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Multi-Year Performance Evaluation and Trend Tracking of Sustainable Suppliers: An Application of a Hybrid Decision Analysis Model

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ABSTRACT

Amid growing global emphasis on sustainability and supply chain transparency, enterprises—particularly in the resource-intensive electronics manufacturing sector—face increasing pressure to integrate sustainable criteria into supplier performance evaluations. This study develops a multi-year supplier assessment framework that enhances conventional evaluation practices by incorporating sustainability-oriented indicators. Building on a real-world case from a publicly listed Taiwanese electronics manufacturer, the proposed model systematically analyzes the annual performance trends of key suppliers. To address expert judgment uncertainty and confidence, this study employs a Z-numbers-based Decision Trial and Evaluation Laboratory (Z-DEMATEL) technique, which integrates Z fuzzy theory to model the interdependencies among evaluation criteria while capturing the inherent ambiguity and subjectivity of expert assessments. The resulting influence weights inform the subsequent application of PROMETHEE-AL (Preference Ranking Organization Method for Enrichment Evaluation based on Aspiration Level), a preference ranking method incorporating aspiration levels, to aggregate supplier performance scores. This dual-method approach allows for the inclusion of ideal target levels in the ranking process, thereby increasing decision relevance and interpretability. The model is applied to historical data spanning multiple years to identify suppliers with stable or improving performance trajectories, while also flagging declining suppliers for managerial intervention. Empirical findings indicate a continued emphasis on traditional criteria such as cost, quality, and delivery, with sustainability-related indicators receiving limited weight—highlighting an opportunity for strategic improvement in the company's sustainability transition. The proposed integrated Z-DEMATEL and PROMETHEE-AL model not only strengthens the scientific and practical robustness of supplier evaluations but also supports long-term strategic planning and sustainable supplier development. The methodology can be readily adapted for use in other industry settings seeking to balance operational excellence with sustainability goals.

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1. Introduction

The contemporary global business landscape is characterized by intricate supply chains susceptible to a myriad of disruptions, including geopolitical tensions, trade conflicts, and the escalating impacts of climate change [1]. These factors highlight the inherent vulnerabilities within global supply networks, which significantly impact raw material procurement, logistics, and production operations. Compounded by the uncertainties of international trade policies and a growing environmental consciousness, enterprises face mounting pressures related to tariffs, trade barriers, and the imperative to adopt sustainable practices [2]. Consequently, Sustainable Supply Chain Management (SSCM) has emerged as a critical strategic approach, enabling businesses to navigate these challenges by integrating economic, environmental, and social considerations [3].

Within SSCM, the selection and performance evaluation of suppliers is pivotal, as suppliers play a central role in a firm's overall sustainability footprint and operational efficacy [4]. The electronics manufacturing industry faces intense pressure due to rapid product lifecycles, high energy consumption, and the use of potentially hazardous materials [5]. For companies like S Company, a prominent electronic lead frame manufacturer, the performance of its copper material suppliers is crucial not only for traditional metrics such as quality, cost, and delivery but also for its broader sustainability objectives. However, existing supplier evaluation mechanisms in many organizations, including S Company, often prioritize short-term financial indicators and lack a systematic approach to comprehensively incorporate long-term performance trends and sustainability aspects. This deficiency can lead to suboptimal supplier selection, increased supply chain risks, and difficulties in achieving strategic sustainability goals. In particular, the absence of longitudinal analysis impedes firms from identifying consistent top performers, detecting early signs of supplier degradation, or recognizing suppliers with improving capabilities. Therefore, implementing a multi-year performance tracking mechanism is essential for ensuring the reliability and resilience of supply networks, as it enables firms to observe supplier development trajectories and align long-term strategic partnerships with sustainability goals. Traditional supplier evaluation methods often struggle to adequately address the inherent uncertainties and subjectivities in expert judgments, as well as the complex interdependencies among various performance criteria. Multi-Criteria Decision Making (MCDM) techniques provide structured frameworks for tackling complex decision problems. However, there is a need for hybrid models that can more effectively capture the nuances of sustainable supplier evaluation, particularly the vagueness in human assessments and the dynamic nature of supplier performance [6].

SSCM integrates environmental, social, and economic considerations into conventional supply chain management [4]. The selection of sustainable suppliers is a cornerstone of Sustainable Supply Chain Management (SSCM), as suppliers' activities directly influence the environmental and social impact of the entire supply chain [7]. Key criteria in sustainable supplier selection typically span economic factors (e.g., cost, quality, delivery), environmental factors (e.g., pollution control, green design, resource consumption), and social factors (e.g., health and safety, labor rights, community impact) [8, 9].

Numerous MCDM methods have been applied to supplier selection. Standard methods include the Analytic Hierarchy Process (AHP) [9], the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [9, 10], and Decision Trial and Evaluation Laboratory (DEMATEL) [11]. DEMATEL is particularly useful for understanding the causal relationships and influence levels among criteria. However, traditional DEMATEL does not adequately handle the uncertainty and vagueness inherent in expert linguistic assessments.

To address this, fuzzy set theory has been integrated with DEMATEL, resulting in methods such as fuzzy DEMATEL [12]. Z-numbers, introduced by Zadeh, offer a more comprehensive approach to modeling uncertainty by considering not only a fuzzy restriction on a variable but also the reliability or confidence in that assessment [13]. This aligns with the principles of granular computing, which deals with the processing of imprecise, uncertain, or partially accurate information [14]. The Z-DEMATEL method utilizes Z-numbers to capture expert judgments with greater fidelity, rendering it a powerful tool for determining criterion weights in complex decision-making environments [15].

The Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) is another widely used MCDM technique for ranking alternatives. It is known for its simplicity in concept and application, as it requires fewer assumptions compared to other methods. PROMETHEE II provides a complete ranking of alternatives [16]. The integration of aspiration levels into PROMETHEE, known as PROMETHEE-AL (PROMETHEE based on the Aspiration Level concept), allows decision-makers to evaluate alternatives not just relative to each other but also against desired performance targets [5]. This is particularly relevant for supplier performance management, where companies often have specific goals for their suppliers [17].

While Z-DEMATEL and PROMETHEE have been used in various contexts, the integrated application of Z-DEMATEL (leveraging Z-numbers for robust criteria weighting under uncertainty and aligning with granular computing) and PROMETHEE-AL (for ranking suppliers against aspiration levels using multi-year data) for sustainable supplier evaluation in the electronics industry, specifically for a key commodity like copper, represents a significant research gap [18]. Existing studies often focus on single-year assessments or do not fully capture the confidence of expert judgments in criteria weighting [19]. This study aims to fill this gap by developing and applying such a hybrid model.

The primary objective of this research is to develop and validate a comprehensive and intelligent decision-making model for evaluating sustainable supplier performance in the electronics industry. The specific objectives are:

i. To establish a sustainable supplier performance evaluation framework for an electronic lead frame company, incorporating traditional criteria (Quality, Delivery, Cost, Flexibility, Cooperation) and a dedicated Sustainability Performance criterion.
ii. To employ the Z-DEMATEL method to determine the interrelationships among these evaluation criteria and derive their influential weights, explicitly considering the uncertainty and confidence levels of expert judgments through Z-numbers.
iii. To utilize the PROMETHEE-AL method, incorporating the criteria weights from Z-DEMATEL and multi-year historical performance data to rank suppliers and assess their performance against defined aspiration levels.
iv. To provide actionable managerial insights and recommendations for the case company (S Company) based on the evaluation results, thereby enhancing its sustainable supplier management strategies.

The remainder of this paper is organized as follows: Section 2 details the research methodology, explaining the Z-DEMATEL and PROMETHEE-AL techniques and their integration. Section 3 presents the empirical case study, including the problem description, application of the proposed model, and the results obtained. Section 4 discusses the findings, managerial implications, and contributions of the study. Finally, Section 5 concludes the paper with a summary, limitations, and directions for future research.

2. Methodology

This study proposes a hybrid MCDM model that integrates Z-DEMATEL and PROMETHEE-AL to evaluate sustainable supplier performance. The research framework involves several stages: (1) Defining sustainable supplier evaluation criteria based on literature and expert input from the case company [20]. (2) Collecting expert judgments on the interrelationships and importance of these criteria. (3) Applying Z-DEMATEL to analyze these judgments, determine criteria weights, and understand their causal relationships. (4) Collecting historical performance data of suppliers against these criteria. (5) Applying PROMETHEE-AL, using the derived criteria weights, to rank suppliers and measure their performance against aspiration levels. (6) Analyzing the results to provide managerial insights.

2.1. Z-DEMATEL Method

The Z-DEMATEL method constitutes an extension of the traditional DEMATEL approach, distinguished by its incorporation of Z-numbers to more effectively address the uncertainty and reliability inherent in expert linguistic assessments. A Z-number, denoted as Z = (A, B), is an ordered pair of fuzzy numbers, wherein A represents a fuzzy restriction on the potential values a variable may assume, and B signifies a fuzzy restriction on the reliability or certainty attendant upon A [13]. This approach is deemed particularly opposed to decision-making problems wherein expert opinions are characterized by subjectivity and may exhibit variability in confidence [21].

The procedural steps integral to the Z-DEMATEL method are delineated as follows:

Step 1: Establishment of Evaluation Criteria and Expert Group

A set of n evaluation criteria, $C_j = \{C_1, C_2, ..., C_n\}$, is formally defined. For the purposes of this study, the designated criteria are Quality (C1), Delivery (C2), Cost (C3), Flexibility & Cooperation (C4), and Sustainability Performance (C5). A group comprising K experts is constituted to provide pairwise comparisons of these criteria.

Step 2: Collection of Expert Judgments employing Z-numbers

Experts are tasked with evaluating the direct influence exerted by criterion C_i upon criterion C_j, utilizing linguistic terms for both the level of influence (e.g., 'No influence' to 'Very high influence') and their confidence in this assessment (e.g., 'Very low reliability' to 'Very high reliability'). These linguistic terms are subsequently converted into triangular fuzzy numbers.

Step 3: Verification of Expert Consensus

The Average Sample Gap (ASG) is employed as a metric to quantify the degree of consensus among the participating experts. Should the ASG be less than or equal to 5%, the expert opinions are deemed to be consistent. The formula is Equation (1):

$$ASG = \left(n\left(n-1\right)\left(p-1\right)\right)^{-1} \times \sum_{k=2}^{p}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\frac{\left|a_{ij}^{(k)} - a_{ij}^{(k-1)}\right|}{a_{ij}^{(k)}}\right) \times 100\% \tag{1}$$

wherein $a_{ij}^{(k)}$ represents the average fuzzy assessment for the influence of C_i on C_j aggregated across all experts. For fuzzy numbers, this calculation is typically executed on the defuzzified values or on a component-wise basis.

Step 4: Construction of Direct Relation Matrix

The judgments elicited from the K experts are aggregated to formulate an initial direct-relation matrix $\mathbf{A}$, wherein A_{ij} signifies the aggregated fuzzy influence of C_i on C_j. This aggregation is customarily achieved by averaging the corresponding fuzzy numbers Equation (2):

$$\min\ z = \sum_{k=1}^{K}\left(l_{ij} - l_{ij}^{k}\right)^2 + \sum_{k=1}^{K}\left(m_{ij} - m_{ij}^{k}\right)^2 + \sum_{k=1}^{K}\left(u_{ij} - u_{ij}^{k}\right)^2 \tag{2}$$

$$s.\ t.\begin{cases} \min_k\ l_{ij}^{k} \le l_{ij} \le \max_k\ l_{ij}^{k}, \\ \min_k\ m_{ij}^{k} \le m_{ij} \le \max_k\ m_{ij}^{k}, \\ \min_k\ u_{ij}^{k} \le u_{ij} \le \max_k\ u_{ij}^{k}, \\ l_{ij} \le m_{ij} \le u_{ij}. \end{cases}$$

k represents the expert, such as k = 1, 2, ..., K, indicating that a total of K experts contributes to the evaluation. Within the framework of expert-based decision analysis, l_{ij}, m_{ij}, and u_{ij} denote the minimum, median, and maximum values of the aggregated group's judgment, respectively. The derivation of l_{ij} is obtained as shown in Equation (3). Following a similar process, m_{ij} and u_{ij} are derived according to Equations (4) and (5).

$$\frac{\partial z}{\partial l_{ij}} = 2\sum_{k=1}^{K}\left(l_{ij} - l_{ij}^{k}\right)\cdot 1 = 0 \quad \Rightarrow l_{ij} = \frac{\sum_{k=1}^{K} l_{ij}^{k}}{K} \tag{3}$$

$$\frac{\partial z}{\partial m_{ij}} = 2\sum_{k=1}^{K}\left(m_{ij} - m_{ij}^{k}\right)\cdot 1 = 0 \quad \Rightarrow m_{ij} = \frac{\sum_{k=1}^{K} m_{ij}^{k}}{K} \tag{4}$$

$$\frac{\partial z}{\partial u_{ij}} = 2\sum_{k=1}^{K}\left(u_{ij} - u_{ij}^{k}\right)\cdot 1 = 0 \quad \Rightarrow u_{ij} = \frac{\sum_{k=1}^{K} u_{ij}^{k}}{K} \tag{5}$$

Where $l_{ij} = \min_k \ l_{ij}^{k}$ represents the lowest assessed value of the degree of influence among all experts. The term $m_{il}{=}\min_k \ m_{ij}^{k}$ denotes the median value of the expert assessments, while $u_{ij} = \min_k \ u_{ij}^{k}$ represents the highest assessed value.

To ensure the accuracy and representativeness of the findings, this research requires the integration of the expert panel's assessments into a direct-relation matrix, as formulated in Equation (6).

$$\otimes \mathrm{A} = \left[\otimes a_{ij}\right]_{n\times n} = \begin{bmatrix} \otimes a_{11} & \otimes a_{12} & \cdots & \otimes a_{1j} & \cdots & \otimes a_{1n} \\ \otimes a_{21} & \otimes a_{22} & \cdots & \otimes a_{2j} & \cdots & \otimes a_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes a_{i1} & \otimes a_{i2} & \cdots & \otimes a_{ij} & \cdots & \otimes a_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes a_{n1} & \otimes a_{n2} & \cdots & \otimes a_{nj} & \cdots & \otimes a_{nn} \end{bmatrix}_{n\times n} ,i = j = 1,\ 2,\ldots,\ n \tag{6}$$

In the direct influence relation matrix, the diagonal elements are set to zero ($\otimes a_{ij} = 0 \ \ (when i = j)$), signifying that a criterion does not influence itself. Each element $\otimes a_{ij} = \left(a_{ij}^{L},\ a_{ij}^{M},\ a_{ij}^{U}\right)$ is a fuzzy number representing the influence degree.

Step 5: Normalization of the Direct-Relation Matrix

To eliminate the influence of data scales and ensure data stability, the expert assessment values for $\otimes a_{ij}$, originally on a scale from 0 to 4, are transformed. This is achieved through min-max normalization, which converts the assessment values to a 0–1 scale, as detailed in Equations (7) and (8).

$$\otimes \mathrm{X} = \left[\otimes x_{ij}\right]_{n\times n} = \begin{bmatrix} \varepsilon\cdot\otimes a_{11} & \varepsilon\cdot\otimes a_{12} & \cdots & \varepsilon\cdot\otimes a_{1j} & \cdots & \varepsilon\cdot\otimes a_{1n} \\ \varepsilon\cdot\otimes a_{21} & \varepsilon\cdot\otimes a_{22} & \cdots & \varepsilon\cdot\otimes a_{2j} & \cdots & \varepsilon\cdot\otimes a_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon\cdot\otimes a_{i1} & \varepsilon\cdot\otimes a_{i2} & \cdots & \varepsilon\cdot\otimes a_{ij} & \cdots & \varepsilon\cdot\otimes a_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon\cdot\otimes a_{n1} & \varepsilon\cdot\otimes a_{n2} & \cdots & \varepsilon\cdot\otimes a_{nj} & \cdots & \varepsilon\cdot\otimes a_{nn} \end{bmatrix}_{n\times n} ,i = j$$

$$= 1,\ 2,\ldots,\ n$$

$$\otimes x_{ij} = \left(x_{ij}^{L},\ x_{ij}^{M},\ x_{ij}^{U} \right) \tag{7}$$

$$\varepsilon = \min\left\{ \frac{1}{\max_i \sum_{j=1}^{n} a_{ij}^{U}}, \frac{1}{\max_j \sum_{i=1}^{n} a_{ij}^{U}} \right\} \tag{8}$$

Step 6: Calculation of the Total Influence Matrix $\otimes\mathrm{T}$

The total influence matrix $\otimes\mathrm{T}$ is calculated according to the formula:

$$\otimes\mathrm{T} = \left[\otimes t_{ij} \right]_{n\times n} = \begin{bmatrix} \otimes t_{11} & \otimes t_{12} & \cdots & \otimes t_{1j} & \cdots & \otimes t_{1n} \\ \otimes t_{21} & \otimes t_{22} & \cdots & \otimes t_{2j} & \cdots & \otimes t_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes t_{i1} & \otimes t_{i2} & \cdots & \otimes t_{ij} & \cdots & \otimes t_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes t_{n1} & \otimes t_{n2} & \cdots & \otimes t_{nj} & \cdots & \otimes t_{nn} \end{bmatrix}_{n\times n} ,i = j = 1,\ 2,\ldots,\ n \tag{9}$$

each element $\otimes t_{ij}$ is represented as a triangular fuzzy number ($\otimes t_{ij} = \left(t_{ij}^{L},\ t_{ij}^{M},\ t_{ij}^{U} \right)$) to denote the degree of influence. The components t_{ij}^{L}, t_{ij}^{M}, and t_{ij}^{U} signify the lower bound, median, and upper bound of the influence value, respectively.

The total influence matrix T, which includes all direct and indirect influence relationships, can be represented by the infinite series $\otimes\boldsymbol{T} = \otimes\boldsymbol{X} + \otimes\boldsymbol{X}^{2} + \cdots + \otimes\boldsymbol{X}^{\infty}$. Since the calculation of this infinite series (Equation (10)) is computationally cumbersome, a more efficient, closed-form solution can be derived, as shown in Equation (11):

$$\otimes\boldsymbol{T} = \otimes\boldsymbol{X} + \otimes\boldsymbol{X}^{2} + \cdots + \otimes\boldsymbol{X}^{\infty} \tag{10}$$

$$\begin{aligned} \otimes\boldsymbol{T} &= \otimes\boldsymbol{X} + \otimes\boldsymbol{X}^{2} + \cdots + \otimes\boldsymbol{X}^{\infty} = \otimes\boldsymbol{X}\left(\boldsymbol{I} + \otimes\boldsymbol{X} + \otimes\boldsymbol{X}^{2} + \cdots + \otimes\boldsymbol{X}^{\infty-1} \right) \\ &= \otimes\boldsymbol{X}\left(\boldsymbol{I} - \otimes\boldsymbol{X}^{\infty} \right)\left(\boldsymbol{I} - \otimes\boldsymbol{X} \right)^{-1} = \otimes\boldsymbol{X}\left(\boldsymbol{I} - \otimes\boldsymbol{X} \right)^{-1} \end{aligned} \tag{11}$$

Where $\otimes\boldsymbol{X}^{\infty} = \left[0 \right]_{n\times n}$ represents the identity matrix, typically serving as a fundamental element for standardization or influence relationship matrix calculations.

Step 7: Calculation of Influence and Prominence Vector

Using Equations (12) and (13), the Total Influence Matrix $\otimes\mathrm{T}$ is summed row-wise to obtain influence degree $\otimes\boldsymbol{r}$. Similarly, using Equations (14) and (15), column-wise summation yields influenced degree $\otimes\boldsymbol{s}$. Influence degree $\otimes\boldsymbol{r}$ and influenced degree $\otimes\boldsymbol{s}$ derived from total influence matrix $\otimes\mathrm{T}$ row and column summations represent total output and input influence degrees, respectively, measuring each criterion's total input influence.

Influence degree $\otimes\boldsymbol{r}$ summation results:

$$\otimes\boldsymbol{r} = \left[\otimes r_i \right]_{n\times 1} = \left(\otimes r_1,\ \otimes r_2,\ldots,\ \otimes r_i,\ldots,\ \otimes r_n \right) \tag{12}$$

$$\left[\otimes r_i \right]_{n\times 1} = \left[\sum_{j=1}^{n} \otimes t_{ij} \right]_{n\times 1} \tag{13}$$

Influenced degree $\otimes\boldsymbol{s}$ summation results:

$$\otimes\boldsymbol{s} = \left[\otimes s_j \right]_{1\times n} = \left(\otimes s_1,\ \otimes s_2,\ldots,\ \otimes s_j,\ldots,\ \otimes s_n \right)^{T} \tag{14}$$

$$\left[\otimes s_j \right]_{1\times n} = \left[\sum_{i=1}^{n} \otimes t_{ij} \right]_{1\times n} = \left[\otimes s_i \right]_{n\times 1}^{T} \tag{15}$$

The sum of influence degree $\otimes \boldsymbol{r}$ and influenced degree $\otimes \boldsymbol{s}$ indicates each criterion's total influence value. Higher combined active or passive influence indicates the criterion is more influential. Additionally, $\otimes r_i = \left(r_i^L,\ r_i^M,\ r_i^U \right)$ and $\otimes s_i = \left(s_i^L,\ s_i^M,\ s_i^U \right)$ represent prominence and relation indicators. When the net influence indicator is positive, the criterion has greater influence on others (influencing criterion). When negative, the criterion is more influenced by others (influenced criterion).

Centroid defuzzification method converts fuzzy values $\otimes \lambda = \left(\lambda^L,\ \lambda^M,\ \lambda^U \right)$ to crisp values $\left(\lambda \right)$ using Equation (16).

$$\lambda = \frac{\left(\lambda^L + \lambda^M + \lambda^U \right)}{3} \tag{16}$$

Through Equation (16), defuzzification of $\otimes r_i$ and $\otimes s_i$ yields r_i and s_i respectively. $r_i + s_i$ reflects each criterion's overall system influence degree. Through Equation (17), influence weights for evaluation criteria are constructed, where w_i represents criterion i's relative importance in the system, ensuring all weights sum to 1. Larger w_i indicates higher criterion influence in the system, identifying it as a critical system criterion. Smaller w_i indicates relatively weaker influence.

Step 8: Derivation of Criteria Weights

The prominence values ($r_i + s_i$) are utilized for the calculation of the normalized weights (w_i) of the criteria:

$$w_i = \frac{\left(r_i + s_i \right)}{\sum_{i=1}^{n} \left(r_i + s_i \right)} \tag{17}$$

Step 9: Construction of the Impact-Relation Map (INRM)

The INRM is plotted with $r_i + s_i$ as the horizontal axis and $r_i - s_i$ as the vertical axis, for the purpose of visualizing the causal relationships extant among the criteria.

2.2. PROMETHEE-AL Method

Within the domain of MCDM methodologies, the PROMETHEE has been extensively employed for decision problems involving multiple evaluation criteria. This method employs pairwise comparison approaches to scientifically assess the performance of various suppliers under different criteria, thereby determining the relative advantages and overall ranking of each supplier, effectively assisting decision-makers in addressing complex and dynamic decision-making requirements.

When evaluating each criterion, the PROMETHEE method utilizes preference functions to transform the performance of different alternatives into preference values, calculating their corresponding preference degrees to form preference indices ranging from 0 to 1. To enhance computational and comparative efficiency, the PROMETHEE method requires the establishment of preference thresholds for each criterion, which serve to determine the preference intensity and indifference zones for specific criteria during comparison. Within the decision-making process, the parameters of preference functions and thresholds directly influence the final ranking results of alternative selection. Therefore, decision-makers must select appropriate function types based on actual contextual requirements to ensure the rationality and accuracy of evaluation results.

Although the computational procedures of the PROMETHEE method are more complex compared to other MCDM approaches and require extensive pairwise comparisons, its rigorous and precise flow calculation mechanism effectively distinguishes the advantages and disadvantages of each supplier under different criteria, thereby providing decision-makers with more objective and reasonable ranking results. Chang et al. [5] indicated that when the PROMETHEE method incorporates aspiration level concepts, PROMETHEE-AL can effectively determine the position of each supplier relative to aspiration levels, thereby providing more reasonable improvement recommendations. The detailed procedures of the PROMETHEE-AL method employed in this research are as follows:

Step 1:Construction of Initial Matrix

For the electronic lead frame company S with m alternative suppliers ($A_1, A_2, \ldots, A_m$) requiring evaluation based on n criteria ($C_1, C_2, \ldots, C_n$), the initial matrix X is constructed as shown in Equation (18). Additionally, the aspiration level (A_{aspire}) is incorporated into the matrix as an additional alternative. Here, x_{ij} represents the performance score of the i-th supplier under the j-th evaluation criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{18}$$

Step 2: Determination of Aspiration and Worst Levels for Criteria

The maximum and minimum values of the evaluation scale are designated as the aspiration level and worst level, respectively, as shown in Equations (19) and (20). In this research, the highest score assigned to supplier evaluation is 100, while the lowest score is 0.

Aspiration level is expressed as: $A_{aspire,j} = \max x_{1j}, x_{2j}, \ldots, x_{mj}$ (19)

Worst level is expressed as: $A_{worst,j} = \min x_{1j}, x_{2j}, \ldots, x_{mj}$ (20)

Step 3: Establishment of Normalized Decision Matrix

This research employs the preference function, which features linear preference with an indifference area (Criterion with linear preference and indifference area), as the normalization equation, as demonstrated in Equation (21).

$$P_j(d) = \begin{cases} 0 & \text{if } d \le q_j \\ \dfrac{d - q_j}{p_j - q_j} & \text{if } q_j < d \le p_j \\ 1 & \text{if } d > p_j \end{cases} \tag{21}$$

Subsequently, the normalized decision matrix R can be expressed as Equation (22):

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{22}$$

Step 4: Calculation of Relative Weighted Preference Functions Based on Criteria

The preference function $P_j(A_a, A_b)$ is employed to measure the degree of advantage of supplier A_a relative to supplier A_b under criterion C_j. It reflects the decision-maker's preference degree between different alternatives as Equation (23):

$$P_j(A_a, A_b) = \begin{cases} 0 & \text{if } r_{aj} \le r_{bj} \\ r_{aj} - r_{bj} & \text{if } r_{aj} > r_{bj} \end{cases} \tag{23}$$

where $0 \le P_j(A_a, A_b) \le 1$

Step 5: Generation of Final Preference Index through Relative Weighting

The criterion weights w_j generated through Z-DEMATEL are multiplied by the preference function $P_j(A_a, A_b)$ to obtain the final preference index $\pi(A_a, A_b)$, which represents the degree to which supplier A_a outperforms supplier A_b in overall performance as Equation (24):

$$\pi(A_a, A_b) = \sum_{j=1}^{n} w_j \cdot P_j(A_a, A_b) \tag{24}$$

Step 6. Calculation of Net Flow for All Relative Weights

In the PROMETHEE-AL method, supplier performance is evaluated through the calculation of three flow indicators: Leaving Flow, Entering Flow, and Net Flow, where $m-1$ represents the total number of comparisons involving supplier A_i. These are calculated using Equations (25), (26), and (27).

When a supplier's net flow indicator $\Phi(A_i)$ is larger, it indicates superior overall performance relative to other suppliers. In ranking, the optimal supplier possesses the highest net flow value.

Leaving Flow indicator: $$\Phi^+(A_i) = \frac{1}{m-1}\sum_{k=1}^{m}\pi(A_i, A_k) \tag{25}$$

Entering Flow indicator: $$\Phi^-(A_i) = \frac{1}{m-1}\sum_{k=1}^{m}\pi(A_k, A_i) \tag{26}$$

Net Flow indicator: $$\Phi(A_i) = \Phi^+(A_i) - \Phi^-(A_i) \tag{27}$$

3. Case Study and Analysis Results

3.1. Case Study Background

This research examines S Company, a prominent international manufacturer specializing in electronic lead frame production with substantial operations in Taiwan. Lead frames constitute critical components in semiconductor packaging, and copper serves as the primary raw material. The performance of copper suppliers directly impacts S Company's operational efficiency, product quality, and cost competitiveness.

S Company currently evaluates eight principal copper suppliers using traditional metrics but seeks to formally integrate sustainability considerations, adopting a more comprehensive and long-term assessment methodology. The evaluation framework was developed through consultations with thirteen experts from diverse functional areas, including manufacturing, research and development, procurement, production management, and quality assurance departments.

The finalized evaluation criteria encompass five critical performance dimensions. Quality (C_1) performance is assessed through defect rates, quality issue recurrence rates, batch rejection rates, and customer complaints attributable to material quality issues. Delivery (C_2) performance evaluation encompasses on-time delivery rates, material shortage incidents, and additional freight costs resulting from delays or expedited shipments.

Cost (C_3) performance assessment incorporates price competitiveness, negotiation flexibility, payment terms, and total cost of ownership considerations. Flexibility and Cooperation (C_4) performance focuses on supplier responsiveness to inquiries, efficiency in handling abnormalities, and proactive communication practices.

Sustainability (C_5)Performance represents the newest evaluation dimension, assessed through supplier responses to sustainability questionnaires, adherence to codes of conduct, and guarantees of conflict-free mineral sourcing. This criterion reflects S Company's strategic commitment to sustainable supply chain management, aligning with evolving regulatory requirements and stakeholder expectations in the global electronics manufacturing industry.

*3.2. Criteria Weighting using Z-DEMATEL**

Table 1 presents the 13 experts provided pairwise comparisons of the five criteria regarding their influence and their confidence in these assessments. The ASG was calculated to be 0.025 (2.5%), which is below the 5% threshold, indicating a good consensus among the experts.

Table 1
Expert Team Consensus Testing Results

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12	Expert 13
ASG	0.018	0.020	0.020	0.042	0.016	0.025	0.017	0.016	0.031	0.030	0.024	0.036	0.028

Subsequently, expert assessments regarding the relationships among criteria are integrated to construct the evaluation matrix. Utilizing Equation (2), the Z-DEMATEL direct influence relationship matrix is derived and decomposed into lower bound, middle bound, and upper bound matrix components. Within the direct influence relationship matrix, the influence of each evaluation criterion on itself, represented by the matrix diagonal elements, is not assessed and is uniformly set to zero, indicating that self-influence relationships are equivalent and meaningless for analytical purposes.

Following acquisition of the normalized influence matrix, Equation (11) is employed to calculate comprehensive influence values for each evaluation criterion, enabling understanding of each criterion's influence degree on others and its importance within the overall evaluation system.

As demonstrated in Table 2, criterion C_2 exerts combined direct and indirect influence on criterion C_1 with values of 0.197, 0.601, and 2.347 for lower bound, middle bound, and upper bound respectively. Additionally, criterion C_1 demonstrates self-influence characteristics with corresponding values of 0.116, 0.488, and 2.283.

These calculated influence values reveal complex interdependencies within the evaluation framework, capturing both immediate relationships and cascading effects throughout the entire system. This comprehensive analysis forms the foundation for determining relative weights and priorities in subsequent supplier evaluation processes.

Table 2
Total Influence Relationship Matrix

	C_1	C_2	C_3	C_4	C_5
C_1	(0.116, 0.488, 2.283)	(0.247, 0.679, 2.568)	(0.276, 0.703, 2.534)	(0.215, 0.636, 2.468)	(0.182, 0.586, 2.419)
C_2	(0.197, 0.601, 2.347)	(0.112, 0.473, 2.239)	(0.220, 0.631, 2.399)	(0.255, 0.652, 2.369)	(0.167, 0.551, 2.295)
C_3	(0.280, 0.703, 2.516)	(0.246, 0.679, 2.580)	(0.125, 0.512, 2.346)	(0.232, 0.656, 2.495)	(0.231, 0.639, 2.467)
C_4	(0.226, 0.644, 2.404)	(0.266, 0.690, 2.494)	(0.212, 0.638, 2.433)	(0.115, 0.481, 2.211)	(0.203, 0.598, 2.348)
C_5	(0.126, 0.430, 1.983)	(0.122, 0.432, 2.034)	(0.131, 0.442, 2.017)	(0.145, 0.444, 1.988)	(0.057, 0.300, 1.791)

Through summation of each row and column within the total influence relationship matrix, fuzzy total influence values and net influence values are calculated. The indicator $\otimes r_i$ represents the numerical value of influence exerted on other criteria, essentially the aggregate degree of influence on others, while $\otimes s_i$ indicates the total influence received from other criteria. These two indicators are calculated through Equations (12), (13), (14), and (15) respectively.

Table 3 consolidates the fuzzy total influence values $\otimes r_i + \otimes s_i$ and net influence values $\otimes r_i - \otimes s_i$ for each evaluation criterion. Using criterion C_1 as an illustration for row summation, the calculation proceeds from left to right as follows: lower bound 0.116 + 0.247 + ... + 0.182 = 1.037, middle bound 0.488 + 0.679 + ... + 0.586 = 3.092, upper bound 2.283 + 2.568 + ... + 2.419 = 12.272. Therefore, the influence degree $\tilde{r}_1$ yields values of 1.037, 3.092, and 12.272.

For criterion C_1 column summation, the calculation proceeds from top to bottom as follows: lower bound 0.116 + 0.197 + ... + 0.126 = 0.945, middle bound 0.488 + 0.601 + ... + 0.430 = 2.866, upper bound 2.283 + 2.347 + ... + 1.983 = 11.533. Consequently, the influenced degree $\otimes r_i$ yields values of 0.945, 2.866, and 11.533.

These calculations establish the foundation for understanding both the influence capacity and influence susceptibility of each criterion within the comprehensive evaluation framework.

Table 3
Fuzzy Total Influence Values and Net Influence Values

	$\otimes r_i$	$\otimes s_i$	$\otimes r_i + \otimes s_i$	$\otimes r_i - \otimes s_i$
C_1	(1.037, 3.092, 12.272)	(0.945, 2.866, 11.533)	(1.982, 5.958, 23.805)	(0.092, 0.225, 0.739)
C_2	(0.952, 2.907, 11.648)	(0.993, 2.953, 11.916)	(1.945, 5.860, 23.564)	(-0.041, -0.045, -0.268)
C_3	(1.115, 3.189, 12.404)	(0.963, 2.924, 11.728)	(2.078, 6.113, 24.132)	(0.152, 0.265, 0.676)
C_4	(1.021, 3.050, 11.890)	(0.963, 2.869, 11.531)	(1.984, 5.919, 23.422)	(0.058, 0.181, 0.359)
C_5	(0.581, 2.048, 9.814)	(0.841, 2.674, 11.320)	(1.421, 4.722, 21.134)	(-0.260, -0.626, -1.507)

All calculations are conducted using fuzzy number operations. To facilitate interpretation of data implications, defuzzification conversion to crisp values is performed through Equation (16), with conversion results presented in Table 4. Based on the defuzzified net influence values, criterion C_3 possesses the highest net influence value ($r_3 - s_3$ = 0.364), indicating that C_3 serves as the core driver influencing other criteria. Conversely, criterion C_5 exhibits a net influence value of -0.798, representing the criterion most significantly influenced by others and occupying a passive role within the system.

Furthermore, $r_i + s_i$ reflects the degree of influence that each criterion exerts on the overall system. Through Equation (17), the influence weight for each criterion can be calculated. Within the sustainable supplier evaluation system, C_3 emerges as the most critical influential criterion ($r_3 + s_3$ = 10.774), corresponding to a weight value w_3 of 0.2098, establishing it as the most essential evaluation criterion within the assessment framework.

Following the ranking of criteria according to their influence degrees, the influence weight ranking results for sustainable supplier evaluation criteria can be determined, yielding the sequence $C_3 \succ C_1 \succ C_2 \succ C_4 \succ C_5$. This hierarchical arrangement provides the foundation for the weighted evaluation process in the subsequent PROMETHEE-AL analysis, ensuring that the relative importance of each criterion is appropriately reflected in the comprehensive supplier performance assessment.

Table 4
Z-DEMATEL Influence Rankings and Weight Assignments

	r_i	s_i	$r_i + s_i$	$r_i - s_i$	Weight	Rank
C_1	5.467	5.115	10.582	0.352	0.2061	2
C_2	5.169	5.287	10.456	-0.118	0.2036	3
C_3	5.569	5.205	10.774	0.364	0.2098	1
C_4	5.320	5.121	10.442	0.199	0.2034	4
C_5	4.147	4.945	9.092	-0.798	0.1771	5

Finally, this research constructs the INRM using $r_i + s_i$ as the horizontal axis and $r_i - s_i$ as the vertical axis, as illustrated in Figure 1. Higher $r_i + s_i$ values indicate greater overall importance of the criterion within the system, while higher $r_i - s_i$ values on the vertical axis represent stronger influence that the criterion exerts on other criteria.

As demonstrated in Figure 1, the upper-right quadrant contains criteria with both high total influence values and high net influence values, specifically C_1, C_2, C_3, and C_4. These criteria cluster on the right side of the diagram, with arrows indicating multiple reciprocal influences among them. Conversely, the lower-left region exhibits lower influence characteristics, as exemplified by C_5. Among all criteria examined, C_3 demonstrates the most significant total influence value.

The INRM visualization provides decision-makers with an intuitive understanding of the complex interrelationships within the evaluation framework. This graphical representation effectively illustrates how different criteria interact and influence one another, enabling more informed strategic decisions regarding supplier evaluation priorities. The positioning of criteria within the INRM facilitates identification of core driving factors, influenced elements, and independent variables, thereby supporting the development of targeted improvement strategies for sustainable supplier management.

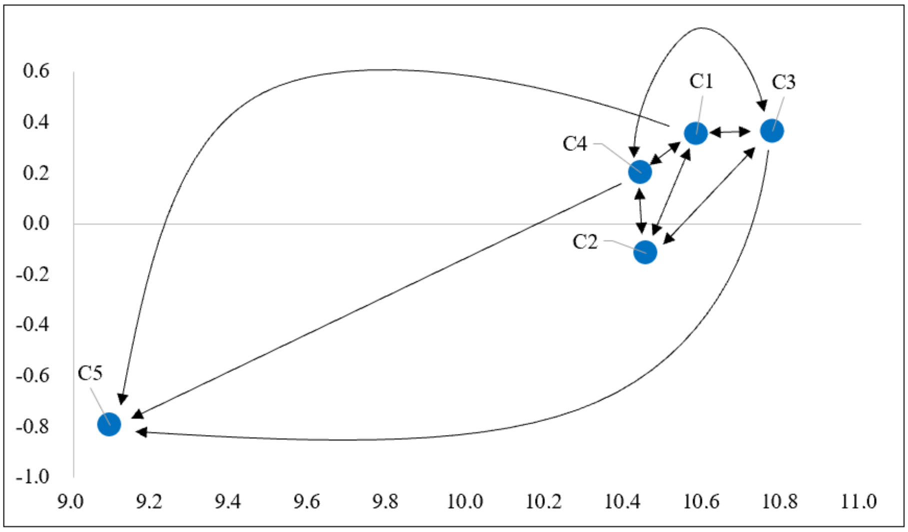

Fig.1. Influence Network Relation Map of This Case

3.3 Application of PROMETHEE for Supplier Performance Assessment and Ranking

This research employs the PROMETHEE-AL method integrated with aspiration-level concepts to conduct comprehensive pairwise comparisons for evaluating supplier performance, thereby establishing a structured and scientific decision-making framework. Table 5 presents the eight copper suppliers collaborating with the case company. Given the inherent variations among suppliers regarding material quality, delivery reliability, pricing structures, technical capabilities, and sustainability performance, single-criterion evaluation proves insufficient for comprehensive value assessment. Consequently, this research implements a multi-criteria evaluation mechanism to assist decision-makers in achieving more objective and accurate ranking and selection processes within complex supply environments.

The research incorporates five years of historical supplier performance data to enhance evaluation stability and predictive capability through time-series trend analysis, providing forward-looking decision recommendations that enable the case company to achieve dual objectives of stable supply and sustainable cooperation.

The PROMETHEE-AL methodology begins with constructing an initial performance matrix where each supplier's actual performance across the five evaluation criteria is systematically recorded. Aspiration levels are established at 100 points, while the worst levels are set at 0 points, reflecting the company's quality policy standards.

Table 5
Supplier Performance Matrix and Ranking Results (2024)

	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6	Supplier 7	Supplier 8	Aspire	Worst
Leaving flow	1.136	1.066	1.047	1.052	0.885	0.924	1.108	1.077	1.861	0.000
Entering flow	0.096	0.132	0.196	0.165	0.656	0.451	0.170	0.151	0.000	8.139
Net flow	1.041	0.934	0.851	0.887	0.228	0.473	0.938	0.926	1.861	-8.139
Gap	0.821	0.928	1.010	0.974	1.633	1.388	0.923	0.935	0.000	10.000
Rank	1	3	6	5	8	7	2	4		

Pairwise preference calculations are subsequently performed using the criterion weights derived from Z-DEMATEL analysis. The final preference indices are computed by multiplying the preference functions by the corresponding criterion weights, generating comprehensive supplier comparisons. The PROMETHEE-AL method calculates three flow indicators for performance evaluation: leaving flow, representing a supplier's advantage over others; entering flow, indicating disadvantage relative to competitors; and net flow, providing the overall performance ranking basis.

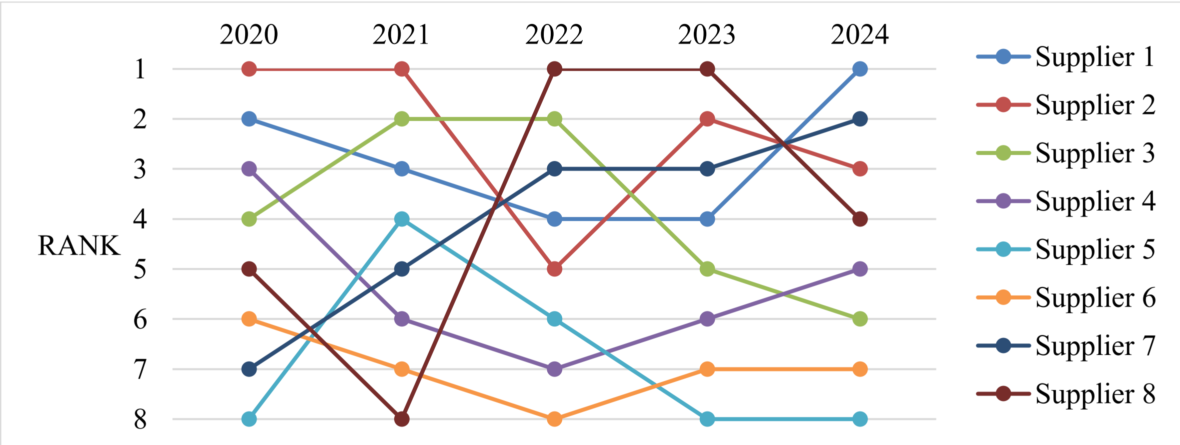

Fig. 2. Five-Year Supplier Performance Ranking Trends (2020-2024)

The analysis reveals distinct supplier performance patterns enabling differentiated management strategies. Supplier 1 demonstrates exceptional 2024 performance with the highest net flow value of 1.041, though maintaining a GAP of 0.821 from aspiration levels, particularly requiring improvement in cost and flexibility cooperation dimensions. Suppliers 7 and 2 exhibit strong performance with net flow values of 0.938 and 0.934 respectively, representing potential strategic partnership candidates.

Figure 2 shows that the five-year trend analysis identifies three supplier categories: consistently high performers (Suppliers 1 and 7) suitable for long-term strategic partnerships, variable performers requiring careful monitoring (Supplier 8 with high volatility despite potential), and consistently underperforming suppliers (Suppliers 5 and 6) necessitating development intervention or strategic reassessment. This comprehensive evaluation framework enables the case company to optimize supplier selection decisions while ensuring alignment with both operational requirements and sustainability objectives.

3.4. Discussion and Managerial Implications

The integrated Z-DEMATEL and PROMETHEE-AL model reveals critical insights for S Company's procurement strategy. The Z-DEMATEL analysis demonstrates that Cost emerges as the most influential criterion, exerting strong causal effects on other key criteria such as Quality, Delivery, Flexibility and Cooperation, and Sustainability. This reflects the current organizational mindset, where decision-makers and departmental managers still prioritize profitability, making cost control the dominant consideration in supplier evaluation. As cost considerations permeate various aspects of supplier performance, they are often viewed as foundational levers that indirectly enhance other performance dimensions. In contrast, Sustainability Performance exhibits a different structural role in the causal network. It is primarily positioned as a result-oriented criterion (being influenced by others rather than exerting influence) and receives the lowest weight among all evaluation factors. This outcome is consistent with the current state of practice in S Company, where sustainability, while recognized as important, has not yet achieved parity with traditional performance measures. Nevertheless, S Company has expressed a clear strategic intent to advance its sustainability agenda, which necessarily depends on close collaboration with its suppliers.

To this end, it is recommended that suppliers demonstrating strong overall performance be engaged as long-term partners in co-developing sustainability-oriented practices and standards. This collaboration may include establishing joint sustainability evaluation frameworks, implementing supplier education and training programs focused on green practices, and launching pilot audits to gradually incorporate environmental and social performance into routine assessments. Furthermore, S Company could introduce incentive mechanisms, such as preferred supplier status or future order prioritization, to motivate suppliers’ alignment with its sustainability vision. Through these initiatives, sustainability can progressively evolve from a reactive assessment factor into a core strategic pillar of supplier development.

The PROMETHEE-AL rankings identify distinct patterns of supplier performance, enabling differentiated management approaches. Supplier 1 and Supplier 7 demonstrate consistent excellence and represent prime candidates for strategic partnership expansion. Supplier 1 demonstrates strength in Quality and Delivery while also exhibiting opportunities for improvement in Cost Efficiency, Flexibility, and Cooperation. Targeted collaboration initiatives could elevate this supplier to aspiration-level performance across all dimensions.

Supplier 8 presents a management challenge due to volatile performance despite achieving top rankings in specific periods. This inconsistency suggests underlying operational instabilities requiring enhanced monitoring protocols and contingency planning. The local suppliers, particularly Supplier 5 and Supplier 6, require immediate development interventions to address consistent underperformance in cost competitiveness and quality metrics.

The model enables S Company to transition from reactive supplier management to proactive strategic planning. The confidence levels captured through Z-numbers provide management with explicit measures of uncertainty for informed risk assessment in supplier selection decisions. The dynamic ranking capability transforms supplier evaluation from static annual assessments to continuous performance monitoring, enabling the early identification of trends and real-time adjustments to order allocation.

For implementation, S Company should establish quarterly supplier review meetings utilizing the model's outputs to discuss performance gaps and development priorities. The gap analysis component provides specific performance targets for each supplier, creating clear communication channels for improvement expectations and ensuring supplier relationships evolve from transactional arrangements to strategic partnerships focused on mutual value creation.

4. Conclusions

This study successfully developed and applied an integrated Z-DEMATEL and PROMETHEE-AL model for evaluating sustainable supplier performance within the electronic lead frame industry, employing S Company as a comprehensive case study. The research addressed the critical need for a more systematic, intelligent, and uncertainty-aware approach to supplier selection and management, particularly given the increasing complexity of global supply chains and the growing emphasis on sustainability imperatives.

The Z-DEMATEL method effectively captured expert knowledge and confidence levels to determine the influential weights of five key evaluation criteria: Quality, Delivery, Cost, Flexibility & Cooperation, and Sustainability Performance. The analysis revealed that Cost emerged as the most influential criterion, underscoring its pivotal role in supplier evaluation decisions. Notably, while Sustainability Performance demonstrated relatively lower weight in the current framework, it exhibited significant potential for independent strategic development, suggesting evolving priorities in supply chain management. The PROMETHEE-AL method, utilizing these derived weights in conjunction with five years of historical performance data, provided dynamic rankings of eight copper suppliers. This approach successfully identified top-performing suppliers, those exhibiting volatile performance patterns, and suppliers requiring targeted development interventions. The subsequent GAP analysis offered granular insights into specific performance areas where suppliers fell short of S Company's established aspiration levels.

This research advances the MCDM literature by demonstrating a practical and robust application of a hybrid model that synergistically combines Z-DEMATEL and PROMETHEE-AL methodologies. The Z-DEMATEL component leverages its strength in handling imprecise information through Z-numbers, aligning with the principles of granular computing. At the same time, PROMETHEE-AL provides enhanced utility in ranking performance against predefined aspiration levels. The study illustrates how these complementary methods can be integrated to improve the intelligence and transparency of complex decision-making processes in sustainable supplier evaluation contexts.

For S Company and comparable manufacturing organizations, this model presents a structured and adaptable framework for enhancing procurement decision-making processes. The practical applications include facilitating more informed and objective supplier selection and order allocation decisions, identifying strategic partnerships and optimizing supplier relationship management, implementing targeted supplier development programs, systematically integrating sustainability considerations into procurement processes, and ultimately enhancing overall supply chain resilience and competitive positioning.

Several limitations warrant acknowledgment in this study. First, the findings are derived from a single case study within the Taiwanese electronics industry, which may constrain the generalizability of results across different industrial sectors and geographical contexts. Future research endeavors could validate the model's applicability across diverse sectors and regional markets. Second, while the Z-DEMATEL approach effectively captures expert subjectivity through confidence measures, the quality of the input remains fundamentally dependent on the expert's experience and judgment. Future investigations could explore the integration of more objective data sources for criteria weighing to complement expert assessments. Third, the current scope of sustainability criteria could be expanded to encompass more comprehensive and specific metrics as relevant data becomes increasingly available. This expansion would enhance the model's capacity to address evolving sustainability requirements and stakeholder expectations.

Future research opportunities include exploring the integration of real-time data analytics and machine learning techniques with the established MCDM framework to develop more adaptive and predictive intelligent decision support systems for sustainable supply chain management.

Additionally, investigating dynamic weighting mechanisms for evaluation criteria based on changing market conditions or evolving strategic priorities would constitute a valuable extension of this research.

The proposed hybrid intelligent decision-making model represents a significant advancement toward more effective and sustainable supplier performance management. By systematically addressing uncertainty, interdependencies, and strategic aspirations, this framework empowers organizations to construct more resilient, responsible, and competitive supply chains. The integration of advanced MCDM techniques with practical industry applications demonstrates the potential for bridging theoretical and methodological developments with real-world supply chain challenges, ultimately contributing to the advancement of sustainable procurement practices in manufacturing environments.

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Conflicts of Interest
The authors declare no conflicts of interest.

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