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A SENSITIVITY INDEX FOR FAIR SUPPLIER SELECTION: ASSESSING SMALL MANUFACTURER DISADVANTAGE IN MCDM METHODS

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ABSTRACT

Supplier selection is a critical decision-making problem in manufacturing and supply chain management, commonly addressed using Multi-Criteria Decision Making (MCDM) methods. While existing research has focused on improving methodological accuracy and robustness, limited attention has been paid to how criteria weighting influences selection outcomes across supplier categories. In particular, the impact of weighting structures on small suppliers remains insufficiently understood.

This study introduces the Small Supplier Sensitivity Index (SSSI), a diagnostic metric that quantifies the sensitivity of supplier rankings to changes in evaluation priorities. Unlike traditional sensitivity analysis approaches that assess overall ranking stability, the proposed index captures ranking shifts experienced specifically by small suppliers under alternative weighting scenarios. The methodology is implemented using two widely adopted MCDM methods, Simple Additive Weighting (SAW) and TOPSIS, and evaluated through both a real-world supplier dataset and a controlled hypothetical scenario.

Results from the real-world case indicate no change in ranking positions for small suppliers under adjusted weighting conditions, yielding an SSSI value of 0 and demonstrating strong structural stability. In contrast, the hypothetical scenario produces a positive SSSI value (SSSI = 2), with small suppliers improving in ranking when greater emphasis is placed on flexibility and reliability. These findings show that the sensitivity of supplier selection outcomes is highly dependent on the distribution of supplier performance, with weighting adjustments having limited impact in highly differentiated environments but significant influence in competitive settings.

The proposed framework extends the role of sensitivity analysis in MCDM from model validation to interpretive insight, providing decision-makers with a transparent tool to understand how evaluation priorities shape procurement outcomes. This contributes to more informed and context-aware supplier selection, particularly in environments where fairness and strategic alignment are of interest.

1. INTRODUCTION

Supplier selection is a critical decision-making process in manufacturing and supply chain management as it directly influences cost efficiency, product quality, delivery reliability, and overall operational performance. Due to the increasing complexity of modern supply chains, organizations rely on structured decision-making approaches to evaluate suppliers across multiple, often conflicting criteria.

Simple Additive Weighting (SAW), Analytical Hierarchy Process (AHP), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are common Multi-Criteria Decision-Making (MCDM) methods widely used for supplier evaluation [1, 2, 3]. These methods are comprehensive as they enable decision-makers to incorporate both qualitative and quantitative criteria such as cost, quality, delivery performance, and flexibility. This enables a unified ranking framework for decision-makers. MCDM techniques have become standard evaluation tools in procurement and supply chain optimization due to their transparency, computational efficiency, and adaptability [2, 4].

Despite their common adoption, these methods are typically evaluated based on decision accuracy, computational efficiency, or alignment with organizational objectives. However, there has been limited attention to how the structure of these models, particularly the selection and weighting of criteria, may systematically influence outcomes across different supplier categories [5, 6]. Commonly emphasized criteria such as cost competitiveness, delivery scale, and production capacity used in various manufacturing contexts tend to favor large suppliers, while small suppliers often compete through flexibility, responsiveness, and innovation capabilities [7, 8, 9]. Therefore, supplier rankings may be influenced not only by performance differences but also by implicit prioritization embedded in the weighting structure, potentially setting small suppliers at a disadvantage without explicit decision-maker bias [6, 10].

This observation reveals an important but underexplored dimension of supplier selection: the sensitivity of ranking outcomes to changes in evaluation priorities. While previous studies have explored sensitivity analysis in MCDM methods, these analyses have primarily focused on model robustness rather than on how changes in weights may affect different supplier groups [11]. Consequently, there is a limited understanding of whether supplier rankings are stable or highly responsive to realistic adjustments in managerial priorities, particularly those that emphasize attributes commonly associated with small suppliers.

To address this gap, this study introduces a fairness-oriented perspective on supplier selection by proposing the Small Supplier Sensitivity Index (SSSI) as a diagnostic metric. The SSSI is not aimed at modifying existing MCDM frameworks, but to evaluate the extent to which the ranking positions of small suppliers change under alternative, yet reasonable, weighting schemes. This approach enables decision-makers to assess whether supplier selection results are robust or sensitive to changes in the importance of criteria, thereby improving transparency in procurement decisions [12].

Firstly, this paper clearly provides a practical and reproducible framework for evaluating fairness sensitivity within existing MCDM-based supplier selection methods without requiring separate data collection or modification of existing decision models. Secondly, it illustrates how sensitivity-based insights can support more informed procurement discussions by revealing potential structural bias rooted in criteria weighting. Through a simplified manufacturing-oriented case illustration, SSSI highlights how small changes in evaluation emphasis can result in different supplier rankings. This tool can be used by researchers and practitioners seeking greater transparency in supplier evaluation.

To formalize the study objectives, this work addresses the following research questions:

- To what extent are supplier rankings in traditional MCDM-based selection models sensitive to changes in criterion weights that favor flexibility and responsiveness-related attributes?
- Can a simple, reproducible index (SSSI) quantify the magnitude of ranking shifts experienced by small suppliers under alternative weighting schemes?
- Under what structural conditions do rebalanced weight adjustments materially change supplier selection outcomes?

2. LITERATURE REVIEW

2.1 MCDM in Supplier Selection

Supplier selection has been deeply explored within the context of manufacturing and supply chain management, which requires decision-makers to evaluate multiple, often conflicting criteria such as cost, quality, delivery performance, and flexibility. To deal with this complexity, MCDM frameworks have been broadly embraced as structured tools for aggregating diverse performance measures into a unified supplier ranking [1, 2, 3].

The widely adopted MCDM methods comprise SAW, AHP, and TOPSIS. These techniques are commonly used due to their transparency, simple implementation, and the ability to incorporate both qualitative and quantitative decision criteria [2, 4]. Their application has been predominant in various industries, including manufacturing, healthcare, and electronics supply chains, demonstrating their capability in handling complex procurement decisions.

Recent literature further confirms the dominance of MCDM methods in supplier selection processes. A comprehensive review study [13] highlights that techniques such as AHP and TOPSIS are still frequently utilized methods, with constant evaluation criteria centered around cost efficiency, product quality, and delivery reliability. These findings emphasize the role of MCDM as a foundational decision-making framework in supplier evaluation.

In addition to traditional applications, recent research has explored the integration of MCDM techniques with advanced tools to better capture real-world complexity. For instance, hybrid approaches combining MCDM with simulation or optimization techniques have been suggested to account for uncertainty and dynamic supply chain conditions [14]. Similarly, sustainability-oriented supplier selection models have incorporated environmental and social criteria alongside operational factors, reflecting evolving managerial priorities [15]. These advancements demonstrate an increased effort to improve the realism and applicability of supplier evaluation models.

Despite these developments, existing MCDM-based supplier selection methods largely enforce improving decision accuracy, computational efficiency, and the incorporation of additional criteria. As summarized in Table 1, the primary focus of recent studies remains on methodological improvement rather than exploring how decision structures influence outcomes across different categories of suppliers. In particular, the selection and weighting of criteria are typically treated as inputs defined by decision-makers, without explicit consideration of how these choices may systematically affect the relative ranking of suppliers with different operational characteristics.

2.2 Advanced and Hybrid MCDM Approaches

Due to the limitations of traditional MCDM techniques in handling uncertainty and complex decision environments, recent studies have heavily focused on the development of advanced and hybrid MCDM approaches. These methods aim to improve decision accuracy by incorporating fuzzy logic, optimization techniques, and data-driven models into common methods such as TOPSIS and AHP.

Fuzzy MCDM methods have gained significant attention due to their ability to deal with uncertainty and ambiguity in decision-making processes. For instance, fuzzy extensions of TOPSIS have been commonly applied to supplier selection scenarios where precise performance evaluations may not be available [16]. In these models, representing criteria values with fuzzy numbers provides a flexible representation of real-world decision environments, especially conditions with incomplete or imprecise information.

Additionally, hybrid MCDM models have been developed to combine the strengths of multiple decision-making techniques. These approaches are usually characterized by the integration of weighting methods such as the Best-Worst Method (BWM) with ranking techniques like TOPSIS to improve consistency and reliability in supplier evaluation [17]. Likewise, latest studies have proposed hybrid frameworks that combine MCDM with optimization or simulation tools to better reflect dynamic supply chain conditions and interdependencies among criteria [14]. The goal of these models is to bridge the gap between theoretical decision methods and practical implementation in complex industrial settings.

Another emerging direction in recent literature involves incorporating advanced computational techniques, including nonlinear programming and data-driven modeling, into MCDM approaches.

Recent work has combined nonlinear optimization with fuzzy TOPSIS to improve the handling of multi-objective decision problems with complex constraint structures [16]. Moreover, the integration of MCDM methods with Industry 4.0 technologies, such as artificial intelligence and data analytics, has enabled the creation of more adaptive and intelligent supplier selection systems [18]. These improvements reflect a broader trend toward increasing methodological complexity in supplier evaluation.

Even with these advancements, the central focus of advanced and hybrid MCDM methods remains on improving decision accuracy, handling uncertainty, and incorporating additional evaluation dimensions such as sustainability and resilience. While these methods improve the technical robustness of supplier selection models, they do not explicitly address how variations in criteria weighting may affect outcomes across different supplier categories. Particularly, the implications of model structure on the relative ranking of small versus large suppliers remain largely unexplored within this stream of research.

2.3 Sensitivity Analysis in MCDM

Sensitivity analysis has been commonly employed in MCDM methods with the aim of evaluating the robustness and stability of decision outcomes. In the context of supplier selection, sensitivity analysis is typically used to measure how variations in input parameters, specifically criteria weights, influence the resulting rankings of alternatives. This assessment is essential given that weight assignment often reflects subjective managerial judgment and may vary across decision contexts.

A growing research area has explored the impact of weight variation on MCDM outcomes. Recent studies have illustrated that even small changes in criteria weights can lead to noticeable differences in supplier rankings, emphasizing the dependence of decision results on the chosen weighting structure [19].To address this, sensitivity analysis is usually used to test the stability of rankings under different weighting scenarios, providing decision-makers with confidence in the consistency of model results.

More broadly, sensitivity analysis in MCDM has been outlined as a tool for validating decision models and ensuring their robustness. For instance, recent research has systematically evaluated the sensitivity of various MCDM techniques to input changes, including weight variations and data uncertainty, to identify models that produce stable and reliable rankings across a range of conditions [20]. Likewise, hybrid MCDM studies often incorporate sensitivity analysis to demonstrate that proposed techniques yield consistent outcomes despite variations in decision parameters [21]. In these environments, sensitivity analysis serves primarily as a verification mechanism, ensuring that decision results are not overly dependent on specific parameter choices.

While these studies emphasize the importance of sensitivity analysis, their interpretation is limited to examining model stability and robustness. Particularly, sensitivity is typically evaluated at the aggregate level, focusing on whether overall rankings change, rather than on how such changes affect specific groups of suppliers. Therefore, the implications of weight changes for different supplier groups, such as small versus large suppliers, remain underexplored.

This limitation is specifically relevant in supplier selection contexts, where different suppliers may exhibit different performance characteristics across evaluation criteria. For instance, small suppliers may perform relatively better on flexibility and responsiveness, while larger suppliers may excel in cost efficiency and production capacity. In these scenarios, variations in weighting may have uneven effects on supplier rankings, even if the overall ranking structure seems stable. However, existing sensitivity analysis efforts do not explicitly quantify these subgroup-level effects.

As illustrated in Table 1, current applications of sensitivity analysis in MCDM primarily focus on methodological validation rather than on interpretive insight. This suggests a gap in the literature regarding the use of sensitivity as a tool for understanding how decision structures affect outcomes across different types of suppliers. Addressing this gap requires a shift from viewing sensitivity solely as a measure of robustness toward interpreting it as an indicator of how evaluation priorities shape decision outcomes.

2.4 Supplier Characteristics and Small Supplier Challenges

Decisions made in supplier selection are inherently influenced by operational characteristics of competing suppliers, which usually differ significantly based on supplier size. In manufacturing and supply chain contexts, large and small suppliers typically show distinct strengths and competitive advantages. Large suppliers usually benefit from economies of scale, enabling higher cost efficiency, superior production capacity, and more consistent delivery performance. On the other hand, small and medium-sized enterprises (SMEs) are frequently characterized by greater flexibility, responsiveness, and adaptability to changing customer requirements [6, 8].

These operational differences have been commonly noticed in supply chain management literature, particularly in studies assessing responsiveness and flexibility within manufacturing systems. For example, prior research has illustrated that small suppliers hold a better position to respond to customized orders and dynamic demand conditions, whereas larger suppliers tend to prioritize efficiency and volume-based production [6]. Consequently, supplier evaluation is not only a matter of absolute performance but also depends on how well the evaluation criteria align with the strategic priorities of the buying organization.

Despite this understanding, the criteria widely used in MCDM-based supplier selection models continue to emphasize attributes such as cost, quality, and delivery reliability [7, 9]. While these criteria are important for operational efficiency, they may not fully capture the value provided by smaller suppliers, especially in contexts where flexibility, innovation, or responsiveness are critical. Consequently, model evaluation structures may implicitly favor large suppliers, even in the absence of explicit bias in decision making [10].

The latest developments in supplier selection research have attempted to broaden evaluation techniques by incorporating additional criteria such as sustainability, resilience, and risk management [15, 17]. These efforts reflect a growing recognition that supplier performance should be assessed across multiple dimensions beyond traditional cost-based metrics. However, while the inclusion of new criteria expands the scope of evaluation, it does not necessarily address how the relative weighting of these criteria influences outcomes across different supplier types.

Particularly, limited attention has been given to how MCDM models capture the trade-offs between scale-based advantages and flexibility-based capabilities. Since small suppliers often drive their competitive advantage from criteria that are assigned lower weights in traditional evaluation techniques, their relative ranking may be highly sensitive to changes in decision-maker priorities. However, this sensitivity is rarely examined explicitly in existing studies, and the potential for structural disadvantage remains largely unquantified.

Table 1 shows that although prior research acknowledges differences in supplier characteristics and has expanded the range of evaluation criteria, it does not explicitly analyze how these differences interact with model structures to influence outcomes. This suggests a gap in understanding how supplier evaluation models may systematically advantage or disadvantage certain supplier groups depending on the weighting criteria. Addressing this issue requires a clearer interpretation of supplier selection models that consider not only performance outcomes, but also the sensitivity of those outcomes to changes in evaluation priorities.

Table 1. Summary of Recent Literature on MCDM-Based Supplier Selection

Year	Paper	Method	Contribution	Identified Gap
2025	[13]	Review (MCDM)	Comprehensive review of MCDM applications in supplier selection	Limited focus on fairness or supplier-type sensitivity
2023	[14]	Hybrid MCDM + Simulation	Integrates uncertainty and real-world complexity	Focus on optimization, not outcome fairness
2024	[15]	Sustainable MCDM	Incorporates environmental and operational criteria	Criteria expansion without analyzing the impact on SMEs
2024	[16]	Fuzzy TOPSIS + NLP	Handles uncertainty and non-linear decision structures	No evaluation of bias across supplier types
2024	[17]	BWM + Fuzzy TOPSIS	Focus on resilience-based supplier selection	Ignores the impact of weighting on supplier categories
2024	[18]	Industry 4.0 MCDM	Integration of AI and smart decision tools	Overlooks interpretability and fairness concerns

2021	[19]	TOPSIS Sensitivity	Shows the dependency of ranking on weights	Lacks a managerial interpretation of sensitivity
2025	[20]	Sensitivity analysis study	Evaluates ranking stability under weight variation	Does not examine subgroup (small supplier) effects
2025	[21]	FTOPSIS-GRA	Includes sensitivity analysis of rankings	Sensitivity used for robustness, not fairness interpretation

3. RESEARCH GAP AND OBJECTIVES

Even with the wide application of MCDM methods in supplier selection, several important limitations remain unaddressed. Sections 2.1 and 2.2 highlighted that previous research primarily focused on improving decision accuracy, incorporating uncertainty, and expanding evaluation criteria through advanced and hybrid MCDM techniques. While these attempts have improved the technical sophistication of supplier evaluation methods, they have largely overlooked how the structure of these models influences outcomes across different categories of suppliers.

Sensitivity analysis, commonly used within MCM frameworks, has been predominantly used as a tool for examining model robustness and stability. Current research areas evaluate how variations in criteria weights affect overall rankings to verify the consistency of decision outcomes under changing assumptions. However, these analyses are usually conducted at an aggregate level and do not assess how weight changes impact specific supplier groups differently. As a result, the interpretation of sensitivity analysis remains limited to methodological validation rather than providing insight into how decision structures shape supplier selection outcomes.

Additionally, existing literature recognizes that suppliers of different sizes show distinct performance characteristics. Small suppliers are often associated with strengths in flexibility, responsiveness, and adaptability, whereas large suppliers tend to excel in cost efficiency and production scale. Despite recent studies expanding the range of evaluation criteria to include dimensions such as sustainability and resilience, limited attention has been given to how the relative weighting of these criteria may systematically influence the ranking of small versus large suppliers.

Collectively, these observations reveal a critical gap in the literature: there is a lack of approaches that explicitly evaluate how sensitivity to criteria weighting affects different categories of suppliers within MCDM-based selection models. Specifically, existing research does not provide a mechanism for diagnosing whether supplier rankings are robust or highly sensitive to realistic shifts in decision-maker priorities, and it does not assess how such sensitivity may differentially impact small suppliers.

To address this gap, this study introduces a rebalanced perspective to supplier selection by proposing a diagnostic metric termed the Small Supplier Sensitivity Index (SSSI). Unlike existing approaches that focus on improving or modifying MCDM techniques, the proposed framework operates on top of established models to evaluate the sensitivity of supplier rankings to alternative weighting schemes. This allows for the assessment of whether observed selection outcomes are driven primarily by supplier performance or by the structure of the evaluation model itself.

The specific objectives of this study are as follows:

- To evaluate the extent to which supplier rankings produced by traditional MCDM techniques are sensitive to changes in criteria weights that reflect alternative managerial priorities.
- To develop and demonstrate a simple, transparent, and reproducible index (SSSI) for quantifying ranking shifts experienced by small suppliers under different weighting scenarios.
- To analyze the structural conditions under which rebalanced weight adjustments materially influence supplier selection outcomes.
- To provide managerial insight into how weighting decisions impact procurement outcomes, thereby improving transparency and supporting more informed decision-making.

4. METHODOLOGY

4.1 Multi-Criteria Decision-Making Methods

MCDM methods provide a structured basis for evaluating alternatives across multiple, often conflicting criteria. In supplier selection scenarios, these techniques enable decision-makers to aggregate diverse performance measures, such as cost, quality, delivery performance, flexibility, and reliability, into a single ranking that supports procurement decisions. Among various MCDM methods, SAW and TOPSIS are widely used due to their transparency, computational efficiency, and ease of implementation [3, 8, 9].

SAW and TOPSIS are selected as representative MCDM methods for this paper to evaluate supplier rankings under different weighting scenarios. The application of two distinct methods allows for validation of results and ensures that observed sensitivity patterns are not specific to a single decision model.

4.1.1 Simple Additive Weighting (SAW)

The SAW method is one of the most straightforward and commonly used MCDM methods. It evaluates each alternative by computing a weighted sum of normalized performance scores across all criteria.

Let x_{ij} denote the performance score of supplier i under criterion j, and let w_j represent the weight assigned to criterion j, where $\sum_{j=1}^{m} w_j = 1$. After normalizing the decision matrix, the overall score of supplier i is calculated as:

$$S_i = \sum_{j=1}^{m} w_j r_{ij} \tag{4.1}$$

Where r_{ij} represents the normalized performance value of supplier i under criterion j.

Suppliers are ranked in descending order of S_i, with higher scores indicating better overall performance. Due to its linear aggregation structure, SAW provides a transparent and interpretable baseline for evaluating how changes in criteria weights influence supplier rankings [8, 10].

4.1.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS evaluates alternatives based on their relative distance to an ideal solution and an anti-ideal solution. The ideal solution represents the best possible performance across all criteria, while the anti-ideal solution represents the worst.

Following normalization and weighting of the decision matrix, the Euclidean distance of each supplier from the ideal (D_i^+) and anti-ideal (D_i^-) solutions is computed. The relative closeness coefficient for supplier i is then defined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{4.2}$$

Where:

- D_i^+ = distance from the ideal solution
- D_i^- = distance from the anti-ideal solution

Suppliers are ranked in descending order of C_i, with higher values indicating closer proximity to the ideal solution [4, 9]. Compared to SAW, TOPSIS provides a more balanced evaluation by simultaneously considering both the best and worst performance benchmarks.

4.1.3 Rationale for Method Selection

The selection of SAW and TOPSIS in this study is motivated by their complementary characteristics and widespread use in supplier selection literature. SAW offers a simple and transparent linear aggregation approach, making it well-suited for analyzing the direct effects of weight changes on ranking outcomes. In contrast, TOPSIS incorporates relative distance measures, allowing for a more detailed evaluation of supplier performance across multiple criteria.

By applying both methods under identical weighting scenarios, this study ensures that the observed sensitivity of supplier rankings is not a result of a particular MCDM technique. Instead, consistent patterns across both methods strengthen the validity and generalizability of the proposed sensitivity analysis framework.

4.2 Small Supplier Sensitivity Index (SSSI)

As established, traditional methods provide a structured approach for ranking suppliers but do not explicitly capture how changes in evaluation criteria influence outcomes across different categories of suppliers. Additionally, existing sensitivity analyses primarily assess overall ranking stability, without examining how weight adjustments may differentially impact specific groups such as small suppliers. This study introduces a diagnostic metric, the Small Supplier Sensitivity Index (SSSI), to address the identified gap.

SSSI is designed to quantify the extent to which the ranking positions of small suppliers change under alternative weighting arrangements that reflect different managerial priorities. Instead of modifying existing MCDM techniques, the index operates on the outputs of standard models such as SAW and TOPSIS, making it compatible with existing decision-making bases.

4.2.1 Conceptual Definition

In the context of this study, rebalanced weights assess the sensitivity of supplier rankings to reasonable changes in criteria weighting. Specifically, the focus is on whether small suppliers experience significant changes in their ranking positions when evaluation emphasis shifts from traditional dominant criteria, such as cost and delivery performance, towards criteria associated with flexibility, responsiveness, and adaptability.

A model is considered highly sensitive if small suppliers experience noticeable improvements or declines in ranking under alternative weighting scenarios. Conversely, low sensitivity indicates that supplier rankings remain largely unchanged despite shifts in evaluation priorities. The SSSI provides a quantitative measure of this sensitivity.

4.2.2 Mathematical Formulation

Let n_s denote the number of suppliers classified as small. For each small supplier i, let:

- $R_i^{(T)}$ = ranking position under the traditional weighting scenario
- $R_i^{(F)}$ = ranking position under the rebalanced weighting scenario

The Small Supplier Sensitivity Index is defined as:

$$SSSI = \frac{1}{n_s}\sum_{i=1}^{n_s}\left(R_i^{(T)} - R_i^{(F)}\right) \tag{4.3}$$

This formulation captures the average change in ranking position for small suppliers when transitioning from a traditional to a rebalanced weighting structure.

A positive SSSI value indicates that small suppliers improve in ranking under the adjusted weighting structure, suggesting that the traditional weight schemes may undervalue certain supplier attributes. A negative value indicates a decline in ranking, while a value close to zero suggests that supplier rankings are largely insensitive to the applied weight changes.

4.2.3 Interpretation of the SSSI

SSSI serves as a diagnostic indicator rather than a prescriptive decision rule. Its primary purpose is to provide insight into how strongly supplier selection outcomes depend on the chosen weighting structure. High SSSI values indicate that rankings are sensitive to changes in evaluation priorities, implying that the decision outcomes may vary significantly depending on how criteria are weighted. On the other hand, low SSSI values suggest that rankings are robust, meaning that performance differences dominate the evaluation regardless of weight adjustments.

Importantly, the SSSI does not imply that one weighting structure is inherently preferable to another. Instead, it highlights the degree to which procurement outcomes are influenced by subjective modeling choices, thereby improving transparency in decision-making.

4.2.4 General Applicability

A key advantage of the SSSI is its flexibility and ease of implementation. Since the index relies solely on ranking outputs, it can be applied to any MCDM method without requiring modification of the underlying model or additional data collection. This makes it particularly suitable for practical applications, where decision-makers may already be using established evaluation frameworks.

Furthermore, the SSSI can be extended to different contexts by adjusting the definition of supplier groups or weighting scenarios. While this study focuses on small suppliers, the same approach can be used to analyze sensitivity for other categories, such as local suppliers, sustainable suppliers, or high-risk suppliers.

4.3 Data Processing and Score Computation

Supplier performance values are first normalized to ensure comparability across criteria with different units and scales. In this study, min-max normalization is used to transform all criteria values to a [0,1] scale.

For the benefit criteria (where higher values are preferred), normalization is performed as:

$$x_{ij}^* = \frac{x_{ij}}{\max(x_j)} \tag{4.4}$$

For cost criteria (where lower values are preferred), normalization is performed as:

$$x_{ij}^* = \frac{\min(x)_j}{x_{ij}} \tag{4.5}$$

Where x_{ij} represents the performance of supplier i on criterion j, and x_{ij}^* is the normalized value.

Following normalization, weighted scores are computed using the selected MCDM method. For the SAW method, the overall score for supplier i is given by:

$$S_i = \sum_{j=1}^{n} w_j x_{ij}^{*} \tag{4.6}$$

Where w_j represents the weight assigned to criterion j.

The resulting scores are then used to rank suppliers under each weighting scenario.

For clarity and reproducibility, a step-by-step numerical example illustrating the normalization and score computation process is provided in Appendix A.

4.4 Experimental Design

A structured experimental design was developed to evaluate the sensitivity of supplier rankings to changes in the weights of different criteria. The goal is to systematically compare supplier selection outcomes under different weighting scenarios while holding performance data constant. This approach isolates the effect of criteria weighting on ranking results and enables consistent evaluation of the proposed SSSI.

The experimental design consists of four main components: (1) data preparation, (2) supplier classification, (3) definition of weighting scenarios, and (4) ranking evaluation using selected MCDM methods.

4.4.1 Data Preparation

The analysis in this paper uses a secondary dataset adapted from an existing supplier selection study [12]. The dataset includes multiple suppliers evaluated across several criteria commonly used in procurement decisions, such as cost, quality, logistics, flexibility, and reliability. These criteria reflect a realistic decision-making environment consistent with manufacturing and supply chain applications.

All supplier performance scores are treated as a fixed input throughout the analysis. This ensures that any observed changes in supplier rankings are attributable only to variations in criteria weighting, not to differences in underlying performance data.

4.4.2 Supplier Classification

To evaluate sensitivity across supplier types, suppliers are categorized based on their dominant operational characteristics. In this study, suppliers are classified as “small” if their competitive strengths are primarily associated with flexibility, responsiveness, or adaptability, rather than scale-dependent attributes such as cost efficiency or production capacity.

This classification is analytical rather than regulatory and is used solely to assess ranking sensitivity. It aligns with prior research indicating that small suppliers often compete through agility and customization capabilities, while larger suppliers benefit from economies of scale [6, 8].

4.4.3 Weighting Scenarios

Two distinct weighting scenarios are defined to represent different managerial priorities:

- Traditional Weighting Scenario (T): emphasizes criteria commonly prioritized in procurement decisions, such as cost efficiency, logistics performance, and quality. This scenario reflects conventional evaluation practices observed in supplier selection literature.
- Rebalanced Weighting Scenario (F): adjusts the relative importance of criteria to increase emphasis on attributes commonly associated with small suppliers, such as flexibility and reliability. This is achieved by proportionally redistributing weight from dominant criteria (e.g., cost and logistics) toward these attributes.

The purpose of this comparison is to analyze how changes in weighting assumptions influence supplier rankings, particularly for suppliers characterized by strengths in flexibility and responsiveness. Both weighting vectors are normalized so that the sum of weights equals one. The magnitude of weight adjustment is selected to represent a realistic managerial shift rather than an extreme redistribution, ensuring that the analysis reflects reasonable decision-making scenarios. This study does not aim to prescribe specific weighting structures, but rather to evaluate how variations in weighting influence decision outcomes.

The rebalanced weighting structure used in this study is scenario-based and intentionally constructed to represent different sets of managerial priorities. The objective is not to determine optimal or empirically defined weights, but rather to examine how variations in weighting assumptions influence supplier ranking outcomes. So, the rebalanced weights are not derived from expert opinions or formal weighting methods but are defined analytically to represent distinct decision scenarios.

In rebalancing the weights, greater relative importance is assigned to flexibility and reliability. This is designed to simulate an alternative set of priorities and to evaluate how such changes affect supplier rankings. This approach enables controlled comparison across weighting scenarios while holding supplier performance constant, allowing the impact of weighting structure on decision outcomes to be isolated and analyzed.

4.4.4 Ranking Evaluation

Supplier rankings are computed under both weighting scenarios using the SAW and TOPSIS methods. For each method, two sets of rankings are obtained:

- Rankings under the traditional weighting scenario
- Rankings under the fairness-oriented weighting scenario

These rankings serve as the basis for evaluating the sensitivity of supplier selection outcomes to changes in criteria weighting.

4.4.5 Sensitivity Measurement

The SSSI is computed using the ranking results obtained from both weighting scenarios. The index quantifies the average change in ranking position for suppliers classified as small.

By comparing SSSI values across different MCDM techniques and scenarios, the analysis provides insight into the extent to which weighting assumptions influence supplier rankings. This enables the identification of conditions under which supplier selection outcomes are robust or sensitive to shifts in evaluation priorities.

4.5 Implementation Procedure

To ensure clarity and reproducibility, the proposed methodology is implemented through a structured sequence of steps. This procedure outlines how supplier rankings are generated under different weighting scenarios and how the SSSI is computed.

Step 1: Construct the Decision Matrix

A decision matrix is formed using supplier performance data across all selected evaluation criteria. Each row represents a supplier, and each column corresponds to a specific criterion (e.g., cost, quality, logistics, flexibility, reliability). The matrix serves as the primary input for the MCDM evaluation.

Step 2: Normalize the Decision Matrix

The decision matrix is normalized to ensure comparability across criteria with different measurement scales. Appropriate normalization techniques are applied depending on whether the criteria are benefit-type (higher values preferred) or cost-type (lower values preferred). The normalized matrix is then used in both SAW and TOPSIS calculations.

Step 3: Define Weighting Vectors

Two weighting vectors are specified in accordance with the experimental design described in Section 4.3:

- A traditional weighting vector, emphasizing cost, logistics, and quality
- A rebalanced weighting vector, with increased emphasis on flexibility and reliability

Both vectors are normalized such that the sum of their weights equals one.

Step 4: Compute Supplier Scores

Supplier performance scores are calculated under each weighting scenario using the selected MCDM methods:

- For the SAW method, weighted sums of normalized criteria values are computed for each supplier.
- For the TOPSIS method, distances to the ideal and anti-ideal solutions are calculated, followed by the relative closeness coefficient

This step results in two sets of scores for each supplier under each method, corresponding to the two weighting scenarios.

Step 5: Generate Supplier Rankings

Suppliers are ranked in descending order based on their computed scores for each method and weighting scenario. This produces four ranking sets: SAW with traditional weights, SAW with fairness-oriented weights, TOPSIS with traditional weights, and TOPSIS with fairness-oriented weights. These rankings form the basis for evaluating sensitivity.

Step 6: Identify Small Suppliers

Suppliers classified as small, based on the criteria defined in Section 4.3, are identified within the ranking results. Their ranking positions under each scenario are extracted for further analysis.

Step 7: Compute the SSSI

The SSSI is calculated using the ranking differences between the traditional and fairness-oriented scenarios for each small supplier. The index is computed as the average change in ranking position, as defined in Section 4.2.

Step 8: Interpret Results

Computed SSSI values are analyzed to assess the sensitivity of supplier rankings to changes in criteria weighting. Higher values indicate greater sensitivity and suggest that ranking outcomes are influenced by weighting assumptions, while lower values indicate robustness of the results.

5. CASE STUDY AND DATA

5.1 Case Study Description and Data Source

To demonstrate the applicability of the proposed methodology, this study uses a secondary dataset adapted from an existing supplier selection case study in a healthcare procurement context [12]. The original study evaluates suppliers using a multi-criteria decision-making framework, incorporating both quantitative and qualitative measures. Even with the application domain being in healthcare, the structure of the decision problem, multiple suppliers evaluated across diverse criteria, is consistent with supplier selection scenarios commonly encountered in manufacturing and industrial environments.

The dataset comprises a set of suppliers assessed across several key performance criteria, such as cost, quality, logistics, flexibility, and reliability. These criteria reflect standard considerations in procurement decisions and are widely used in MCDM-based supplier evaluation models [3, 5]. Each supplier is assigned a performance score for every criterion, forming the decision matrix used in the analysis.

The selection of this dataset is motivated by several factors. First, it provides a realistic and structured evaluation environment, including predefined criteria, supplier performance scores, and an established weighting structure. Second, the dataset allows for controlled analysis, where supplier performance values remain fixed while criteria weights are systematically adjusted. This aligns with the experimental design described in Section 4.3, which isolates the effect of weighting changes on supplier rankings.

It is important to note that the goal of this study is not to re-evaluate or validate the original case study results. Instead, the dataset is used as a representative platform to examine how supplier rankings respond to changes in evaluation priorities. By maintaining the original data and modifying only the weighting structure, the analysis focused on the sensitivity of decision outcomes rather than differences in supplier capabilities.

To complement the real-world dataset, a simplified analytical scenario is introduced in later sections to illustrate the behavior of the proposed SSSI under controlled conditions. This dual-case approach, combining a real-world dataset with a controlled experimental scenario, improves both the practical relevance and interpretability of the results.

5.2 Supplier Evaluation Criteria

The supplier evaluation process in this study is based on a set of criteria commonly used in procurement and supply chain decision-making. These criteria reflect both operational efficiency and service-oriented performance, ensuring a comprehensive assessment of supplier capabilities. The selected criteria include cost, quality, logistics, flexibility, and reliability, which are widely recognized in MCDM-based supplier selection literature [3, 5, 7].

Each criterion captures a distinct dimension of supplier performance, as described below:

- Cost: represents the overall procurement cost associated with each supplier, including unit price and related expenses. Cost is typically treated as a cost-type criterion, where lower values are preferred. It is one of the most influential factors in traditional supplier selection decisions.
- Quality: reflects the ability of the supplier to meet product specifications and maintain consistent standards. This includes defect rates, compliance with requirements, and overall product reliability. Quality is treated as a benefit-type criterion, where higher values indicate better performance.
- Logistics: captures the supplier's delivery performance, including lead times, delivery reliability, and distribution efficiency. This criterion is critical in ensuring smooth supply chain operations and is generally considered a benefit-type attribute.
- Flexibility: represents the supplier's ability to respond to changes in demand, accommodate customization requests, and adapt to varying production requirements. Flexibility is particularly relevant in a dynamic manufacturing environment and is often associated with small suppliers that emphasize responsiveness.

- Reliability: reflects the consistency and dependability of the supplier over time, including adherence to delivery schedules and fulfillment commitments. Reliability complements logistics performance by emphasizing long-term consistency rather than short-term efficiency.

These criteria collectively provide a balanced evaluation basis that captures both efficiency-oriented and adaptability-oriented dimensions of supplier performance. While traditional supplier selection models often emphasize cost, quality, and logistics, the inclusion of flexibility and reliability enables a broader assessment of supplier capabilities, particularly those related to responsiveness and operational adaptability.

As discussed in Section 2.4, different suppliers may exhibit varying strengths across these criteria. Specifically, small suppliers often demonstrate competitive advantages in flexibility and responsiveness, while larger suppliers tend to perform strongly in cost efficiency and logistics. This distinction is central to the analysis conducted in this study, as changes in the relative importance of these criteria form the basis for evaluating ranking sensitivity using the proposed SSSI.

5.3 Weighting Structure

To evaluate the impact of decision-maker priorities on supplier selection outcomes, this study defines two distinct weighting structures: a traditional weighting scheme and a fairness-oriented weighting scheme. These weighting vectors represent different managerial perspectives and are used to assess how changes in criteria importance influence supplier rankings.

The traditional weighting structure reflects commonly observed procurement priorities, where greater emphasis is placed on cost efficiency, logistics performance, and quality. These criteria are typically associated with operational efficiency and are widely used in supplier evaluation models [3, 7]. In contrast, the rebalanced weighting structure reallocates emphasis toward flexibility and reliability, which are often linked with the strengths of smaller suppliers, as discussed in Section 2.4.

The adjustment from traditional to rebalanced weighting structure is achieved by proportionally reducing the weights assigned to dominant criteria, such as cost and logistics, and increasing the weights associated with flexibility and reliability. This shift is designed to represent a realistic change in managerial priorities rather than an extreme redistribution of importance. Both weighting vectors are normalized such that the total weight across all criteria equals one.

The specific weighting values used in this study are presented in Table 2.

Table 2. Weight Vectors Used in the Analysis

Criterion	Traditional Weight	Rebalanced Weight
Logistics	0.513	0.350

Quality	0.129	0.150
Cost	0.262	0.200
Flexibility	0.063	0.200
Reliability	0.033	0.100

Following the introduction of the weight structures, supplier rankings are computed under both scenarios using the MCDM methods described in Section 4.1. By maintaining identical supplier performance data and modifying only the weighting vectors, the analysis isolates the effects of criteria prioritization on ranking outcomes.

This comparison provides the foundation for evaluating sensitivity using the SSSI, as defined in Section 4.2. Differences in supplier rankings between the two weighting scenarios are used to quantify the extent to which selection outcomes depend on the chosen evaluation framework.

5.4 Supplier Classification

To evaluate the impact of weighting changes on different categories of suppliers, a classification of suppliers is introduced within the case study. In this study, suppliers are categorized based on their dominant performance characteristics rather than formal size definitions such as revenue or number of employees.

A supplier is classified as “small” if its relative strengths are primarily associated with flexibility, responsiveness, and adaptability-related criteria, as opposed to scale-driven attributes such as cost efficiency and logistics capacity. This analytical classification aligns with the conceptual framework discussed in Section 2.4, where small suppliers are typically characterized by agility and the ability to respond to dynamic operational requirements [6, 8].

The classification is applied to the supplier dataset used in this study to enable targeted analysis of ranking changes under different weighting scenarios. Specifically, the ranking positions of suppliers identified as small are tracked across both the traditional and fairness-oriented weighting structures. These ranking differences form the basis for computing the SSSI.

It is important to state that this classification is context-specific and is used solely for analytical purposes within the scope of this study. The objective is not to establish a universal definition of supplier size, but rather to distinguish between suppliers with different competitive profiles to evaluate how model structure influences selection outcomes.

6. RESULTS AND DISCUSSION

6.1 Real-World Case Results

The results of applying the proposed methodology to the real-world supplier dataset described in Section 5.1 are presented in this section. Supplier rankings are first computed under the traditional weighting structure, followed by the fairness-oriented weighting scenario. The results are analyzed to assess the sensitivity of supplier selection outcomes to changes in criteria prioritization.

Under the traditional weighting structure, supplier rankings are obtained using the SAW method, with results summarized in Table 3. The ranking reflects a strong emphasis on cost and logistics performance, which together account for most of the total weight. As a result, suppliers with advantages in scale-dependent attributes achieve higher overall scores.

Table 3. Supplier Ranking under Traditional Weights

Supplier	Score	Rank
S_1	0.507	1
S_3	0.312	2
S_2 (Small)	0.181	3

As shown in Table 2, the top-ranked supplier achieves a significantly higher score compared to the others, indicating clear dominance under the traditional evaluation approach. The small supplier, identified based on the classification described in Section 5.4, is ranked lower despite demonstrating competitive performance in flexibility-related criteria. This outcome is consistent with expectations, as flexibility receives relatively low weight under the traditional scenario.

To assess the impact of alternative decision priorities, the same supplier performance data is re-evaluated using the rebalanced weighting structure, with results presented in Table 4.

Table 4. Supplier Ranking under Rebalanced Weights

Supplier	Score	Rank
S_1	0.476	1
S_3	0.338	2
S_2 (Small)	0.187	3

The results indicate that, despite a considerable increase in the weights assigned to flexibility and reliability, the overall supplier ranking remains unchanged. While minor variations in performance scores are observed, these changes are not sufficient to alter the relative ordering of suppliers. Specifically, the small supplier maintains its original ranking position under the adjusted weighting structure.

These results suggest a low level of sensitivity in the supplier selection model for this specific dataset. Despite the weight adjustments to account for criteria where small suppliers excel, the dominance of scale-related performance factors, such as cost and logistics, continues to drive the final ranking. The same rankings were obtained from TOPSIS.

To further illustrate the effect of weight adjustments on supplier scores, a comparison of performance under both weighting scenarios is presented in Figure 1.

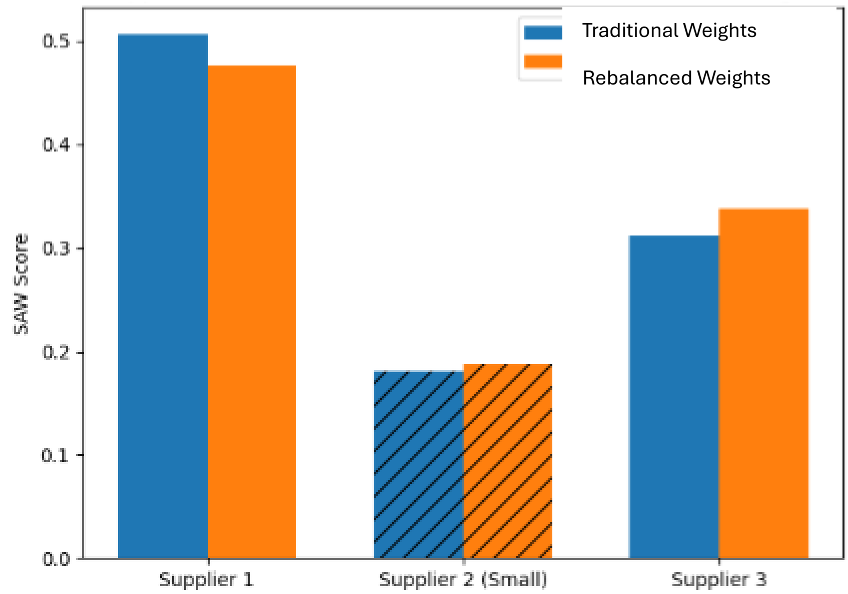

Figure 1. Supplier Scores Under Traditional vs. Rebalanced Weights

Figure 1 shows that while individual suppliers' scores change in response to adjusted weights, the relative differences between suppliers remain largely consistent. This indicates that the underlying performance gaps between suppliers are sufficiently large to outweigh the impact of moderate changes in criteria weighting.

From a managerial perspective, these findings highlight a potential disconnect between intended and actual evaluation outcomes. Although decision-makers may adjust criteria weights to reflect broader priorities, such as flexibility and responsiveness, the resulting supplier rankings may remain largely unaffected if the performance differences across suppliers are substantial. This reinforces the importance of not only selecting appropriate criteria but also understanding how weighting decisions interact with the distribution of supplier performance.

Overall, the real-world case study results demonstrate that supplier selection models may exhibit structural rigidity, where ranking outcomes are relatively insensitive to reasonable changes in evaluation priorities. This observation provides a foundation for further analysis using the SSSI, which quantifies the magnitude of ranking change for small suppliers under alternative weighting scenarios.

6.2 Sensitivity Analysis Results

To quantify the impact of weight changes on supplier rankings, the SSSI is computed using the ranking results obtained under the traditional and rebalanced weighting scenarios. The SSSI captures the average change in ranking position for suppliers classified as small, providing a direct measure of sensitivity to shifts in evaluation priorities.

Based on the ranking results presented in Tables 3 and 4, the positions of small suppliers remain unchanged across both weighting scenarios. Consequently, the computed SSSI value is equal to zero:

$$SSSI = 0$$

This indicates that the supplier selection model exhibits no observable sensitivity with respect to the ranking of small suppliers under the applied weight adjustments. Despite the intentional increase in the importance of flexibility and reliability-related criteria, the relative ordering of suppliers is preserved.

From an analytical perspective, this outcome suggests that underlying performance differences among suppliers outweigh the influence of criteria weighting. Suppliers with strong performance in cost and logistics maintain their ranking advantage even when the relative importance of these criteria is reduced. As a result, moderate adjustments in the weighting structure are insufficient to change decision outcomes.

These observations are consistent with Section 6.1, where score variations did not translate into ranking changes. The SSSI formalizes this observation by providing quantitative confirmation that the ranking positions of small suppliers are insensitive to the tested weighting scenarios.

From a methodological standpoint, the result highlights an important limitation of relying solely on weight adjustments to influence supplier selection outcomes. While decision-makers may attempt to incorporate broader evaluation priorities through reweighting, the effectiveness of such adjustments depends on the distribution of supplier performance across criteria. If performance gaps are substantial, ranking outcomes may remain stable even under alternative weighting structures.

From a managerial perspective, an SSSI value of zero implies that efforts to promote attributes associated with smaller suppliers may not lead to different procurement decisions unless more significant structural changes are introduced. These may include redefining evaluation criteria, introducing threshold-based selection rules, or explicitly incorporating strategic considerations beyond standard MCDM frameworks.

Additionally, the absence of sensitivity in this case stresses the importance of interpreting SSSI values in context. A low or zero SSSI does not necessarily indicate that the evaluation model is biased or flawed; rather, it reflects that the current supplier performance model is robust to the tested variations in weighting. This emphasizes the role of SSSI as a diagnostic tool, enabling decision-makers to distinguish between cases where rankings are inherently stable and those where they are highly dependent on subjective modeling choices.

Overall, the SSSI results demonstrate that, for the given dataset, supplier selection outcomes are structurally stable under realistic shifts in criteria weighting. This motivates the need for further analysis using controlled scenarios, where the effects of performance distribution and weighting adjustments can be more explicitly examined.

6.3 Hypothetical Scenario Analysis

To complement the real-world case study and further evaluate the behavior of the proposed SSSI, a controlled hypothetical scenario is constructed. The purpose of this analysis is to examine conditions under which supplier rankings are sensitive to changes in criteria weighting, thereby illustrating the informative value of the SSSI in a setting where performance differences are less dominant.

In contrast to the real-world dataset, where significant performance gaps between suppliers limit the impact of weight adjustments, the hypothetical scenario is designed to reduce these disparities. Specifically, supplier performance values are defined so that competing suppliers exhibit more balanced strengths across criteria. Hence, no single supplier overwhelmingly dominates in cost, logistics, or quality. This creates a more competitive decision environment in which weighting choices play a greater role in determining ranking outcomes.

Using the same set of evaluation criteria and weighting structures defined in Section 5.3, supplier rankings are computed under both the traditional and rebalanced scenarios. The results under the traditional weighting structure are presented in Table 5.

Table 5. Hypothetical Scenario (Traditional Weights)

Supplier	Cost	Quality	Logistics	Flexibility	Reliability	SAW Score	Rank
S_1	0.90	0.80	0.85	0.60	0.65	0.812	1
S_2	0.85	0.82	0.80	0.65	0.70	0.795	2
$S_3(Small)$	0.70	0.78	0.75	0.90	0.88	0.772	3
S_4	0.75	0.76	0.78	0.70	0.72	0.756	4

Under the traditional weighting scenario, suppliers with relatively stronger performance in cost and logistics achieve higher rankings, consistent with the emphasis placed on these criteria. However, due to the reduced performance gaps, the differences in overall scores between suppliers are relatively small compared to those observed in the real-world case.

The rankings obtained under the fairness-oriented weighting structure are presented in Table 6.

Table 6. Hypothetical Scenario (Rebalanced Weights)

Supplier	SAW Score	Rank
S_1	0.746	3

S_2	0.758	2
$S_3(Small)$	0.812	1
S_4	0.742	4

Unlike the real-world case, the results in this scenario show noticeable changes in supplier rankings when the weighting structure is adjusted. Specifically, suppliers that are characterized by stronger performance in flexibility and reliability experience improvements in their ranking positions, while those relying primarily on cost and logistics experience relative declines. The same rankings were obtained from TOPSIS. These ranking changes are captured quantitatively through the SSSI, which yields a positive value in this scenario:

$$SSSI = (3 - 1) = 2 > 0$$

This suggests that small suppliers improve their average ranking position under the fairness-oriented weighting structure. The positive SSSI value reflects a higher level of sensitivity in the supplier selection model, where changes in criteria importance directly influence decision outcomes.

The contrast between this scenario and the real-world case highlights the importance of performance distribution in determining sensitivity. When supplier performance is relatively balanced, weighting decisions have a more evident impact on rankings. Conversely, when performance differences are substantial, as observed in Section 6.1, ranking outcomes tend to be more stable and less responsive to weight adjustments.

From a methodological perspective, this analysis demonstrates the utility of the SSSI as a diagnostic tool for identifying conditions under which supplier selection outcomes are influenced by subjective modeling choices. The index not only quantifies the magnitude of ranking changes but also provides insight into the direction of those changes, particularly with respect to supplier categories.

From a managerial standpoint, the results suggest that efforts to promote certain supplier attributes through weighting adjustments are more likely to be effective in competitive environments where suppliers exhibit comparable performance levels. In such contexts, decision-makers have greater flexibility to align procurement outcomes with strategic priorities, including support for smaller or more agile suppliers.

Overall, the hypothetical scenario reinforces the central contribution of this study by demonstrating that the sensitivity of supplier rankings is context dependent. The SSSI provides a practical means of assessing this sensitivity, enabling more transparent and informed decision-making across a range of supplier selection environments.

6.4 Discussion and Managerial Insights

The results provide several important insights into the role of criteria weighting in MCDM-based supplier selection and the implications for decision-making in practice.

A key finding of this study is that the sensitivity of supplier rankings to changes in criteria weighting is highly dependent on the underlying distribution of supplier performance. In the real-world case study, where performance differences between suppliers are relatively pronounced, ranking outcomes remain stable despite meaningful adjustments in criteria weights. This is reflected in an SSSI value of zero, indicating that the relative positions of small suppliers are unaffected by shifts in evaluation priorities. In contrast, the hypothetical scenario demonstrates that when supplier performance is more balanced, weighting changes can lead to significant ranking shifts, resulting in a positive SSSI value.

The findings highlight an important distinction between robustness and responsiveness in supplier selection models. While robustness is often desirable, indicating consistency in decision outcomes, excessive stability may also suggest that the model is insensitive to managerial preferences. In such cases, adjustments to criteria weights, commonly used as a tool for aligning decisions with strategic priorities, may have limited practical impact. Conversely, in more competitive environments, where supplier performance is comparable, weighting decisions play a more influential role in shaping outcomes.

From a methodological perspective, this study extends the role of sensitivity analysis in MCDM beyond its traditional use as a validation tool. Rather than focusing solely on whether rankings change, the proposed SSSI provides a structured way to interpret how and for whom these changes occur. By focusing specifically on small suppliers, the index introduces a fairness-oriented lens to supplier evaluation, enabling a more detailed understanding of how model structure influences outcomes across different supplier categories.

From a managerial standpoint, the results offer several practical implications:

- *Awareness of Model Influence*: Decision-makers should recognize that supplier rankings are not solely determined by performance data but are also influenced by how evaluation criteria are weighted. The SSSI provides a transparent mechanism for assessing this influence.
- *Limitations of Weight Adjustments*: Simply adjusting criteria weights may not be sufficient to achieve desired procurement outcomes, particularly in cases where performance differences between suppliers are significant. Alternative approaches, such as revising evaluation criteria or incorporating additional decision rules, may be necessary.
- *Strategic Use of Sensitivity Analysis*: Sensitivity analysis can be used not only to validate model robustness but also to explore how different strategic priorities affect supplier selection. The SSSI enables decision-makers to identify scenarios in which small suppliers are more likely to be competitive.
- *Context-Dependent Decision-Making*: The effectiveness of weighting adjustments depends on the competitive environment of suppliers. In environments with closely matched suppliers, decision-makers have greater flexibility to influence outcomes

through weighting, whereas in highly differentiated environments, rankings may remain stable regardless of preference shifts.

While the SSSI captures whether and how supplier rankings change under different weighting scenarios, it does not quantify the magnitude of weight adjustments required to produce such changes. In practice, decision-makers may also be interested in determining the minimum variation in criteria weights necessary to alter ranking outcomes.

This concept, referred to here as sensitivity threshold, represents the degree of change in weighting required to influence supplier rankings. Incorporating threshold-based sensitivity analysis could provide additional insight into the robustness of decision models and the responsiveness of rankings to changes in managerial priorities.

Overall, the findings emphasize that supplier selection is not purely an objective process, but rather a structured decision influenced by both data and modeling choices. By introducing a diagnostic measure that captures the sensitivity of rankings to these choices, this study contributes to more transparent and informed procurement decision-making.

7. LIMITATIONS AND FUTURE WORK

7.1 Limitations

While the proposed methodology provides valuable insights into the sensitivity of supplier selection outcomes, several limitations should be acknowledged.

First, the analysis is based on a limited number of case studies, including a single real-world dataset and a controlled hypothetical scenario. Although this dual-case approach improves both practical relevance and conceptual clarity. The findings may not fully generalize to all supplier selection contexts, particularly different industries or procurement environments, which may exhibit varying performance distributions and evaluation priorities, which could influence the observed sensitivity patterns.

Second, the classification of suppliers as “small” is based on performance characteristics rather than formal organizational metrics such as firm size, revenue, or workforce. While this analytical classification aligns with the objectives of this study, it may not capture all dimensions of what constitutes a small or medium-sized enterprise in practice. Future work could explore alternative classification approaches that incorporate both operational and structural attributes.

Third, the proposed SSSI relies on ranking changes between two predefined weighting scenarios. Although these scenarios are designed to represent realistic managerial priorities, they do not capture the full range of possible weighting configurations. As a result, the analysis provides a directional understanding of sensitivity rather than a complete characterization of all potential outcomes under varying decision preferences.

Fourth, the study focuses on two widely used MCDM methods, SAW and TOPSIS. While these methods are representative and provide a solid foundation for analysis, other MCDM approaches, especially those incorporating fuzzy logic, stochastic modeling, or machine learning, may exhibit different sensitivity behaviors. Extending the proposed framework to additional methods would further strengthen its general applicability.

Fifth, the analysis assumes that supplier performance data is accurate and static. In real-world settings, performance measures may be subject to uncertainty, estimation errors, or temporal variation. Incorporating dynamic or uncertain data into the sensitivity analysis could provide a more realistic assessment of supplier selection outcomes.

Finally, the proposed Small Supplier Sensitivity Index (SSSI) is designed to evaluate ranking changes specifically for suppliers classified as small, which introduces a perspective-dependent bias. Rather than providing a neutral assessment across all suppliers, the metric focuses on a particular subgroup to highlight differential impacts of weighting structures.

This focus is intentional and aligned with the objective of the study, which is to examine how changes in criteria weighting affect suppliers with characteristics often underrepresented in traditional evaluation models. However, this implies that the SSSI does not capture sensitivity effects for other supplier categories, such as large or highly cost-efficient suppliers.

As a result, the interpretation of SSSI should be understood within the context of its defined scope, and conclusions drawn from the metric should not be generalized to all supplier types.

7.2 Future Work

Building on these limitations, several directions for future research could be explored. A primary avenue for future work is the application of the proposed methodology to larger and more diverse real-world datasets across different industries. This would enable a more comprehensive evaluation of sensitivity patterns and improve the external validity of the findings

Future research could also extend the SSSI framework by exploring alternative formulations that capture additional dimensions of sensitivity, such as variability in score differences or changes in supplier group rankings beyond average position shifts. This could provide a more detailed understanding of how evaluation structures influence decision outcomes.

Another promising direction is the integration of the SSSI with advanced MCDM methods, including fuzzy, stochastic, or hybrid approaches. Investigating how sensitivity behaves in these more complex models would help bridge the gap between methodological advancements and interpretability.

In addition, future studies could examine the role of multi-stakeholder decision-making, where different decision-makers assign different weights to criteria. Incorporating multiple perspectives into the analysis would provide a richer understanding of how conflicting priorities influence supplier selection outcomes.

Moreover, future research could extend the proposed framework by incorporating threshold-based sensitivity analysis to determine the minimum changes in criteria weights required to alter supplier rankings. This would provide a more detailed understanding of the relationship between weighting structures and decision outcomes.

An additional extension of this work is the integration of the SSSI framework into an optimization-based sensitivity model. Rather than evaluating only predefined weighting scenarios, an optimization formulation could be developed to determine the minimum changes required in criteria weights to alter supplier rankings or improve the position of specific supplier groups. In such a framework, the criteria weights would serve as decision variables, while ranking-change conditions would act as constraints. The objective could be formulated to minimize the total deviation from the original weighting structure while achieving a desired ranking outcome. Integrating SSSI into an optimization framework would provide decision-makers with a more systematic method for identifying sensitivity thresholds and understanding the extent of weighting adjustments required to influence supplier selection outcomes.

Finally, the concept of sensitivity-based evaluation could be extended beyond supplier selection to other decision-making contexts, such as project selection, resource allocation, and risk assessment. This would broaden the applicability of the proposed approach and contribute to the development of more transparent and robust decision-support systems.

8. CONCLUSION

This study investigates the role of criteria weighting in MCDM-based supplier selection and its impact on ranking outcomes, with particular focus on small suppliers. While existing research has emphasized the analysis of methodological advancements and robustness, limited attention has been given to how weighting structures influence outcomes across different categories of suppliers. To address this gap, this study introduced the SSSI, a diagnostic metric designed to quantify the sensitivity of supplier rankings to changes in evaluation priorities.

The proposed approach was demonstrated using both a real-world dataset and a controlled hypothetical scenario. The results show that the sensitivity of supplier rankings is highly dependent on the distribution of supplier performance. In the real-world case, where performance differences were significant, ranking outcomes remained stable despite adjustments in criteria weights, resulting in an SSSI value of zero. In contrast, the hypothetical scenario revealed that when supplier performance is more balanced, weighting changes can significantly influence rankings, leading to a positive SSSI value and improved positions for small suppliers.

The findings highlight that supplier selection outcomes are not solely determined by performance data, but are also shaped by modeling choices, particularly the assignment of criteria weights. The SSSI provides a practical and transparent tool for evaluating this influence, enabling decision-makers to better understand when and how their preferences affect procurement outcomes.

From a methodological perspective, this study extends the use of sensitivity analysis in MCDM by shifting its focus from model validation to interpretative insight. Rather than asking whether rankings change, the proposed framework emphasizes understanding how and for whom these changes occur. This perspective contributes to a more detailed and transparent approach to decision-making in supplier evaluation.

From a practical standpoint, the results suggest that decision-makers should carefully consider both the structure of evaluation models and the competitive environment of suppliers when making procurement decisions. In environments with significant performance differences, ranking outcomes may remain robust to changes in weighting, limiting the effectiveness of preference adjustments. Conversely, in more competitive settings, weighting decisions can play a critical role in shaping outcomes and aligning supplier selection with strategic objectives.

Overall, this study demonstrates that sensitivity is a key dimension of supplier selection that has been largely overlooked in existing literature. By introducing a simple and adaptable metric for evaluating sensitivity across supplier groups, this work provides a foundation for more informed, transparent, and context-aware decision-making in MCDM-based evaluation frameworks.

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APPENDIX A: Example of Score Computation

A.1 Raw Data

Supplier	**Cost ($)**	**Quality (%)**
A	100	90
B	80	85

A.2 Normalization

Supplier	**Cost (norm)**	**Quality (norm)**
A	0.80	1.00
B	1.00	0.94

A.3 Apply weights (e.g., 0.6, 0.4)

Supplier	**Score**
A	0.88
B	0.98

For example, Supplier A achieves a normalized cost score of 0.80 and a quality score of 1.00. Applying weights results in a final score of 0.88, which is used for ranking.