final outcomes (Wang, 2025). Weighting techniques are typically classified into three groups: subjective, objective, and integrated approaches (Yin, 2025). Subjective methods, determine weights by employing soft computing analysis through expert, common approaches include the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), the Decision-Making Trial and Evaluation Laboratory (DEMATEL), and the Best–Worst Method (BWM) (Chang, 2021). Experts provide qualitative judgments or pairwise comparisons to establish the relative importance of the criteria (Ramanathan, 2010). The main advantages of these methods lie in their ability to combine expert knowledge and experience. They enable the integration of professional expertise, practical insights, and subjective judgments of decision-makers into the model, which is particularly valuable when addressing complex qualitative criteria (Chang, 2021; El Fadli, 2025). Moreover, these methods are well aligned with the objectives of decision-makers, serving as effective tools to establish priorities and achieve desired outcomes by incorporating perspectives from multiple decision-makers or across diverse criteria (Lo, 2025). Nevertheless, despite their ability to incorporate expert knowledge and align with decision-makers’ objectives, these methods are not without limitations. Their reliance on human judgment makes them vulnerable to subjective bias and inconsistency, particularly when the number of criteria increases and pairwise comparisons become overly complex (El Fadli, 2025; Ramanathan, 2010; Lo H. W., 2023). Moreover, the transformation of qualitative assessments into quantitative values may distort decision-makers’ intentions, while small variations in assigned weights can lead to substantial differences in outcomes (El Fadli, 2025). Finally, the dependence on expert involvement often demands considerable time and resources, making these approaches less practical in certain contexts (Wang, 2025). Objective methods, such as the Entropy Weight Method (EWM), Principal Component Analysis, random forest-based suitability assessment (Yifan Gao, 2025; Lv, 2025) and the CRITIC method, derive weights directly from the statistical properties of data, thereby reducing human influence and strengthening objectivity (Diakoulaki, 1995). In particular, the weights are calculated directly from performance data, reflecting the intrinsic characteristics of the dataset (Chang, 2021). For instance, the Entropy method determines weights by measuring the degree of variation within the data of each criterion (Xu, 2023). Furthermore, as data-driven decision-making models, these methods do not require expert involvement, which makes them more efficient and less resource-intensive compared to subjective approaches (Lo H. W., 2025; Chang, 2021). In this context, objective weighting methods provide more reproducible results.

In addition to weighting techniques, the ranking phase is a decisive step in multi-criteria decision-making (MCDM), as it transforms weighted performance scores into a prioritized order of alternatives. The literature highlights a wide range of ranking methods, which can be broadly grouped into distance-based, value/utility-based, compromise, and outranking approaches (Liu H. C., 2021). The most prominent method in this group is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Hwang, 1981).TOPSIS measures the relative closeness of each alternative to the ideal and anti-ideal solutions. (Abdel-Basset M, 2018) developed an integrated framework that combines interval-valued neutrosophic ANP and TOPSIS to address sustainable supplier selection challenges. Other studies have applied different fuzzy extensions of TOPSIS to capture environmental competencies in supplier evaluation, including fuzzy TOPSIS (Shen L, 2013; Kannan D, 2014),intuitionistic fuzzy TOPSIS (Memari A, 2019; Rouyendegh B, 2020),and interval type-2 fuzzy TOPSIS (Mousakhani S, 2017).Furthermore, (dos Santos B, 2019) proposed a hybrid approach integrating fuzzy TOPSIS with the entropy method for green supplier evaluation, while (Yu C, 2019a) applied an entropy-based TOPSIS in an interval-valued Pythagorean fuzzy environment. Compromise methods, such as the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), emphasize achieving a solution that represents a compromise between conflicting criteria (Opricovic & Tzeng, 2004). This approach is particularly suitable for decision contexts where stakeholders aim to reach consensus and where the aspiration level plays an essential role. Nevertheless, the choice of parameters in VIKOR, such as the weight of the majority and individual regret measures, may substantially affect the ranking, raising concerns about stability and interpretability (Mardani et al., 2016). Outranking methods, exemplified by the ELimination Et Choix Traduisant la REalité (ELECTRE), adopt a fundamentally different perspective by constructing pairwise dominance relations among alternatives (Roy, 1991). ELECTRE is advantageous in addressing problems with qualitative criteria, imprecise data, or non-compensatory decision rules, making it flexible in practical contexts. Yet, its complexity, dependence on threshold parameters, and potential for incomparability between alternatives limit its usability for broader applications (Govindan & Jepsen, 2016). Despite the growing use of these methods, the literature reveals a clear research gap: comparative analyses across ranking categories remain limited. Existing studies often apply one ranking method in isolation, leading to context-dependent outcomes and making it difficult to generalize findings (Behzadian et al., 2012; Mardani et al., 2016). Few works have systematically contrasted distance-based, compromise, and outranking approaches under similar decision contexts, leaving uncertainty regarding their relative strengths, weaknesses, and suitability across different industries or decision environments.

## 3. METHODOLOGY

The proposed methodology of the study is outlined as follows. Building upon the literature review, which identified the relevant criteria for sustainable supplier evaluation, the subsequent step involves determining the weights of these criteria. Specifically, the Entropy method is applied to quantitative data, while Interval Entropy is employed for qualitative data. The derived weights are then incorporated into three ranking techniques—TOPSIS, VIKOR, and ELECTRE—to assess and prioritize suppliers. Finally, the outcomes obtained from these alternative approaches are compared, and conclusions are drawn accordingly. **Figure 1** summarizes the overall research methodology of the paper.

### 3.1 Weighting criteria using Entropy and Interval Value Entropy

For the quantitative criteria (cost, delivery time, …), we applied the Entropy Weight Method (EWM) to determine their objective importance. Suppose that the decision matrix is given as $X = [x_{ij}]_{m\times n}$, where $x_{ij}$ denotes the performance value of alternative i $(i = 1,2, \dots, m)$ under criterion j $(j = 1,2, \dots, n)$.

**Step 1:** The normalization step is conducted as:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \quad \forall i, j$$

where $P_{ij}$ is the normalized projection of alternative $i$ under criterion $j$.

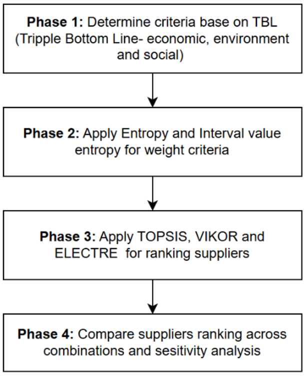


**Fig 1**. Research methodology

**Step 2:** The entropy value of criterion $j$ is then calculated by:

$$E_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij}, \quad k = \frac{1}{\ln m}$$

with the convention $P_{ij} \ln P_{ij} = 0$ when $P_{ij} = 0$. The degree of divergence is defined as:

$$d_j = 1 - E_j$$

**Step 3:** The objective weight of criterion $j$ is obtained by normalizing:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

Thus, the higher the dispersion of data across alternatives, the larger the divergence $d_j$, and consequently the greater the assigned weight $w_j$.

For qualitative criteria assessed by linguistic terms, we employed the **Interval-Valued Entropy (IVE)** framework to capture fuzziness in expert judgments. Let the qualitative assessment of criterion $j$ for alternative $i$ be expressed as an interval-valued fuzzy set:

$$A_{ij} = [\mu_{ij}^{-}, \mu_{ij}^{+}] \subseteq [0,1]$$

where $\mu_{ij}^{-}$ and $\mu_{ij}^{+}$ denote the lower and upper bounds of membership degrees, respectively.

Following Zeng and Li (2006), the entropy of an interval-valued fuzzy set $A$ is defined as:

$$E(A) = 1 - \frac{1}{m} \sum_{i=1}^{m} \left| \mu_{ij}^{-} + \mu_{ij}^{+} - 1 \right|$$

or equivalently using quadratic form:

$$E(A) = 1 - \sqrt{\frac{1}{m} \sum_{i=1}^{m} \left( \mu_{ij}^{-} + \mu_{ij}^{+} - 1 \right)^2}$$

The entropy value reflects the degree of fuzziness: higher entropy indicates greater uncertainty and lower discriminative power of the criterion.

To obtain the final weight, the divergence of criterion $j$ is computed as:

$$d_j = 1 - E_j$$

and the normalized weight is:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

### 3.2 Ranking suppliers using TOPSIS, VIKOR and ELECTRE

3.2.1 TOPSIS

TOPSIS (for the Technique for Order Preference by Similarity to Ideal Solution) was developed by (Hwang, 1981). The basic concept of this method is that the selected alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution in some geometrical sense.

**Step 1:** Construct the normalized decision matrix. Given the original decision matrix $X = [x_{ij}]$ with $m$ alternatives (suppliers) and $n$ criteria, the normalized value is obtained as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad \forall i, j$$

Using the weights of criteria $w_j$, the weighted normalized matrix is defined as:

$$v_{ij} = w_j \cdot r_{ij}, \quad \forall i, j$$

**Step 2:** Determine the positive ideal solution, denoted as $A^+$ and negative ideal solution, denoted as $A^-$

$$A^+ = \{v_1^+, v_2^+, \dots, v_n^+\}, \quad A^- = \{v_1^-, v_2^-, \dots, v_n^-\}$$

where:

- For benefit criteria: $v_j^+ = \max_i v_{ij},\ v_j^- = \min_i v_{ij}$.
- For cost criteria: $v_j^+ = \min_i v_{ij},\ v_j^- = \max_i v_{ij}$.

**Step 3:** Calculate the separation measures**.**

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}$$

Where $S_i^+$ is the distance (in the Euclidean sense) of each alternative from the positive ideal solution,

$S_i^-$ is the distance of each alternative from the negative ideal solution

**Step 4:** Calculate the Relative closeness to the Ideal Solution:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, \quad 0 \le C_i \le 1$$

Suppliers are ranked in descending order of $C_i$. The larger the $C_i$, the closer the supplier is to the ideal solution, and hence the better its ranking.

3.2.2 VIKOR

Vlsekriterijumska Optimizacija I Kompromisno Resenje (i.e. VIKOR) method was developed by (Opricovic, 1998) for multi-criteria optimization of complex systems. VIKOR focuses on ranking and sorting a set of alternatives against various, or possibly conflicting and non-commensurable, decision criteria assuming that compromising is acceptable to resolve conflicts. The VIKOR method was developed with the form of $L_p$ metric, shown as follows:

$$L_{p,j} = \left\{ \sum_{i=1}^{n} \left[ w_i \cdot \frac{f_i^* - x_{ij}}{f_i^* - f_i^-} \right]^p \right\}^{1/p}, \quad 1 \le p \le \infty$$

The VIKOR method deploys $L_{1,j}$ (as $S_j$) and $L_{\infty,j}$ (as $R_j$) to formulate the ranking measure. The solution obtained by $min_j S_j$is with a maximum group utility (''majority'' rule), and the solution obtained by $min_j R_j$ is with a minimum individual regret of the ''opponent''. The compromise solution F c is a feasible solu on that is the ''closest'' to the ideal F , and compromise means an agreement established by mutual concessions, as is illustrated in Fig. 1 by $\Delta f_1 = f_1^* - f_1^c$

and $\Delta f_2 = f_2^* - f_2^c$

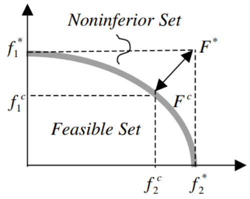


**Fig 2**. Ideal and copromise solutions

3.2.3 ELECTRE I

The ELECTRE method (short for *Elimination and Choice Expressing Reality*, translated from French) was originally proposed by (Benayoun, 1966). At its core, ELECTRE addresses the concept of "outranking relations," where alternatives are evaluated through pairwise comparisons based on each criterion independently. Over time, multiple versions of the ELECTRE method have been developed. There are many variants of the ELECTRE method. The organization of the origanal version of the ELECTRE is illustrated in the following steps (Benayoun, 1966):

**Step 1:** Given the decision matrix $X = [x_{ij}]$, each entry $x_{ij}$ denotes the performance of supplier $A_i$ on criterion $f_j$. To remove dimensionality effects, the data are first normalized using vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

For cost criteria, transformation is applied such that all criteria are oriented in the same "larger is better" direction. The weighted normalized matrix is then obtained as:

$$y_{ij} = w_j \cdot r_{ij}, \quad \forall i = 1, \dots, m;\ j = 1, \dots, n$$

**Step 2**: Determine the Concordance and Discordance Sets:

- Concordance set: $C_{k\ell} = \{j \mid y_{kj} \geq y_{\ell j}\}$ representing criteria on which $A_k$ is at least as good as $A_\ell$.
- Discordance set: $D_{k\ell} = \{j \mid y_{kj} < y_{\ell j}\}$ representing criteria on which $A_k$ performs worse than $A_\ell$.

**Step 3:** Construct the Concordance and Discordance Matrices:

The *concordance index* quantifies the overall weight of evidence supporting the assertion that $A_k$ outranks $A_\ell$:

$$c_{k\ell} = \sum_{j \in C_{k\ell}} w_j$$

The *discordance index* measures the strongest opposition against the assertion:

$$d_{k\ell} = \frac{\max_{j \in D_{k\ell}} |y_{kj} - y_{\ell j}|}{\max_{j} |y_{kj} - y_{\ell j}|}$$

Thus, $c_{k\ell}$ reflects "how much" supports outranking, while $d_{k\ell}$ reflects "how strongly" any criterion contradicts it.

**Step 4:** Thresholds and dominance matrices

Thresholds are defined to separate significant from insignificant concordance and discordance values. Following the original ELECTRE I procedure, *the concordance threshold* $c_0$ is typically set to the mean of all $c_{k\ell}$, while the *discordance threshold* $d_0$ is set to the mean of all $d_{k\ell}$.

Binary dominance matrices are then constructed as:

$$f_{k\ell} = \begin{cases} 1, & c_{k\ell} \geq c_0 \\ 0, & \text{otherwise} \end{cases} \qquad g_{k\ell} = \begin{cases} 1, & d_{k\ell} \leq d_0 \\ 0, & \text{otherwise} \end{cases}$$

**Step 5:** Outranking relation and kernel identification

## 4. RESULT AND DISCUSSION

The dataset was obtained from Kaggle and pertains to an electronics company with six suppliers operating in the same product category. A total of 17 sub-criteria are employed in the data implementation stage, with their descriptions provided in Table 2.

**Table 2.** Data Types, Scales, and Objectives of criteria

| Sub- criteria | Data type | Scale | Objective |
|---|---|---|---|
| Cost per unit ($EC_1$) | Quantitative | Ratio | Minimize |
| Logistics cost ($EC_2$) | Quantitative | Ratio | Minimize |

| | | | |
|---|---|---|---|
| Quality rating ($EC_3$) | Qualitative | Ordinal (1-5) | Maximize |
| Historical performance ($EC_4$) | Qualitative | Ordinal (Low/Medium/High) | Maximize |
| Return rate ($EC_5$) | Quantitative | Ratio | Minimize |
| Delivery time ($EC_6$) | Quantitative | Ratio | Minimize |
| On-time delivery ($EC_7$) | Quantitative | Ratio | Minimize |
| Order fullfilment ($EC_8$) | Quantitative | Ratio | Maximize |
| Contract duration ($EC_9$) | Quantitative | Ratio | Maximize |
| Compliance to contract ($EC_{10}$) | Qualitative | Ratio | Maximize |
| Risk level ($EC_{11}$) | Qualitative | Ordinal (Low/Medium/High) | Minimize |
| Total cost of ownership ($EC_{12}$) | Quantitative | Ratio | Maximize |
| Carbon footprint ($EV_1$) | Quantitative | Ratio | Minimize |
| Water usage ($EV_2$) | Quantitative | Ratio | Minimize |
| Sustainability certifications ($EV_3$) | Quantitative | Interval (0–5 scale) | Maximize |
| Labor right complince ($SO_1$) | Qualitative | Ordinal (Compliant/ Non compliant) | Maximize |
| Governance pratice ($SO_2$) | Qualitative | Ordinal (Transparent/ Excellent) | Maximize |

**4.1 Results**

The application of the Entropy and Interval-Valued Entropy (IVE) methods provided an objective basis for determining the relative importance of the evaluation criteria. The resulting weights, presented in **Table 3**, highlight a clear differentiation between high- and low-priority factors in supplier assessment. Notably, governance, contractual, and risk-related dimensions emerged as more influential than cost- or sustainability-oriented indicators. This distribution of weights establishes a structured foundation for the subsequent ranking of suppliers using MCDM methods.

**Table 3.** Critera weights

| **No** | **Criteria** | **Weights** | **No** | **Criteria** | **Weights** |
|---|---|---|---|---|---|
| 1 | Delivery Time ($EC_6$) | 0.1875 | 10 | Total Cost of Ownership (TCO) ($EC_{12}$) | 0.0129 |
| 2 | Governance Practices ($SO_2$) | 0.144 | 11 | Logistics cost ($EC_2$) | 0.001639 |
| 3 | Contract Duration ($EC_9$) | 0.127 | 12 | Water Usage ($EV_2$) | 0.001485 |
| 4 | Risk Level ($EC_{11}$) | 0.1257 | 13 | Carbon Footprint ($EV_1$) | 0.000946 |
| 5 | Labor Rights Compliance ($SO_1$) | 0.1257 | 14 | Compliance to Contract ($EC_{10}$) | 0.00041 |
| 6 | Return Rate ($EC_5$) | 0.1152 | 15 | Order Fulfillment Rate ($EC_8$) | 0.000295 |
| 7 | Historical Performance ($EC_4$) | 0.1047 | 16 | On-Time Delivery ($EC_7$) | 0.000175 |
| 8 | Cost per Unit ($EC_1$) | 0.0371 | 17 | Sustainability Certifications ($EV_3$) | 0.000..93 |
| 9 | Quality Rating ($EC_3$) | 0.01516 | | | |

To compare supplier performance, three MCDM techniques—TOPSIS, VIKOR, and ELECTRE—were applied. The results, summarized in Tables Y–Z, reveal that although the methods share some similarities, they also highlight notable differences in supplier prioritization.

TOPSIS produced a clear ranking with S001 emerging as the top alternative, while VIKOR emphasized compromise solutions, assigning the highest position to S017. Meanwhile, the ELECTRE outranking procedure also favored S001, but distributed the subsequent positions more evenly among the remaining suppliers. These variations illustrate the methodological sensitivity of supplier rankings, particularly when dealing with closely performing alternatives.

**Table 4.** Supplier Evaluation Metrics under TOPSIS and VIKOR Methods

| **Supplier code** | **TOPSIS** | | | | **VIKOR** | | | |
|---|---|---|---|---|---|---|---|---|
| | $C_i$ | $S_i^+$ | $S_i^-$ | **Rank** | $S_j$ | $R_j$ | $Q_j$ | **Rank** |
| *S001* | 0.8363 | 0.0195 | 0.0999 | **1** | 0.1738 | 0.1437 | 0.2352 | **3** |
| *S006* | 0.5525 | 0.0576 | 0.0715 | **3** | 0.3055 | 0.1271 | 0.3426 | **4** |
| *S012* | 0.5908 | 0.0434 | 0.0626 | **2** | 0.301 | 0.1047 | 0.2007 | **2** |
| *S017* | 0.4928 | 0.0568 | 0.0552 | **4** | 0.223 | 0.1114 | 0.1179 | **1** |
| *S023* | 0.394 | 0.0726 | 0.0472 | **5** | 0.2444 | 0.1538 | 0.4082 | **5** |
| *S028* | 0.2152 | 0.0981 | 0.0269 | **6** | 0.4906 | 0.1875 | 1 | **6** |

**Table 5.** Concordance and Discordance Matrices in the ELECTRE Method

| **ELECTRE** | | *S001* | *S006* | *S012* | *S017* | *S023* | *S028* |
|---|---|---|---|---|---|---|---|
| $c_{k\ell}$ | *S001* | 0 | 0.827267 | 0.837994 | 0.825782 | 0.827267 | 0.827267 |
| | *S006* | 0.529021 | 0 | 0.702231 | 0.726274 | 0.688856 | 0.985315 |
| | *S012* | 0.427355 | 0.693153 | 0 | 0.748573 | 0.750058 | 0.880653 |
| | *S017* | 0.645757 | 0.774021 | 0.646637 | 0 | 0.947863 | 0.998759 |
| | *S023* | 0.644272 | 0.811144 | 0.682275 | 0.810069 | 0 | 0.999054 |
| | *S028* | 0.529021 | 0.757212 | 0.514731 | 0.501241 | 0.501241 | 0 |
| $d_{k\ell}$ | *S001* | 0 | 0.303576 | 0.380482 | 0.259694 | 0.188054 | 0.154346 |
| | *S006* | 1 | 0 | 1 | 1 | 0.792548 | 0.002253 |
| | *S012* | 1 | 0.89065 | 0 | 1 | 0.612423 | 0.249715 |
| | *S017* | 1 | 0.816429 | 0.742208 | 0 | 0.348878 | 0.001939 |
| | *S023* | 1 | 1 | 1 | 1 | 0 | 0.006787 |
| | *S028* | 1 | 1 | 1 | 1 | 1 | 0 |

**Table 6**. Binary Outranking Matrices and Final Supplier Ranking in ELECTRE

| **ELECTRE** | | *S001* | *S006* | *S012* | *S017* | *S023* | *S028* |
|---|---|---|---|---|---|---|---|
| $f_{k\ell}$ | *S001* | 0 | 1 | 1 | 1 | 1 | 1 |
| | *S006* | 0 | 0 | 0 | 0 | 0 | 1 |
| | *S012* | 0 | 0 | 0 | 1 | 1 | 1 |
| | *S017* | 0 | 1 | 0 | 0 | 1 | 1 |
| | *S023* | 0 | 1 | 0 | 1 | 0 | 1 |
| | *S028* | 0 | 1 | 0 | 0 | 0 | 0 |
| $g_{k\ell}$ | *S001* | 0 | 1 | 1 | 1 | 1 | 1 |
| | *S006* | 0 | 0 | 0 | 0 | 0 | 1 |
| | *S012* | 0 | 0 | 0 | 0 | 1 | 1 |
| | *S017* | 0 | 0 | 0 | 0 | 1 | 1 |
| | *S023* | 0 | 0 | 0 | 0 | 0 | 1 |
| | *S028* | 0 | 0 | 0 | 0 | 0 | 0 |
| $f_{k\ell} \times g_{k\ell}$ | *S001* | 0 | 1 | 1 | 1 | 1 | 1 |
| | *S006* | 0 | 0 | 0 | 0 | 0 | 1 |
| | *S012* | 0 | 0 | 0 | 0 | 1 | 1 |
| | *S017* | 0 | 0 | 0 | 0 | 1 | 1 |
| | *S023* | 0 | 0 | 0 | 0 | 0 | 1 |
| | *S028* | 0 | 0 | 0 | 0 | 0 | 0 |
| **Outdegree** | | 5 | 1 | 2 | 2 | 1 | 0 |
| **Rank** | | **1** | **3** | **2** | **2** | **3** | **4** |

### 4.2 Sensitivity analysis

To examine the robustness of the supplier rankings obtained from the three MCDM methods, a sensitivity analysis was conducted using Spearman's rank correlation coefficient. This non-parametric measure evaluates the degree of agreement between two rankings by assessing the monotonic relationship between their orderings. The coefficient is defined as:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

Where $d_i$ is the difference in rank position for each supplier between two methods, and $n$ is the number of alternatives. The resulting correlation coefficients were then visualized through a heatmap (Figure 1) to provide an intuitive comparison of consistency across the methods.

The heatmap reveals that TOPSIS and ELECTRE exhibit the highest correlation (ρ=0.85), indicating strong alignment in their supplier rankings. The correlation between VIKOR and ELECTRE is moderate (ρ=0.79), while TOPSIS and VIKOR demonstrate the lowest level of agreement (ρ=0.60). These findings suggest that although all three methods share a degree of consistency, the divergence between TOPSIS and VIKOR highlights their differing prioritization logic—TOPSIS focusing on distance to ideal solutions, while VIKOR balances collective utility and individual regret. Overall, the sensitivity analysis confirms that ELECTRE provides the most stable and balanced outcomes, as it shows relatively strong agreement with both TOPSIS and VIKOR. This implies that ELECTRE may serve as a reliable compromise approach when methodological robustness is a priority in supplier selection.

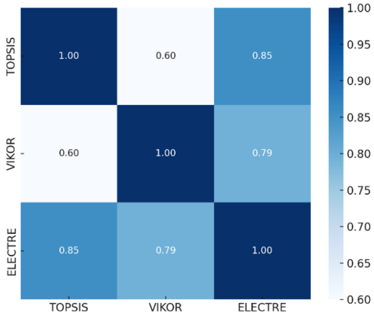


**Fig 3.** Spearman Rank Correlation among MCDM Methods (TOPSIS, VIKOR, ELECTRE)

### 4.3 Discussion

a) Weighting method: Entropy and Interval value Entropy

The criteria weights, as determined through the Entropy and Interval Entropy methods, are presented in Table 3. A key finding of this analysis is the high importance assigned to 'Delivery Time'. This outcome contrasts notably with studies that utilize subjective weighting techniques, such as the AHP or BWM, where cost-related criteria are frequently prioritized (Erkan Celik, 2021; Ghosh, 2023). This divergence is attributable to the fundamental principle of the entropy method, which determines weights based on the degree of variability within the dataset for each criterion. Specifically, criteria exhibiting significant dispersion across the evaluated suppliers (a high divergence value, $d_j$) are considered more informative for differentiation and are consequently assigned a greater weight $(w_j)$. Conversely, criteria with near-uniform values contribute little to the decision-making process and receive lower weights. In the context of the present study, 'Delivery Time' received the highest weighting because the performance data for this criterion showed considerable variation among suppliers. In contrast, cost-related indicators and 'Sustainability Certifications' were assigned lower weights. This was not due to a lack of strategic importance, but rather because the data collected showed minimal variance among the suppliers for these criteria. The core distinction lies in the nature of the weighting approach: subjective methods reflect managerial priorities and strategic emphasis, whereas the entropy method provides a purely data-driven assessment of a criterion's informational content. While entropy's objectivity is a significant advantage, its limitation is the inability to reflect strategic priorities if the corresponding data lacks sufficient variation.

b) Ranking method: TOPSIS, VIKOR and ELECTRE

The comparative analysis of supplier rankings generated by TOPSIS, VIKOR, and ELECTRE highlights both methodological convergence and divergence. TOPSIS identified supplier S001 as the top-performing alternative, emphasizing its relative closeness to the ideal solution. In contrast, VIKOR ranked S017 first, as the method prioritizes compromise between maximizing group utility and minimizing individual regret. Meanwhile, ELECTRE also favored S001, but distributed the remaining suppliers more evenly, reflecting its outranking-based logic rather than absolute distance or compromise measures.

The observed differences can be attributed to the intrinsic characteristics of each method. TOPSIS is geometrically oriented, relying on the Euclidean distance from the positive and negative ideal solutions. As a result, suppliers with balanced performance across many criteria (e.g., S001) are favored. VIKOR, however, incorporates a dual perspective: the utility measure (S) evaluates the overall group benefit, while the regret measure (R) captures the worst-case criterion performance. This explains why S017, which may not dominate across all dimensions but avoids extreme underperformance, emerges as the compromise solution. ELECTRE, in contrast, adopts a pairwise outranking framework, where concordance reflects the proportion of criteria supporting one alternative over another, and discordance highlights significant opposition. In ELECTRE's results, some suppliers share the same outdegree value—such as S012 and S017 both ranked 2$^{nd}$, or S006 and S023 both ranked 3$^{rd}$—because the method relies on binary "outrank/not outrank" relations rather than a continuous scoring scale. The ranking procedure is essentially eliminative, which can leave a subset of alternatives that are not eliminated yet cannot be distinguished from one another, thereby receiving the same rank. The philosophy of ELECTRE thus accepts a partial ordering instead of a complete ranking, reflecting the complexity and uncertainty inherent in real-world decision-making (Triantaphyllou, 2000). By emphasizing dominance relations rather than absolute distances, ELECTRE produces a ranking that, while consistent with TOPSIS in prioritizing S001, remains more conservative in differentiating among middle-ranked suppliers.

Despite these methodological contrasts, the correlation analysis confirms partial consistency. The strongest alignment is found between TOPSIS and ELECTRE (ρ = 0.85), as both methods emphasize performance relative to an "ideal" reference, albeit through different mathematical structures. VIKOR and ELECTRE also show moderate agreement (ρ = 0.79), indicating that both account for trade-offs in criteria performance, though through distinct compromise and outranking mechanisms. The lowest correlation appears between TOPSIS and VIKOR (ρ = 0.60), underscoring their divergent prioritization logic—TOPSIS rewards suppliers closest to ideal averages, while VIKOR is more sensitive to outliers and compromise solutions.

Taken together, these findings suggest that supplier rankings are not solely data-dependent but also method-dependent. The overlap between TOPSIS and ELECTRE implies robustness in identifying clear leaders such as S001, whereas VIKOR provides valuable insights into compromise candidates like S017. Therefore, applying multiple MCDM methods in parallel enhances the reliability of decision-making, as it reveals both consensus and divergence in prioritization, allowing managers to align final decisions with strategic preferences such as minimizing risks, ensuring compromise, or emphasizing best-in-class performance.

## 5. CONCLUSION

This study developed a comprehensive framework for sustainable supplier selection in the electronics industry by combining entropy and interval entropy weighting with three prominent MCDM methods—TOPSIS, VIKOR, and ELECTRE. The use of entropy-based weighting enabled an objective assessment of criteria importance based on data variability, revealing that "Delivery Time" emerged as the most influential factor, whereas cost-related indicators and sustainability certifications received relatively lower weights due to limited variance across suppliers.

The comparative application of TOPSIS, VIKOR, and ELECTRE produced both convergent and divergent results. While TOPSIS and ELECTRE consistently prioritized Supplier S001 as the leading candidate, VIKOR identified Supplier S017 as the compromise solution, highlighting its methodological focus on balancing group utility and individual regret. The Spearman correlation analysis confirmed partial alignment across methods, with the strongest agreement between TOPSIS and ELECTRE (ρ = 0.85) and the weakest between TOPSIS and VIKOR (ρ = 0.60). These findings underscore the methodological sensitivity of MCDM approaches: distance-based methods (TOPSIS), compromise-based solutions (VIKOR), and outranking procedures (ELECTRE) each capture different dimensions of decision-making.

From a managerial perspective, this suggests that relying on a single method may risk overlooking valuable insights. Instead, employing multiple complementary MCDM techniques provides a richer understanding of supplier performance and helps decision-makers align choices with strategic priorities—whether that is selecting best-in-class suppliers, identifying compromise candidates, or emphasizing robustness and balance.

Overall, the research confirms the utility of combining objective weighting with multiple ranking methods to enhance transparency and robustness in supplier selection. Future work may extend this approach by incorporating expert-driven weighting schemes, hybridizing MCDM with machine learning, and testing the framework in other industries facing sustainability-driven procurement challenges.

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