# A HYBRID AHP-BWM-ENTROPY FRAMEWORK FOR IDEAL SUPPLIER SELECTION

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**ABSTRACT**

Strategic and efficient supplier selection is a crucial issue that significantly shapes a company's success in a highly competitive and volatile business environment. The need for a resilient and sustainable supply chain is evident in such an environment. This study extends the existing literature by presenting an integrated multi-criteria decision-making (MCDM) framework for evaluating suppliers, taking into account not only traditional criteria such as cost, quality, and delivery but also modern issues such as environmental sustainability and digital transformation. The study initially examines three weighting methods in detail: the Analytical Hierarchy Process (AHP), the Best-Worst Method (BWM), and Entropy. The weights derived from these methods are subsequently used in the Simple Additive Weighting (SAW) procedure to rank the suppliers. The model combines expert-based (AHP, BWM) and objective (Entropy) approaches to provide an integrated and balanced assessment of supplier performance. The findings illustrate that supplier rankings vary depending on the weighting method, thus emphasizing the importance of weighting methods in the decision-making process. Notably, suppliers S3 and S8 consistently ranked lowest across all methods. The results highlight the importance of methodological awareness in decision-making processes and reveal strong patterns in supplier performance. The proposed framework provides managers with a practical tool to align supplier strategies with broader operational and strategic objectives under different evaluation scenarios.

**Keywords:** Analytical Hierarchy Process (AHP); Best-Worst method (BWM); Entropy; Simple Additive Weighting (SAW); supplier selection; decision-making

## 1. Introduction

In today's competitive and constantly evolving world, supply chain management is strategically important to avoid falling behind in the market (Li et al., 2006). Global challenges in areas such as sustainability, green management, digitalization, carbon footprint reduction, the transition from Industry 4.0 to Industry 5.0, and Logistics 5.0 necessitate the development of appropriate strategies (Rame et al., 2024).

Supply chain management has been studied for decades and remains highly relevant to current challenges (Knight et al., 2022). In this context, it is a key element of organizational


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success. Businesses carefully manage supplier sourcing while considering multiple important criteria. One of the most critical steps in supply chain management is the selection and evaluation of suppliers (Araz & Özkarahan, 2007). Supplier evaluation should consider not only cost, quality, and delivery, but also collaborative capability, responsiveness to company needs, and environmental policies (Cayir Ervural, 2024). These criteria collectively form the supplier evaluation process. To ensure a comprehensive and objective evaluation, critical factors affecting supplier performance must be identified. Determining criteria weights is essential for making sound decisions (Dobos & Vörösmarty, 2019).

In a competitive and rapidly changing global economy, supplier evaluation plays a vital role in supplier selection. Strategic decisions are made based on carefully defined criteria and alternatives in order to effectively manage supply chain processes. Therefore, multi-criteria decision-making (MCDM) methods are valuable tools for decision-makers operating under complex conditions (Cayir Ervural, 2024). This is particularly evident in the manufacturing sector, where competition has intensified, especially following the pandemic. Efficient and adaptable suppliers are essential for the stable functioning of supply chains. Supplier selection is a holistic process involving both qualitative and quantitative factors related to competitive objectives, risks, and uncertainty. The complex nature of this process, involving multiple decision-makers, criteria, and alternatives, necessitates the use of MCDM methods (Barretta et al., 2023).

In MCDM problems, determining criteria weights is one of the most critical and challenging steps (Paramanik et al., 2022). These weights reflect the extent to which each criterion influences the final evaluation. Criteria weighting methods can be classified into three main groups: subjective, objective, and hybrid approaches (Ghorabaee et al., 2015).

Subjective weighting methods rely on decision-makers' judgments. However, as the number of criteria increases, these methods may become less reliable due to inconsistencies in evaluations (Ghorabaee et al., 2015). In contrast, objective methods are based on mathematical models and do not incorporate decision-makers' preferences. Hybrid methods combine both approaches. The Analytic Hierarchy Process (AHP), introduced by Saaty, is a widely used subjective method that evaluates the consistency of decision-makers' judgments and ranks criteria based on their importance (Canco et al., 2021).

The Best-Worst Method (BWM), proposed by Rezaei (2015), is another widely used MCDM technique. It requires fewer pairwise comparisons than AHP and provides consistent and reliable results (Xu et al., 2021).

The Entropy method is an objective weighting technique that determines criterion weights based on data variability in the decision matrix (Sitorus & Brito-Parada, 2020). It is considered a data-driven and robust method for handling uncertainty and redundancy in evaluation processes (Mizrak et al., 2024).

This study examines both subjective and objective weighting approaches and evaluates their impact on consistency, diversity, and accuracy. Subjective methods provide flexibility


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and incorporate expert knowledge, while objective methods offer more consistent and data-driven results (Murugesan et al., 2023).

Unlike most existing studies that integrate two approaches, this study combines three different weighting methods (AHP, BWM, and Entropy) within the Simple Additive Weighting (SAW) framework. This integrated approach enhances the robustness and multidimensionality of supplier evaluation in supply chain management and provides practical insights for manufacturing firms seeking to balance multiple criteria.

The study applies AHP-based SAW, BWM-based SAW, and Entropy-based SAW methods to evaluate suppliers from a multidimensional perspective. Criteria weights are first determined using each method and then used to rank suppliers via SAW. This approach offers a structured and comprehensive framework that integrates both subjective and objective perspectives.

## 2. Literature review

Supplier selection has long been recognized as a challenging problem due to its complex and multidimensional nature (Cayir Ervural, 2024). In view of this complexity, the literature still strongly facilitates the use of various multi-criteria decision-making (MCDM) methods. The so-called popular methods are AHP (Saaty, 1980), ANP (Saaty, 1996), Data Envelopment Analysis (DEA) (Charnes et al., 1978), and TOPSIS (Hwang & Yoon, 1981). However, as these methods are very transparent and easy to understand, they may not be able to handle a large number of criteria and alternatives (Kuo et al., 2010; Junior et al., 2014).

Alongside with supplier selection models, data analytics and machine learning are new developments that have been integrated into the traditional methods (Ho et al. 2010). Besides that, a new type of hybrid methods have been combining artificial intelligence with MCDM have also been demonstrated in terms of better decision-making capabilities (e.g., Golmohammadi et al., 2009; Ha & Krishnan, 2008; Fallahpour et al., 2016; Abdulla et al., 2019).

Recent research indicates that the Best-Worst Method (BWM) is often combined with other methods such as compromise solution methods, goal programming, and fuzzy logic systems. While it is true that AHP, BWM, and Entropy methods are used separately for supplier evaluation, there are very few studies that combine all three methods within a single framework.

Several hybrid approaches have been proposed in the literature. For example, Tavana (2021) developed a model integrating the Fuzzy Group Best-Worst Method (FG-BWM) and Fuzzy Combined Compromise Solution (FCoCoSo) for reverse supply chain supplier selection. Rostami et al. (2023) proposed a hybrid framework combining goal programming and fuzzy BWM for supplier evaluation in the medical device industry. Similarly, Hailiang et al. (2023) applied FBWM using a multi-stage fuzzy sustainability index while considering the impacts of COVID-19. Ecer and Pamucar (2020) combined


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FBWM with CoCoSo to address sustainable supply chain management under fuzzy conditions.

Other studies have explored different hybridizations of MCDM methods. Shang et al. (2022) combined BWM and Entropy methods within a fuzzy MULTIMOORA framework, while Vaezi et al. (2024) integrated BWM with MULTIMOORA and optimization models. Masoomi et al. (2022) proposed a hybrid fuzzy BWM–COPRAS–WASPAS approach for green supplier selection. Similarly, Wang et al. (2021) developed a fuzzy entropy-based MULTIMOORA model, and Lahri et al. (2021) combined BWM, TOPSIS, and optimization techniques for supply chain network design.

Additional approaches include fuzzy TOPSIS (Hajiaghaei-Keshteli et al., 2023), modified TODIM methods (Wang et al., 2023), and multi-stage fuzzy BWM-based models (Hendiani et al., 2020), all of which highlight the growing interest in handling uncertainty in supplier selection.

Overall, the literature demonstrates that supplier selection problems are increasingly addressed באמצעות integrated and fuzzy decision-making approaches. However, while several studies have combined two methods, no study explicitly combining AHP, BWM, and Entropy within a unified SAW-based framework has been identified. Therefore, this study contributes to the literature by proposing a novel integrated approach that evaluates both subjective and objective weighting methods and examines their impact on decision-making consistency and accuracy.

## 3. Methodology

In this section, the AHP, BWM, Entropy, and SAW methods are presented. These methods are selected to integrate both subjective and objective weighting approaches and to provide a comprehensive framework for supplier evaluation.

### 3.1 Analytical Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), developed by Saaty (1977), is a widely used MCDM method for analyzing complex decision problems. It structures problems hierarchically and derives criteria weights through pairwise comparisons. The method supports both qualitative and quantitative data and incorporates expert judgments. The AHP methodology involves the following key steps:

1. *Problem Definition and Objective Setting:* Begin by clearly outlining the decision problem and establishing the main goal to guide the process.
2. *Hierarchy Construction:* Break down the problem into a hierarchical model, with the overarching goal at the top level, followed by criteria and sub-criteria, and finally the decision alternatives at the bottom.
3. *Pairwise Comparisons:* Evaluate elements at each level of the hierarchy by comparing them in pairs to determine their relative importance. This is usually done on a scale from 1 to 9, where 1 represents the lowest level of importance and 9 signifies extreme importance of one element over another.


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4. *Deriving Weights:* Calculate the relative weights of each element based on the pairwise comparisons. This step involves normalizing the comparison matrices and determining the principal eigenvector.
5. *Consistency Check:* Evaluate the consistency of the judgments using the Consistency Index (CI) and Consistency Ratio (CR). A CR of 0.10 or lower is considered acceptable; higher values indicate the need for review.
6. *Results Synthesis:* Aggregate the weights of criteria and sub-criteria to calculate a final score for each alternative. This is done by multiplying the alternative scores by the corresponding criteria weights and summing the results.
7. *Decision Making:* Select the option with the highest overall score as the preferred choice.

One of the main characteristics of the AHP is that it can collect the views of experts through a complex pairwise comparison procedure. On the other hand, the BWM mainly relies on a straightforward questionnaire, but the AHP provides a more thorough and systematic assessment framework.

### 3.2 Best-Worst Method (BWM)

BWM has gained popularity among researchers, practitioners, and organizations in recent years. The BWM was introduced by Rezaei (2015) and compared the best and/or worst criteria to establish the relative importance of all criteria based on judgment (Rezaei, 2015). Assessing criteria may take the form of both numerical and qualitative (verbal) assessments. The verbal assessment is converted into numerical values using a 9-point scale system to define the best-to-worst ratio. Because the AHP shares some similarities with the BWM, critics have suggested that the BWM could be considered an alternative to the AHP due to its simplicity, processing speed, and the fact that it requires fewer pairwise comparisons. The steps in conducting a BWM analysis are shown below:

Step 1 - *Identify the Decision Criteria*
At this stage, a set of criteria $\{c_1, c_2, \ldots, c_n\}$ is established, which will serve as the foundation for making the final decision.

Step 2- *Select the Best and Worst Criteria*
The decision-makers determine which criterion is considered the most important $(C_B)$ and which one is the least important $(C_W)$among the set.

Step 3 – *Rate the Best Criterion Against the Others*
The relative preference of the best criterion over each of the remaining criteria is assessed using a scale from 1 to 9. This creates a vector:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$$

where each $A_B$ value represents how strongly the best criterion is preferred over criterion *j*.

Step 4 – *Rate the Other Criteria Against the Worst*


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Each of the remaining criteria are compared to the worst criterion using the same 1 to 9 scale. This generates a second vector:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{\mathrm{n}W})$$

In this vector, each $a_{\mathrm{j}W}$ indicates how much more important criterion *j* is compared to the worst criterion.

Step 5- *Calculate the Optimal Weights*

The final step involves computing the optimal weights $\{w_1, w_2, \dots, w_n\}$ assigned to the criteria by solving an optimization model. This step also considers the value *ε*, which is used to assess the consistency of the judgments.

To determine the ideal weights for each criterion, an optimization model is used. This model minimizes the maximum deviation *ε*, which also serves as a measure of consistency in the decision-making process. The model is structured in Equation 1 as follows:

$$\begin{gathered} \min \varepsilon \\ s.t. \\ \left| \frac{\mathrm{W}_B}{\mathrm{W}_j} - a_{Bj} \right| \leq \varepsilon, \forall j \\ \left| \frac{\mathrm{W}_j}{\mathrm{W}_W} - a_{jW} \right| \leq \varepsilon, \forall j \\ \sum_j \mathrm{w}_j = 1 \\ \mathrm{w}_j \geq 0, \forall j \end{gathered} \tag{1}$$

Step 6- *Evaluate the Consistency Ratio*

After solving the model and determining *ε*, the consistency of the results is assessed using the Consistency Ratio (CR) is calculated as follows in Equation 2:

$$\textit{Consistency ratio (CR)} = \frac{\varepsilon}{Consistency\ index\ (CI)} \tag{2}$$

A *CR* close to 0 reflects that the pairwise comparisons are very consistent, while a value around 1 indicates less consistency. In order to better estimate the weights, one can also determine upper and lower bounds for each criterion weight by solving two different optimization problems as shown in Equation 3 (for maximizing aim and minimizing aim for each weight):


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$$\begin{aligned} & max\ \ \mathrm{w}_j\ or\ min\ \mathrm{w}_j \\ & \left|\frac{\mathrm{W}_B}{\mathrm{W}_j} - a_{Bj}\right| \leq \varepsilon, \forall j \\ & \left|\frac{\mathrm{W}_j}{\mathrm{W}_W} - a_{jW}\right| \leq \varepsilon, \forall j \\ & \sum_j \mathrm{w}_j = 1 \\ & \mathrm{w}_j \geq 0, \forall j \end{aligned} \tag{3}$$

This operation allows an interval of confidence for each weight to be established, thus leading to a more reliable decision-making process.

### 3.3 Entropy method

Entropy, which is a concept from various scientific disciplines such as physics, chemistry, and mathematics, is applied in the field of information theory as a measure of the amount of unpredictability of information. In decision-making, the Entropy approach is utilized to determine the weight of criteria considering the decision matrix, which is compiled from the hierarchical approach. The Entropy method consists of following steps:

Step 1 – *Construct the Decision Matrix*
The initial step includes the preparation of a decision matrix of dimension $m \times n$:

$$\begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}_{m*n}$$

where $x_{ij}$ represents the performance or score of alternative $i$ under criterion with $i = 1,2, \ldots, m$ and $j = 1,2, \ldots, n$.

Step 2- *Normalize the Decision Matrix*
Each element in the matrix is then normalized based on the formula described in Equation 4:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{j} x_{ij}} \tag{4}$$

This results in finding a set of normalized values $r_{ij}$, which denote the relative performance measurements of different alternatives relative to each criterion.

Step 3- *Calculate Entropy for Each Criterion*
The values of entropy vary according to the amount of disorder or uncertainty associated with each criterion. The entropy of criterion $i$ is calculated as in Equation 5:


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$$e_j = -k \sum_{j=1}^{n} r_{ij} \ln(r_{ij}) \qquad i = 1 \dots m \; j = 1 \dots n \tag{5}$$

where $k = 1/\ln(m)$ is a normalization constant and $e_j$ is the entropy score for criterion j.

Step 4- *Determine the Degree of Diversification*
The degree of diversification $d_j$ which measures the amount of useful information contained in each criterion for each alternative is calculated as shown below in Equation 6:

$$d_j = 1 - e_j \tag{6}$$

Step 5- *Calculate the Weights of the Criteria*
The final weights assigned to each criterion based on the extent of diversification defined in Equation 7:

$$w_j = \frac{d_j}{\sum_{i=1}^{m} d_j} \tag{7}$$

The weights $w_j$ represent the relative importance of each criterion, and they are normalized such that their sum equals 1 (Equation 8):

$$\sum_{i=1}^{n} w_j = 1 \tag{8}$$

**3.4 Simple Additive Weighting**

The Simple Additive Weighting (SAW) method is a prominently applied MCDM tool for evaluating and ranking alternatives using various factors. In this approach, alternatives are rated against criteria that have an associated weight reflecting their significance. The final score of each alternative is obtained by summing the weighted criterion values, which makes it relatively simple to compare and select the best alternative.
The general steps for applying the SAW method are as follows:
Step 1- *Define the Criteria*
Criteria for evaluating the alternatives have to be defined.

Step 2- *Normalize the Data*
Since the criteria may have different units or scales, their values must be normalized to ensure comparability. For this purpose, different normalization methods such as minimum and maximum scaling and z-score standardization can be used.

Step 3- *Assign Weights to Criteria*
The relative importance of each criterion must be determined. These weights should sum to 1 (or 100%) to ensure consistency in the evaluation.


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Step 4- *Calculate the Weighted Sum*
For each alternative, multiply the normalized value of each criterion by its corresponding weight. Sum these weighted values to obtain an overall score for each alternative.

Step 5- *Rank the Alternatives*
The alternatives are ranked based on the scores obtained.
The SAW method is straightforward and a transparent tool which is commonly believed to be an efficient method for decision-making in situations with multiple criteria. However, the accuracy of SAW results mainly relies on the normalization process and the correctness of the weights assigned to the criteria.

## 4. Application of the method

Choosing the right supplier is a difficult decision-making problem which involves multiple, often conflicting criteria and alternatives. One effective approach to addressing this problem is to use MCDM methods that have been extensively used in the supplier selection process. Numerous studies such as (Fallahpour et al., 2017; Govindan et al., 2015; Kannan et al., 2014; Luthra et al., 2017; Memari et al., 2019) have demonstrated the advantages and applications of such techniques in real situations. The specific criteria set used for evaluation is described in Table 1.

Table 1
Definition of the variables

| **Variables** | **Definition** |
|---|---|
| Price | The cost per unit of the material provided by the supplier. |
| Quality | Quality refers to how well a product conforms to predetermined qualitative and quantitative standards. The score indicates how well the supplier meets the product requirements. |
| Delivery Performance | The supplier’s ability to deliver the correct quantities on time, expressed as the percentage of on-schedule and accurate deliveries. |
| Environmental Sensitivity | The supplier’s commitment to environmental protection and pollution reduction, as well as the extent to which their products align with eco-friendly standards. |
| Digital Transformation Efforts | The supplier's efforts to implement and digitally store data and manage processes through technologies. It entails utilization of systems such as ERP systems (e.g., SAP), digital documentation in place of paper-records, and the usage of software platforms for workflow management. |

In MCDM, one of the most difficult steps is assigning the relative weights for each criterion, and this is often done subjectively. Since in most cases the weights were assigned through the views of a group of decision makers or experts in the field, there has been a


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need to ensure the weights are judged in an objective way in order to compensate for the existing biases in the approach. The supplier selection process in this study consisted of three decision-makers (DMs), all of whom had substantial expertise and held managerial positions in the logistics, quality assurance, and purchasing departments of the company. These individuals were intentionally chosen due to their direct participation in supplier evaluation and procurement activities, which guaranteed that their decisions were based on practical experience and knowledge of the domain.
In this study, three different supplier selection techniques were used to get reliable results: the AHP-based SAW, BWM-based SAW, and entropy-based SAW. The SAW method was selected due to its transparency, simplicity, and ease of implementation. SAW makes it possible to directly aggregate criteria weights derived from various weighting methods and gives final results that are easy to understand, which is an important aspect in practical applications of supplier selection. Other MCDM methods such as TOPSIS and VIKOR are more robust and have been used more frequently in supplier selection, however, the focus of the study was only on the comparison of different weighting methods and not on the ranking algorithm. Therefore, the SAW method was chosen to maintain clarity and practical applicability.

These methods were used to identify and prioritize key factors by determining the criteria weights and ranking them accordingly. Initially, the AHP and BWM were used to determine the relative significance of the factors affecting optimal supplier selection by computing their weights subjectively. Following that, the SAW method was used to rank the suppliers based on the derived criteria weights. Figure 1 illustrates the hierarchical structure used for evaluating the ideal supplier selection problem, considering both main and sub-criteria.

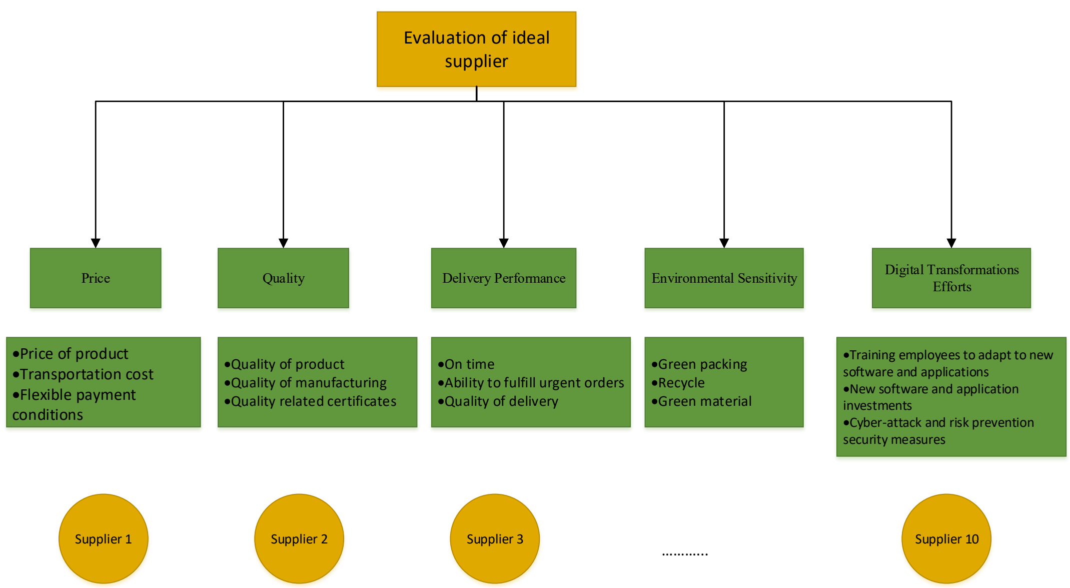


Figure 1 Hierarchy diagram


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This study aims to identify suitable suppliers for a packaging company (manufacturing company) by using main and sub-criteria determined through a comprehensive literature review, as well as the opinions of managers working in the logistics, quality, and purchasing departments of the company. According to some researchers, excessive pairwise comparisons can cause participants to become disengaged and tired (Saaty & Ozdemir, 2003). Therefore, the aim of this study is to obtain efficient and practical analysis by performing a sufficient number of pairwise comparisons. The AHP hierarchy in Figure 1 demonstrates the criteria and sub-criteria used in this study. The hierarchy aims to evaluate the significance of five main criteria at the second level, and sub-criteria at the third level.

A comprehensive set of supplier selection factors was gathered from relevant literature to identify the most suitable criteria for choosing the optimal supplier. The supply chain management unit then assessed and prioritized five main criteria using the AHP, BWM, and Entropy methods.

The criteria included in this study were price, quality, delivery performance, environmental sensitivity, and digital transformation efforts. Each main criterion was divided into sub-criteria as stated below. A total of 15 sub-criteria were determined in the AHP application.

To evaluate the relative importance of the five main criteria at the second level of the AHP hierarchy, pairwise comparison matrices were developed by three decision-makers and subsequently combined using the geometric mean method. The judgments of the three DMs were collected through pairwise comparisons of criteria and sub-criteria in the AHP framework. To consolidate the expert opinions into a single decision matrix, the geometric mean method was employed. This aggregation approach is widely accepted in AHP applications as it effectively balances individual preferences while minimizing the impact of extreme values.

Next, at the third level of the hierarchy, pairwise comparisons were carried out for the sub-criteria under each of the five main categories, price, quality, delivery performance, environmental sensitivity, and digital transformation efforts, with three comparisons conducted within each category. To assess the consistency of each decision-maker's evaluations, the CR was calculated for every pairwise comparison matrix. All CR values were below the commonly accepted threshold of 0.10 (10%), indicating satisfactory internal consistency in judgments. The acceptable CR values and aggregation technique contribute to the robustness and reliability of the final weightings

The evaluations of DMs 1, 2 and 3 are given in Appendix 1. Table 2 shows an aggregated evaluation of the opinions of the three decision makers. The pairwise comparison matrix for sub-criteria of price, quality, delivery, environmental sensitivity, and digital transformation are given in Appendix 2.


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Table 2
Aggregated opinions of the decision makers

| | DM1 | DM2 | DM3 | Aggregated Weights |
|---|---|---|---|---|
| Price | 0.316 | 0.306 | 0.352 | 0.3241 |
| Quality | 0.380 | 0.352 | 0.264 | 0.3281 |
| Delivery performance | 0.175 | 0.201 | 0.207 | 0.1938 |
| Environmental sensitivity | 0.084 | 0.098 | 0.120 | 0.0996 |
| Digital transformation efforts | 0.045 | 0.044 | 0.057 | 0.0483 |

Table 3 presents the global priorities of the main criteria and sub criteria.

Table 3
Global weights and local weights of criteria and sub-criteria (Priorities)

| | Weights | | Local Weights | Global Weights | Rank |
|---|---|---|---|---|---|
| Price | 0.324 | Price of product | 0.648 | 0.210 | 1 |
| | | Transportation cost | 0.23 | 0.075 | 5 |
| | | Flexible payment conditions | 0.122 | 0.040 | 8 |
| | | | | | |
| Quality | 0.328 | Quality of product | 0.582 | 0.191 | 2 |
| | | Quality of manufacturing | 0.309 | 0.101 | 4 |
| | | Quality related certificates | 0.109 | 0.036 | 10 |
| | | | | | |
| Delivery Performance | 0.194 | On time | 0.594 | 0.115 | 3 |
| | | Ability to fulfill urgent orders | 0.249 | 0.048 | 6 |
| | | Quality of delivery | 0.157 | 0.030 | 11 |
| | | | | | |
| Environmental sensitivity | 0.099 | Green packaging | 0.443 | 0.044 | 7 |
| | | Recycling | 0.387 | 0.038 | 9 |
| | | Green material | 0.169 | 0.017 | 13 |
| | | | | | |
| Digital transformation efforts | 0.048 | Training employees to adapt to new software and applications | 0.413 | 0.020 | 12 |

| | Weights | | Local Weights | Global Weights | Rank |
|---|---|---|---|---|---|
| | | New software and application investments | 0.26 | 0.012 | 15 |
| | | Cybersecurity and risk prevention security measures | 0.327 | 0.016 | 14 |

The comparison matrix for the main criteria at the second level of the AHP hierarchy, along with five pairwise comparison matrices for the sub-criteria at the third level is presented. Since the AHP relies on subjective judgments, some degree of inconsistency may occur in the results. To evaluate the reliability of these comparisons, the consistency ratio is calculated; values below 10% indicate that the judgments are consistent and acceptable. The CR is calculated to assess the reliability of pairwise comparisons. Values below 0.1 are generally accepted as consistent. CR values close to or exceeding this threshold indicate potential inconsistency, which may reduce confidence in the derived weights. In such cases, re-evaluation of judgments or sensitivity analyses are recommended. In this study, CR values for all matrices were below 0.1, confirming acceptable consistency.

The overall global priorities of the main attributes as well as the local priorities of the sub-attributes were obtained by normalizing the combined values. This guarantees that the overall sum of global priority for all main attributes is 1, and the local priorities for each attribute category sum to 1 as well. (Saaty, 2006; Saaty, 2008) Table 3 shows the global priorities of the five main attributes, the local priorities of their respective sub-attributes, and the resulting global priorities of each sub-attribute.

Among the main factors identified in the evaluation, quality was the leading one, with price, delivery performance, environmental sensitivity and digital transformation efforts coming afterward in the order of importance. A more detailed study of the local preferences showed that price of the product was the most important sub-component of the price component. Product quality was the highest in the quality section. On-time delivery was the first in the delivery performance category. Green packaging was the most important sub-attribute in the environmental sensitivity theme. Finally, the most important sub-attribute under the digital transformation efforts category was training employees to use new software and applications.

The global priority for each sub-attribute was calculated by multiplying its local priority by the global priority of its corresponding main attribute. This analysis identified the top five sub-attributes with the highest global priorities as 'price of product,' 'on-time delivery,' 'quality of product,' 'green packaging'' and 'training employees to adapt to new software and applications.' On the other hand, the sub-attributes with the lowest global priorities were found to be 'quality-related certificates,' 'flexible payment conditions,' and 'quality of delivery'.

Once the criteria weights were determined using the AHP method, the SAW method was employed in the second stage to rank the suppliers by evaluating fifteen key sub-criteria


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based on their assigned importance. In the SAW approach, the decision matrix was first normalized linearly, followed by multiplying the normalized values by the AHP-derived weights. The results were then ranked in descending order based on the calculated scores (as shown in Tables 4–5).

Table 4
Decision matrix for SAW method

| Weights | 0.030 | 0.043 | 0.038 | 0.016 | 0.019 | 0.012 | 0.015 |
|---|---|---|---|---|---|---|---|
| | C33 | C41 | C42 | C43 | C51 | C52 | C53 |
| S1 | 10 | 10 | 10 | 9 | 8 | 7 | 8 |
| S2 | 7 | 9 | 8 | 10 | 7 | 8 | 7 |
| S3 | 6 | 8 | 8 | 8 | 8 | 7 | 8 |
| S4 | 9 | 8 | 8 | 8 | 10 | 9 | 10 |
| S5 | 9 | 7 | 6 | 7 | 6 | 5 | 6 |
| S6 | 9 | 7 | 7 | 7 | 8 | 8 | 8 |
| S7 | 7 | 8 | 8 | 8 | 7 | 8 | 7 |
| S8 | 7 | 6 | 7 | 7 | 8 | 8 | 8 |
| S9 | 10 | 7 | 6 | 6 | 7 | 8 | 7 |
| S10 | 10 | 10 | 9 | 9 | 5 | 4 | 5 |

| Weights | 0.210 | 0.074 | 0.039 | 0.191 | 0.101 | 0.035 | 0.115 | 0.048 |
|---|---|---|---|---|---|---|---|---|
| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 |
| S1 | 10 | 9 | 8 | 10 | 9 | 9 | 10 | 9 |
| S2 | 4 | 3 | 4 | 9 | 8 | 8 | 7 | 7 |
| S3 | 8 | 7 | 8 | 6 | 6 | 7 | 6 | 5 |
| S4 | 4 | 5 | 5 | 8 | 8 | 8 | 9 | 8 |
| S5 | 5 | 6 | 5 | 7 | 6 | 6 | 10 | 9 |
| S6 | 3 | 3 | 4 | 5 | 5 | 5 | 10 | 9 |
| S7 | 7 | 7 | 7 | 5 | 6 | 5 | 7 | 6 |
| S8 | 6 | 6 | 5 | 3 | 4 | 4 | 7 | 6 |
| S9 | 8 | 7 | 9 | 4 | 5 | 4 | 10 | 10 |
| S10 | 9 | 8 | 8 | 9 | 9 | 8 | 10 | 10 |

Table 5
Normalized decision matrix for SAW

| Weights | 0.210 | 0.074 | 0.039 | 0.190 | 0.101 | 0.035 | 0.115 | 0.048 |
|---|---|---|---|---|---|---|---|---|
| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 |
| S1 | 0.3 | 0.333 | 0.5 | 1 | 1 | 1 | 1 | 0.9 |
| S2 | 0.75 | 1 | 1 | 0.9 | 0.888 | 0.888 | 0.7 | 0.7 |
| S3 | 0.375 | 0.428 | 0.5 | 0.6 | 0.666 | 0.777 | 0.6 | 0.5 |
| S4 | 0.75 | 0.6 | 0.8 | 0.8 | 0.888 | 0.888 | 0.9 | 0.8 |
| S5 | 0.6 | 0.5 | 0.8 | 0.7 | 0.666 | 0.666 | 1 | 0.9 |
| S6 | 1 | 1 | 1 | 0.5 | 0.555 | 0.555 | 1 | 0.9 |
| S7 | 0.428 | 0.428 | 0.571 | 0.5 | 0.666 | 0.555 | 0.7 | 0.6 |
| S8 | 0.5 | 0.5 | 0.8 | 0.3 | 0.444 | 0.444 | 0.7 | 0.6 |
| S9 | 0.375 | 0.428 | 0.444 | 0.4 | 0.555 | 0.444 | 1 | 1 |
| S10 | 0.333 | 0.375 | 0.5 | 0.9 | 1 | 0.888 | 1 | 1 |

| Weights | 0.030 | 0.043 | 0.038 | 0.01 | 0.019 | 0.012 | 0.015 |
|---|---|---|---|---|---|---|---|
| | C33 | C41 | C42 | C43 | C51 | C52 | C53 |
| S1 | 1 | 1 | 1 | 0.9 | 0.8 | 0.777 | 0.8 |
| S2 | 0.7 | 0.9 | 0.8 | 1 | 0.7 | 0.888 | 0.7 |
| S3 | 0.6 | 0.8 | 0.8 | 0.8 | 0.8 | 0.777 | 0.8 |
| S4 | 0.9 | 0.8 | 0.8 | 0.8 | 1 | 1 | 1 |
| S5 | 0.9 | 0.7 | 0.6 | 0.7 | 0.6 | 0.555 | 0.6 |
| S6 | 0.9 | 0.7 | 0.7 | 0.7 | 0.8 | 0.888 | 0.8 |
| S7 | 0.7 | 0.8 | 0.8 | 0.8 | 0.7 | 0.888 | 0.7 |
| S8 | 0.7 | 0.6 | 0.7 | 0.7 | 0.8 | 0.888 | 0.8 |
| S9 | 1 | 0.7 | 0.6 | 0.6 | 0.7 | 0.888 | 0.7 |
| S10 | 1 | 1 | 0.9 | 0.9 | 0.5 | 0.444 | 0.5 |

The final rankings, presented in Table 6, indicate that Suppliers 2, 4, and 6 achieved the top three positions, while Supplier 8 ranked the lowest.

Table 6
AHP weighted SAW scores and suppliers' ranks

| **Suppliers** | **AHP weighted SAW Score** | **Rank** |
|---|---|---|
| S2 | 0.823 | 1 |
| S4 | 0.805 | 2 |
| S6 | 0.790 | 3 |
| S1 | 0.760 | 4 |
| S10 | 0.733 | 5 |
| S5 | 0.699 | 6 |
| S7 | 0.573 | 7 |
| S9 | 0.570 | 8 |
| S3 | 0.569 | 9 |
| S8 | 0.527 | 10 |


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**BWM Application:**
Table 7 shows the criteria weights obtained using the BWM approach. It includes the weight values that determine the importance levels of the main criteria and sub-criteria. The weight values reflect the relative importance of the criteria in the decision-making process and show the rates at which they will affect the results. Consistency analysis is crucial for assessing the reliability of the results. When the consistency value approaches zero, this indicates that the evaluations are consistent. As a result of the calculations, all criteria were consistent. The experts were asked to re-evaluate the surveys with inconsistent results in the calculated consistency rates and consistency was ensured through these re-evaluations. The pairwise matrix best to others and others to worst matrix were constructed based on the decision maker's opinion.

Table 7
Evaluation of main criteria and sub criteria

**Evaluation of main criteria**

| Best criteria: Quality (C1) | Least important criteria: Digital transformation efforts (C5) | | | | |
|---|---|---|---|---|---|
| The best to others (C1) | C1 | C2 | C3 | C4 | C5 |
| | 1 | 2 | 3 | 4 | 5 |
| Others to worst (C5) | C1 | C2 | C3 | C4 | C5 |
| | 4 | 4 | 3 | 2 | 1 |
| *CR:0.20; Associated threshold:0.2306* | | | | | |

**Evaluation of Price criteria**

| Best criteria: Price of product (C11) | Least important criteria: Flexible payment conditions (C13) | | |
|---|---|---|---|
| The best to others (C11) | C11 | C12 | C13 |
| | 1 | 2 | 5 |
| Others to worst (C13) | C11 | C12 | C13 |
| | 5 | 3 | 1 |
| *CR:0.05; Associated threshold:0.1354* | | | |

**Evaluation of Quality criterion**

| Best criteria: Quality of product (C21) | Least important criteria: Quality related certificates (C23) | | |
|---|---|---|---|
| The best to others (C21) | C21 | C22 | C23 |
| | 1 | 2 | 5 |
| Others to worst (C23) | C21 | C22 | C23 |
| | 5 | 3 | 1 |
| *CR:0.05; Associated threshold:0.1354* | | | |


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| | | | |
|---|---|---|---|
| **Evaluation of Delivery performance criterion** | | | |
| Best criteria: On time (C31) | Least important criteria: Ability to fulfill urgent orders (C33) | | |
| The best to others (C31) | C31 | C32 | C33 |
| | 1 | 2 | 4 |
| Others to worst (C33) | C31 | C32 | C33 |
| | 3 | 2 | 1 |
| *CR:0.083; Associated threshold:0.1121* | | | |
| **Evaluation of Environmental sensitivity criterion** | | | |
| Best criteria: Green packaging (C41) | Least important criteria: Green material (C43) | | |
| The best to others (C41) | C41 | C42 | C43 |
| | 1 | 2 | 1 |
| Others to worst (C43) | C41 | C42 | C43 |
| | 3 | 2 | 1 |
| *CR:1* | | | |
| **Evaluation of Digital transformation efforts criterion** | | | |
| Best criteria: New software investment (C51) | Least important criteria: Training employees to adapt to new software and applications (C53) | | |
| The best to others (C51) | C51 | C52 | C53 |
| | 1 | 2 | 4 |
| Others to worst (C53) | C51 | C52 | C53 |
| | 3 | 2 | 1 |
| *CR:0.083; Associated threshold:0.1121* | | | |

Table 8 demonstrates global and local weights of criteria and sub-criteria.


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Table 8
Global weights and local weights of criteria and sub-criteria

| Main criteria | Weights | Sub-criteria | Local weights | Global weights | Rank |
|---|---|---|---|---|---|
| Price | 0.24 | Price of product | 0.583 | 0.139 | 2 |
| | | Transportation cost | 0.305 | 0.073 | 5 |
| | | Flexible payment conditions | 0.111 | 0.026 | 12 |
| | | | | | |
| Quality | 0.40 | Quality of product | 0.583 | 0.233 | 1 |
| | | Quality of manufacturing | 0.305 | 0.122 | 3 |
| | | Quality related certificates | 0.111 | 0.044 | 8 |
| | | | | | |
| Delivery performance | 0.16 | On time | 0.538 | 0.086 | 4 |
| | | Ability to fulfill urgent orders | 0.307 | 0.049 | 7 |
| | | Quality of delivery | 0.153 | 0.024 | 13 |
| | | | | | |
| Environmental sensitivity | 0.12 | Green packaging | 0.444 | 0.053 | 6 |
| | | Recycling | 0.333 | 0.039 | 10 |
| | | Green material | 0.222 | 0.026 | 11 |
| | | | | | |
| Digital transformation efforts | 0.08 | Training employees to adapt to new software and applications | 0.538 | 0.043 | 9 |
| | | New software and application investments | 0.307 | 0.024 | 14 |
| | | Cybersecurity and risk prevention security measures | 0.153 | 0.012 | 15 |

The results highlight the significance of the overall criteria in the decision-making process for selecting the ideal supplier within the manufacturing sector under consideration. According to the results obtained, quality ranks first, price ranks second, delivery performance ranks third, environmental sensitivity ranks fourth, and digital transformation efforts rank last. In the evaluations, for the main criterion of quality, the sub-criterion of ‘product quality’ is ranked first and ‘manufacturing quality’ is ranked third. For the main criterion of price, the ‘price of the product’ was ranked second. For the main criterion of ‘delivery performance,’ the sub-criterion of ‘on time’ is ranked fourth.

After determining the criteria weights using the BWM method, the ideal supplier ranking was established by evaluating fifteen key criteria as determined by the SAW method in the second stage. In the SAW approach, the decision matrix was first linearly normalized, after which the BWM-derived weights were applied and the results were ranked in descending order according to the calculated values (shown in Tables 9-11).

The weights considered in the light of the evaluations seen in Table 9 show the level of importance and effectiveness of the main and sub-criteria in the selection process for suppliers.

Table 9
Decision matrix for BWM

| Weights | 0.139 | 0.073 | 0.026 | 0.233 | 0.122 | 0.044 | 0.086 | 0.049 |
|---|---|---|---|---|---|---|---|---|
| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 |
| S1 | 9 | 8 | 7 | 9 | 8 | 8 | 9 | 10 |
| S2 | 2 | 3 | 3 | 10 | 9 | 7 | 8 | 7 |
| S3 | 7 | 8 | 8 | 5 | 5 | 6 | 7 | 5 |
| S4 | 3 | 4 | 5 | 7 | 9 | 8 | 8 | 7 |
| S5 | 4 | 5 | 4 | 6 | 5 | 6 | 9 | 7 |
| S6 | 3 | 4 | 3 | 4 | 4 | 4 | 9 | 8 |
| S7 | 6 | 6 | 5 | 4 | 5 | 5 | 7 | 5 |
| S8 | 5 | 5 | 6 | 4 | 3 | 3 | 7 | 5 |
| S9 | 7 | 8 | 7 | 5 | 6 | 5 | 9 | 10 |
| S10 | 8 | 10 | 7 | 7 | 8 | 7 | 10 | 9 |

| Weights | 0.024 | 0.053 | 0.039 | 0.026 | 0.043 | 0.024 | 0.012 |
|---|---|---|---|---|---|---|---|
| | C33 | C41 | C42 | C43 | C51 | C52 | C53 |
| S1 | 9 | 10 | 10 | 9 | 7 | 7 | 7 |
| S2 | 6 | 8 | 9 | 9 | 9 | 10 | 7 |
| S3 | 7 | 7 | 7 | 7 | 7 | 8 | 7 |
| S4 | 9 | 7 | 7 | 7 | 9 | 10 | 8 |
| S5 | 8 | 6 | 5 | 6 | 7 | 6 | 5 |
| S6 | 7 | 6 | 6 | 6 | 8 | 8 | 8 |
| S7 | 8 | 8 | 8 | 8 | 6 | 7 | 8 |
| S8 | 6 | 7 | 6 | 6 | 9 | 8 | 6 |
| S9 | 9 | 6 | 5 | 5 | 6 | 7 | 6 |
| S10 | 9 | 8 | 8 | 8 | 5 | 4 | 4 |

Table 10 provides the weighted normalized matrix.

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Table 10
Weighted normalized matrix

| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 |
|---|---|---|---|---|---|---|---|---|
| Weights | 0.139 | 0.073 | 0.026 | 0.233 | 0.122 | 0.044 | 0.086 | 0.049 |
| S1 | 0.222 | 0.375 | 0.428 | 0.9 | 0.888 | 1 | 0.9 | 1 |
| S2 | 1 | 1 | 1 | 1 | 1 | 0.875 | 0.8 | 0.7 |
| S3 | 0.285 | 0.375 | 0.375 | 0.5 | 0.555 | 0.75 | 0.7 | 0.5 |
| S4 | 0.666 | 0.75 | 0.6 | 0.7 | 1 | 1 | 0.8 | 0.7 |
| S5 | 0.5 | 0.6 | 0.75 | 0.6 | 0.555 | 0.75 | 0.9 | 0.7 |
| S6 | 0.666 | 0.75 | 1 | 0.4 | 0.444 | 0.5 | 0.9 | 0.8 |
| S7 | 0.333 | 0.5 | 0.6 | 0.4 | 0.555 | 0.625 | 0.7 | 0.5 |
| S8 | 0.4 | 0.6 | 0.5 | 0.4 | 0.333 | 0.375 | 0.7 | 0.5 |
| S9 | 0.285 | 0.375 | 0.428 | 0.5 | 0.666 | 0.625 | 0.9 | 1 |
| S10 | 0.25 | 0.3 | 0.428 | 0.7 | 0.888 | 0.875 | 1 | 0.9 |

| Weights | C33 | C41 | C42 | C43 | C51 | C52 | C53 | Score |
|---|---|---|---|---|---|---|---|---|
| S1 | 0.024 | 0.053 | 0.039 | 0.026 | 0.043 | 0.024 | 0.012 | |
| S2 | 1 | 1 | 1 | 1 | 0.777 | 0.7 | 0.875 | 0.760 |
| S3 | 0.666 | 0.8 | 0.9 | 1 | 1 | 1 | 0.875 | 0.931 |
| S4 | 0.777 | 0.7 | 0.7 | 0.777 | 0.777 | 0.8 | 0.875 | 0.545 |
| S5 | 1 | 0.7 | 0.7 | 0.777 | 1 | 1 | 1 | 0.782 |
| S6 | 0.888 | 0.6 | 0.5 | 0.666 | 0.777 | 0.6 | 0.625 | 0.630 |
| S7 | 0.777 | 0.6 | 0.6 | 0.666 | 0.888 | 0.8 | 1 | 0.620 |
| S8 | 0.888 | 0.8 | 0.8 | 0.888 | 0.666 | 0.7 | 1 | 0.547 |
| S9 | 0.666 | 0.7 | 0.6 | 0.666 | 1 | 0.8 | 0.75 | 0.512 |
| S10 | 1 | 0.6 | 0.5 | 0.5555 | 0.666 | 0.7 | 0.75 | 0.574 |
| S1 | 1 | 0.8 | 0.8 | 0.888 | 0.555 | 0.4 | 0.5 | 0.668 |

The obtained BWM-weighted SAW results are shown in Table 11.


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Table 11
BWM weighted SAW results

| Suppliers | Score | Rank |
|---|---|---|
| S2 | 0.932 | 1 |
| S4 | 0.783 | 2 |
| S1 | 0.761 | 3 |
| S10 | 0.668 | 4 |
| S5 | 0.630 | 5 |
| S6 | 0.620 | 6 |
| S9 | 0.574 | 7 |
| S7 | 0.547 | 8 |
| S3 | 0.545 | 9 |
| S8 | 0.512 | 10 |

In the entropy method, the first step was to obtain the normalized decision matrix which is presented in Table 12.

Table 12
Normalized decision matrix

| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 |
|---|---|---|---|---|---|---|---|---|
| S1 | 0.620 | 0.620 | 0.620 | 0.110 | 0.110 | 0.110 | 0.113 | 0.113 |
| S2 | 0.014 | 0.014 | 0.014 | 0.102 | 0.102 | 0.102 | 0.087 | 0.087 |
| S3 | 0.036 | 0.036 | 0.036 | 0.099 | 0.099 | 0.099 | 0.065 | 0.065 |
| S4 | 0.015 | 0.015 | 0.015 | 0.102 | 0.102 | 0.102 | 0.109 | 0.109 |
| S5 | 0.017 | 0.017 | 0.017 | 0.099 | 0.099 | 0.099 | 0.113 | 0.113 |
| S6 | 0.012 | 0.012 | 0.012 | 0.100 | 0.100 | 0.100 | 0.113 | 0.113 |
| S7 | 0.049 | 0.049 | 0.049 | 0.099 | 0.099 | 0.099 | 0.085 | 0.085 |
| S8 | 0.016 | 0.016 | 0.016 | 0.088 | 0.088 | 0.088 | 0.090 | 0.090 |
| S9 | 0.121 | 0.121 | 0.121 | 0.096 | 0.096 | 0.096 | 0.113 | 0.113 |
| S10 | 0.099 | 0.099 | 0.099 | 0.104 | 0.104 | 0.104 | 0.113 | 0.113 |

| | C33 | C41 | C42 | C43 | C51 | C52 | C53 |
|---|---|---|---|---|---|---|---|
| S1 | 0.113 | 0.128 | 0.128 | 0.128 | 0.103 | 0.103 | 0.103 |
| S2 | 0.087 | 0.128 | 0.128 | 0.128 | 0.103 | 0.103 | 0.103 |
| S3 | 0.065 | 0.103 | 0.103 | 0.103 | 0.103 | 0.103 | 0.103 |
| S4 | 0.109 | 0.103 | 0.103 | 0.103 | 0.121 | 0.121 | 0.121 |
| S5 | 0.113 | 0.077 | 0.077 | 0.077 | 0.094 | 0.094 | 0.094 |
| S6 | 0.113 | 0.077 | 0.077 | 0.077 | 0.103 | 0.103 | 0.103 |
| S7 | 0.085 | 0.103 | 0.103 | 0.103 | 0.098 | 0.098 | 0.098 |
| S8 | 0.090 | 0.077 | 0.077 | 0.077 | 0.103 | 0.103 | 0.103 |
| S9 | 0.113 | 0.077 | 0.077 | 0.077 | 0.103 | 0.103 | 0.103 |
| S10 | 0.113 | 0.128 | 0.128 | 0.128 | 0.071 | 0.071 | 0.071 |


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The entropy scores for the criteria are provided in Table 13. In the previous table, the normalized values were multiplied by their respective logarithmic values. These results were then summed to obtain the entropy value. The entropy coefficient $k$ in the formula was calculated as $1/ln10$ (0.434), and incorporated into the formula.

Table 13
Entropy values

| C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 | C33 |
|---|---|---|---|---|---|---|---|---|
| -0.296 | -0.296 | -0.296 | -0.242 | -0.242 | -0.242 | -0.246 | -0.246 | -0.246 |
| -0.060 | -0.060 | -0.060 | -0.233 | -0.233 | -0.233 | -0.212 | -0.212 | -0.212 |
| -0.120 | -0.120 | -0.120 | -0.228 | -0.228 | -0.228 | -0.178 | -0.178 | -0.178 |
| -0.064 | -0.064 | -0.064 | -0.233 | -0.233 | -0.233 | -0.242 | -0.242 | -0.242 |
| -0.069 | -0.069 | -0.069 | -0.230 | -0.230 | -0.230 | -0.246 | -0.246 | -0.246 |
| -0.054 | -0.054 | -0.054 | -0.231 | -0.231 | -0.231 | -0.246 | -0.246 | -0.246 |
| -0.147 | -0.147 | -0.147 | -0.229 | -0.229 | -0.229 | -0.209 | -0.209 | -0.209 |
| -0.067 | -0.067 | -0.067 | -0.214 | -0.214 | -0.214 | -0.217 | -0.217 | -0.217 |
| -0.255 | -0.255 | -0.255 | -0.225 | -0.225 | -0.225 | -0.246 | -0.246 | -0.246 |

| C41 | C42 | C43 | C51 | C52 | C53 |
|---|---|---|---|---|---|
| -0.263 | -0.263 | -0.263 | -0.234 | -0.234 | -0.234 |
| -0.263 | -0.263 | -0.263 | -0.234 | -0.234 | -0.234 |
| -0.234 | -0.234 | -0.234 | -0.234 | -0.234 | -0.234 |
| -0.234 | -0.234 | -0.234 | -0.255 | -0.255 | -0.255 |
| -0.197 | -0.197 | -0.197 | -0.222 | -0.222 | -0.222 |
| -0.197 | -0.197 | -0.197 | -0.234 | -0.234 | -0.234 |
| -0.234 | -0.234 | -0.234 | -0.228 | -0.228 | -0.228 |
| -0.197 | -0.197 | -0.197 | -0.234 | -0.234 | -0.234 |
| -0.197 | -0.197 | -0.197 | -0.234 | -0.234 | -0.234 |

As shown in Table 14, the degrees of entropy of the factors and the corresponding weight values for each criterion were determined as follows.


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Table 14
Entropy and weight values of factors

| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | |
|---|---|---|---|---|---|---|---|---|
| Entropy | 0.492 | 0.492 | 0.492 | 0.897 | 0.897 | 0.897 | 0.887 | |
| $w_j$ | 0.181 | 0.181 | 0.181 | 0.037 | 0.037 | 0.037 | 0.040 | |
| | C32 | C33 | C41 | C42 | C43 | C51 | C52 | C53 |
| Entropy | 0.887 | 0.887 | 0.876 | 0.876 | 0.876 | 0.915 | 0.915 | 0.915 |
| $w_j$ | 0.040 | 0.040 | 0.044 | 0.044 | 0.044 | 0.030 | 0.030 | 0.030 |

The results of the entropy-based SAW method are presented in Table 15.

Table 15
Entropy based SAW results

| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 | C33 | C41 | C42 | C43 | C51 | C52 | C53 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weights | 0.1815 | 0.1815 | 0.1815 | 0.0368 | 0.0368 | 0.0368 | 0.0403 | 0.0403 | 0.0403 | 0.0444 | 0.0444 | 0.0444 | 0.0303 | 0.0303 | 0.0303 |
| S1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.852 | 0.852 | 0.852 |
| S2 | 0.023 | 0.023 | 0.023 | 0.934 | 0.934 | 0.934 | 0.770 | 0.770 | 0.770 | 1.000 | 1.000 | 1.000 | 0.852 | 0.852 | 0.852 |
| S3 | 0.058 | 0.058 | 0.058 | 0.900 | 0.900 | 0.900 | 0.580 | 0.580 | 0.580 | 0.800 | 0.800 | 0.800 | 0.852 | 0.852 | 0.852 |
| S4 | 0.025 | 0.025 | 0.025 | 0.934 | 0.934 | 0.934 | 0.970 | 0.970 | 0.970 | 0.800 | 0.800 | 0.800 | 1.000 | 1.000 | 1.000 |
| S5 | 0.027 | 0.027 | 0.027 | 0.908 | 0.908 | 0.908 | 1.000 | 1.000 | 1.000 | 0.600 | 0.600 | 0.600 | 0.778 | 0.778 | 0.778 |
| S6 | 0.020 | 0.020 | 0.020 | 0.917 | 0.917 | 0.917 | 1.000 | 1.000 | 1.000 | 0.600 | 0.600 | 0.600 | 0.852 | 0.852 | 0.852 |
| S7 | 0.079 | 0.079 | 0.079 | 0.906 | 0.906 | 0.906 | 0.750 | 0.750 | 0.750 | 0.800 | 0.800 | 0.800 | 0.815 | 0.815 | 0.815 |
| S8 | 0.026 | 0.026 | 0.026 | 0.806 | 0.806 | 0.806 | 0.800 | 0.800 | 0.800 | 0.600 | 0.600 | 0.600 | 0.852 | 0.852 | 0.852 |
| S9 | 0.195 | 0.195 | 0.195 | 0.874 | 0.874 | 0.874 | 1.000 | 1.000 | 1.000 | 0.600 | 0.600 | 0.600 | 0.852 | 0.852 | 0.852 |
| S10 | 0.160 | 0.160 | 0.160 | 0.951 | 0.951 | 0.951 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.593 | 0.593 | 0.593 |

The rankings based on the Entropy weighted SAW method are given in Table 16.


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Table 16
Obtained scores and ranks

| Supplier | Score | Rank |
|---|---|---|
| S1 | 0.987 | 1 |
| S10 | 0.500 | 2 |
| S9 | 0.481 | 3 |
| S4 | 0.432 | 4 |
| S2 | 0.419 | 5 |
| S7 | 0.414 | 6 |
| S6 | 0.390 | 7 |
| S5 | 0.387 | 8 |
| S3 | 0.385 | 9 |
| S8 | 0.357 | 10 |

Table 17
Comparison of the obtained results

| **AHP-weighted SAW** | | **BWM-weighted SAW** | | **Entropy-weighted SAW** | |
|---|---|---|---|---|---|
| Suppliers | Rank | Suppliers | Rank | Suppliers | Rank |
| S2 | 1 | S2 | 1 | S1 | 1 |
| S4 | 2 | S4 | 2 | S10 | 2 |
| S6 | 3 | S1 | 3 | S9 | 3 |
| S1 | 4 | S10 | 4 | S4 | 4 |
| S10 | 5 | S5 | 5 | S2 | 5 |
| S5 | 6 | S6 | 6 | S7 | 6 |
| S7 | 7 | S9 | 7 | S6 | 7 |
| S9 | 8 | S7 | 8 | S5 | 8 |
| S3 | 9 | S3 | 9 | S3 | 9 |
| S8 | 10 | S8 | 10 | S8 | 10 |

As presented in Table 17, the top three suppliers identified in the AHP-weighted SAW method are S2, S4, and S6, whereas S9, S3, and S8 are ranked the lowest. In the BWM-weighted SAW method, S2, S4, and S1 are deemed the highest-ranked suppliers, with S7, S3, and S8 occupying the lowest positions. In the entropy-weighted SAW method, S1, S10, and S9 are ranked as the top suppliers, while S5, S3, and S8 are ranked the lowest. A comparison of the results across the three methods reveals generally consistent rankings. Notably, S2 and S4 are consistently ranked as the most important suppliers in both the AHP and BWM-based SAW methods. Conversely, S3 and S8 are consistently identified as the least important suppliers. ranked last in all methodologies.

The ranking variation exists among the AHP-based SAW, BWM-based SAW, and Entropy-based SAW due to their inherent methodological differences. Both the AHP and


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BWM are subjective weighting methods based on expert judgments, but BWM involves fewer pairwise comparisons and is expected to be less inconsistent. On the other hand, Entropy is an objective method, depending on the variability of data, hence focusing on different factors in supplier performance. Variations in ranking indicate the importance of taking into consideration both subjective insights from experts and objective data-driven measures in the evaluation of suppliers.

- The AHP depends upon subjective pairwise comparisons.
- BWM strengthens consistency as it reduces the number of comparisons, and
- Entropy is purely data-driven, thereby reflecting the variation in input data without any subjective judgment.

The ranking variations point to the influence of subjectivity versus objectivity in MCDM methods and bring into sharp focus the critical issue of method selection within a supplier evaluation process. This should provide some insight for decision-makers regarding how methodological choices might bias their priority results.

We conducted a Spearman rank correlation analysis as a method for measuring the degree of association for the ranked results from the AHP-weighted SAW, BWM-weighted SAW, and Entropy-weighted SAW approaches. The ranked values of each supplier for the three approaches were analyzed in SPSS, and the Spearman rank correlation coefficients were obtained. The findings are presented in Table 18 below.

Table 18
Spearman's correlation matrix

| **Correlations** | **AHP_rank** | **BWM_rank** | **Entropy_rank** |
|---|---|---|---|
| AHP_rank | 1 | 0.915 | 0.491 |
| BWM_rank | 0.915 | 1 | 0.648 |
| Entropy_rank | 0.491 | 0.648 | 1 |

To determine the agreement of these ranking results, an additional Spearman rank correlation analysis was performed (refer to Table 18). The results showed a very strong correlation between the AHP and the BWM ($\rho = 0.915$, $p < 0.01$), thus demonstrating a high level of agreement between the expert-based models. The correlations between Entropy and the subjective approaches were both moderate and positive ($\rho = 0.648$, $p < 0.05$ with the BWM; $\rho = 0.491$, $p > 0.05$ with the AHP). These findings are not in conflict with the results, they just emphasize the complementarity of the weighting schemes of subjective and objective natures. The moderate correlation of Entropy with the other methods signals that it identifies different yet still valid aspects of supplier performance, thus adding to the overall evaluation perspective.

The Spearman rank correlation between the methods is consistent with the results presented. They highlight the complementarity of the methods from a different perspective.


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The AHP and the BWM yield very similar rankings, which both confirm subjective consistency, while the Entropy model adds a an independent perspective that is based on data-driven variability. The moderate correlation between subjective and objective methods shows that the Entropy approach reveals different yet important supplier performance features, thus offering more comprehensive decision-making insights.

In fact, the results provide a framework that managers may use to apply different weighting methods for the purpose of a more objective assessment of the supplier selection process. On the one hand, a purely subjective approach can be biased; on the other hand, a purely objective approach may overlook certain human factors. Decision-makers can elevate a few key criteria such as quality and price to the top with great assurance since the rankings are stable. Additionally, sensitivity and correlation analyses help companies assess the extent to which changes in weights and fluctuations in data matters, thus paving the way to smarter and more versatile supplier selection strategies.

## 5. Sensitivity analysis

The sensitivity analysis involved changing the weights of the key criteria by ±10% to see how the supplier ranking results would be consistent or not across three weighting methods: the AHP weighted SAW, the BWM weighted SAW, and Entropy weighted SAW. Different weight changes for the evaluation criteria allowed to verify the robustness of the proposed decision-making framework through a detailed sensitivity analysis.


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Table 19
BWM, AHP and Entropy results of the sensitivity analysis

| BWM | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Current rank** | **case 0 equal weights** | **case 1 C11 %10+** | **case 2 C11 %10-** | **case 3 C21 %10+** | **case 4 C21 %10-** | **case 5 C22 %10+** | **case 6 C22 %10-** |
| **S2** | S2 | S2 | S2 | S2 | S2 | S2 | S2 |
| **S4** | S4 | S4 | S4 | S4 | S4 | S4 | S4 |
| **S1** | S1 | S1 | S1 | S1 | S1 | S1 | S1 |
| **S10** | S6 | S10 | S10 | S10 | S10 | S10 | S10 |
| **S5** | S10 | S5 | S5 | S5 | S5 | S5 | S5 |
| **S6** | S5 | S6 | S6 | S6 | S6 | S6 | S6 |
| **S9** | S7 | S9 | S9 | S9 | S9 | S9 | S9 |
| **S7** | S9 | S7 | S7 | S3 | S7 | S7 | S7 |
| **S3** | S3 | S3 | S3 | S7 | S3 | S3 | S3 |
| **S8** | S8 | S8 | S8 | S8 | S8 | S8 | S8 |

| AHP | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Current rank** | **case 0 equal weights** | **case 1 C11 %10+** | **case 2 C11 %10-** | **case 3 C21 %10+** | **case 4 C21 %10-** | **case 5 C31 %10+** | **case 6 C31 %10-** |
| **S2** | S4 | S2 | S2 | S2 | S2 | S2 | S2 |
| **S4** | S2 | S4 | S4 | S4 | S4 | S4 | S4 |
| **S6** | S1 | S6 | S6 | S6 | S6 | S6 | S6 |
| **S1** | S6 | S1 | S1 | S1 | S1 | S1 | S1 |
| **S10** | S10 | S10 | S10 | S10 | S10 | S10 | S10 |
| **S5** | S5 | S5 | S5 | S5 | S5 | S5 | S5 |
| **S7** | S7 | S7 | S7 | S7 | S9 | S9 | S7 |
| **S9** | S9 | S9 | S9 | S3 | S7 | S7 | S3 |


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| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **S3** | S3 | S3 | S3 | S9 | S3 | S3 | S9 |
| **S8** | S8 | S8 | S8 | S8 | S8 | S8 | S8 |

**Entropy**

| **Current rank** | **case 0 equal weights** | **case 1 C11 %10+** | **case 2 C11 %10-** | **case 3 C12 %10+** | **case 4 C12 %10-** | **case 5 C13 %10+** | **case 6 C13 %10-** |
|---|---|---|---|---|---|---|---|
| **S1** | S1 | S1 | S1 | S1 | S1 | S1 | S1 |
| **S10** | S4 | S10 | S10 | S10 | S10 | S10 | S10 |
| **S9** | S10 | S9 | S9 | S9 | S9 | S9 | S9 |
| **S4** | S2 | S4 | S4 | S4 | S4 | S4 | S4 |
| **S2** | S9 | S2 | S2 | S2 | S2 | S2 | S2 |
| **S7** | S6 | S7 | S7 | S7 | S7 | S7 | S7 |
| **S6** | S7 | S6 | S6 | S6 | S6 | S6 | S6 |
| **S5** | S5 | S5 | S5 | S5 | S5 | S5 | S5 |
| **S3** | S3 | S3 | S3 | S3 | S3 | S3 | S3 |
| **S8** | S8 | S8 | S8 | S8 | S8 | S8 | S8 |


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In the case (Case 0) of equal changes of all criteria weights, only slight changes of the ranking order were noticed, which is a natural and expected result due to the uniform variation of all factors. Table 19 presents the results obtained from the sensitivity analysis. Further, more focused analysis was carried out by individually increasing and reducing the weight of the three most important criteria by 10%. The results clearly indicated that there were no significant changes in the rankings as almost all the positions held the same ranking through the combination of the AHP, BWM, and Entropy weight calculation methodologies together with the SAW ranking approach.

An important point to note here is that the rankings generated by BWM are quite stable, and no changes are observed in the rankings despite any changes in weighting. Although some changes were noticed in the rankings produced by the AHP and Entropy methods, mainly for the increased weight of criteria C11 by 10%, these changes did not have any effect on the prioritization. The results have reaffirmed the reliability and validity of the MCDM method employed in this research.

Overall, these results confirm that the supplier selection framework is solid while some criteria have a very strong effect on ranking stability. Sensitivity analysis increases the trust in the findings and gives decision-makers a great way to think about weight uncertainties in multi-criteria evaluation processes.

## 6. Conclusions and future directions

Supply chain management is inherently complex and involves a hierarchy of criteria, sub-criteria, and alternatives. To survive in today's fiercely competitive and rapidly changing market, handling such complexity requires a sophisticated methodology. Modern MCDM methods such as the AHP, BWM, and techniques based on Entropy provide a scientific means of managing complex decisions in supply chain contexts by simultaneously considering several conflicting criteria. The approach used guarantees the effectiveness of the decisions made. Management of the supply chain using MCDM basically comes down to selecting the criteria, sub-criteria, and alternatives that are the most relevant. Therefore, the main aim of the suggested method is to present a systematic way of dealing with the complexities of the supply chain.

The study serves as a reference to supplier selection literature which not only extends the classic dimensions (cost, quality, and delivery) but explores fairly new ones like environmental sensitivity and digital transformation initiatives. This feature is heavily influenced by the top supply chain issues as well as the needs for sustainability and technological advancement. Supply chain executives to change their supplier evaluation approaches based on the results of this research to be consistent with corporate objectives and the preferences of the decision-maker.

Decision-making can be greatly enhanced through evaluation by using a mix of decision-making and data-driven approaches. By highlighting new criteria in supplier evaluation such as environmental impact and digital transformation, management is given a tool to


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harmonize supplier selection with a high-level corporate sustainability and innovation. The research results offer managers various ways to change supplier evaluation methods that are consistent with the firm's priorities. For example, managers can decide which elements to compromise on in the balance between cost, quality, sustainability, and innovation. The combined approach helps to determine weights in a more objective way and get a detailed ranking, which in turn makes it possible to make supplier selection decisions faster and more reliably even in very complicated situations. A comparison of the different methods shows that according to the AHP and BWM quality is always the most important factor, whereas the Entropy method points to price as the leading criterion, thus reflecting the differences between subjective and objective weighting approaches. The differences in the ranking emphasize the importance of method selection in decision contexts and therefore reveal that MCDM models are very sensitive to the weighting technique used. The agreement among methods on the lowest-ranked suppliers also provides decision-makers with a safe and reliable indication of which to exclude.

Limitations of this study include the small number of decision-makers and the fixed set of criteria, which might not reflect the full diversity of real-world supply chains. Furthermore, the static nature of the analysis limits its ability to respond to market changes.

Future research should consider expanding the decision-maker group for enhanced reliability, applying fuzzy or dynamic MCDM models to better handle uncertainty and temporal variations, and testing the framework in various industries beyond a packaging company. Integration of machine learning techniques with MCDM could also be explored to automate and refine supplier evaluation processes further.

**Data availability statement: The data from this study are available upon request to the corresponding author, to both the editorial team and the general community for replicability and transparency reasons.**

## REFERENCES

Abdulla, A., Baryannis. G., & Badi, I. (2019). *Weighting the key features affecting supplier selection using machine learning techniques.* 7th International Conference on Transport and Logistics, Niš, Serbia. https://doi.org/10.20944/preprints201912.0154.v1

Araz, C., & Ozkarahan, I. (2007). Supplier evaluation and management system for strategic sourcing based on a new multicriteria sorting procedure. *International Journal of Production Economics*, *106*(2), 585–606. https://doi.org/10.1016/j.ijpe.2006.08.008

Barretta, R., Taherdoost, H., & Madanchian, M. (2023). Multi-Criteria Decision Making (MCDM) methods and concepts. *Encyclopedia*, *3*(1), 77–87. https://doi.org/10.3390/ENCYCLOPEDIA3010006

Canco, I., Kruja, D., & Iancu, T. (2021). AHP, a reliable method for quality decision making: A case study in business. *Sustainability, 13*(24), 13932. https://doi.org/10.3390/SU132413932

Cayir Ervural, B. (2024). *An integrated best-worst method and entropy approach for sustainable supplier selection*. International Society on the Analytic Hierarchy Process. https://doi.org/10.13033/isahp.y2024.013

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Dobos, I., & Vörösmarty, G. (2019). Inventory-related costs in green supplier selection problems with Data Envelopment Analysis (DEA). *International Journal of Production Economics*, *209*, 374–380. https://doi.org/10.1016/j.ijpe.2018.03.022

Ecer, F., & Pamucar. D. (2020). Sustainable supplier selection: A novel integrated fuzzy best worst method (F-BWM) and fuzzy CoCoSo with Bonferroni (CoCoSo'B) multi-criteria model. *Journal of Cleaner Production*, 266, 121981.

Fallahpour. A., Olugu, E. U., Musa, S. N., Khezrimotlagh, D., & Wong, K. Y. (2016). An integrated model for green supplier selection under fuzzy environment: application of data envelopment analysis and genetic programming approach. *Neural Computing and Applications*, *27*, 707–725. https://doi.org/10.1007/s00521-015-1890-3

Fallahpour, A., Olugu, E. U., Musa, S. N., Wong, K. Y., & Noori, S. (2017). A decision support model for sustainable supplier selection in sustainable supply chain management. *Computers & Industrial Engineering*, 105, 391–410. https://doi.org/10.1016/j.cie.2017.01.005

Ghorabaee, M. K., Zavadskas, E. K., Olfat, L., & Turskis, Z. (2015). Multi-criteria inventory classification using a new method of evaluation based on Distance from

Average Solution (EDAS). *Informatica, 26*(3), 435–451. https://doi.org/10.15388/INFORMATICA.2015.57

Golmohammadi, D., Creese, R. C., Valian, H., & Kolassa, J. (2009). Supplier selection based on a neural network model using genetic algorithm. *IEEE Transactions on Neural Networks, 20*(9), 1504–1519. https://doi.org/10.1109/tnn.2009.2027321

Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: a literature review. *Journal of Cleaner Production*, *98*, 66–83. https://doi.org/10.1016/j.jclepro.2013.06.046

Goudarzi, A., & Gholamian, M. R. (2024). A group BWM-PROMETHEE-Cloud and order allocation model for green supplier selection in oil refinery applications. *Journal of Cleaner Production, 444,* 141216. https://doi.org/10.1016/j.jclepro.2024.141216

Ha, S. H., & Krishnan, R. (2008). A hybrid approach to supplier selection for the maintenance of a competitive supply chain. *Expert Systems with Applications*, *34*(2), 1303–1311. https://doi.org/10.1016/j.eswa.2006.12.008

Hailiang, Z., Khokhar, M., Islam, T., & Sharma, A. (2023). A model for green-resilient supplier selection: fuzzy best–worst multi-criteria decision-making method and its applications. *Environmental Science and Pollution Research, 30*, 54035–54058. https://doi.org/10.1007/s11356-023-25749-4

Hajiaghaei-Keshteli, M., Cenk, Z., Erdebilli, B., Özdemir, Y. S., & Gholian-Jouybari, F. (2023*). Pythagorean fuzzy TOPSIS for green supplier selection in the food industry. Expert Systems with Applications, 224*, 120036. https://doi.org/10.1016/j.eswa.2023.120036

Hendiani, H., Shahanaghi, K., & Zandieh, M. (2020). A multi-stage fuzzy BWM decision model with a new sustainable supplier index definition for choosing the most appropriate supplier. *Expert Systems with Applications, 140*, 112900. https://doi.org/10.1016/j.eswa.2019.112900

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24. https://doi.org/10.1016/j.ejor.2009.05.009

Hwang, C. L., & Yoon, K. P. (1981*). Multiple attribute decision making: Methods and applications.* Springer-Verlag. https://doi.org/10.1007/978-3-642-48318-9

Junior, F. R. L., Osiro, L., & Carpinetti, L. C. R. (2014). A comparison between Fuzzy AHP and Fuzzy TOPSIS methods to supplier selection. *Applied Soft Computing, 21*, 194–209. https://doi.org/10.1016/j.asoc.2014.03.014

Kannan, D., de Sousa Jabbour, A. B. L., & Jabbour, C. J. C. (2014). Selecting green suppliers based on GSCM practices: Using fuzzy TOPSIS applied to a Brazilian


*ISSN 1936-6744*
*https://doi.org/10.13033/ijahp.v18i1.1319*

electronics company. *European Journal of Operational Research, 233*(2), 432–447. https://doi.org/10.1016/j.ejor.2013.07.023

Knight, L., Tate, W., Carnovale, S., Di Mauro, C., Bals, L., Caniato. F., ... & Wagner, S. M. (2022). Future business and the role of purchasing and supply management: Opportunities for 'business-not-as-usual' PSM research. *Journal of Purchasing and Supply Management, 28*(1), 100753. https://doi.org/10.1016/j.pursup.2022.100753

Kuo, R. J., Hong, S. Y., & Huang, Y. (2010). Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection. *Applied Mathematical Modelling, 34*(12), 3976–3990. https://doi.org/10.1016/j.apm.2010.03.033

Lahri, V., Shaw, K., & Ishizaka, A. (2021). Sustainable supply chain network design: Integrated BWM, TOPSIS, possibilistic programming and ε-constraint approach. *Expert Systems with Applications, 168*, 114373. https://doi.org/10.1016/j.eswa.2020.114373

Li, S., Ragu-Nathan, B., Ragu-Nathan, T. S., & Rao, S. S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega, 34*(2), 107–124. https://doi.org/10.1016/j.omega.2004.08.002

Luthra, S., Govindan, K., Kannan, D., Mangla, S. K., & Garg, C. P. (2017). An integrated framework for sustainable supplier selection and evaluation in supply chains. *Journal of Cleaner Production, 140*, 1686–1698. https://doi.org/10.1016/j.jclepro.2016.09.078

Masoomi, B., Sahebi, I. G., Fathi, M., Yıldırım, F., & Ghorbani, S. (2022). Strategic supplier selection for renewable energy supply chain under green capabilities (fuzzy BWM-WASPAS-COPRAS approach). *Energy Strategy Reviews, 40*, 100815. https://doi.org/10.1016/J.ESR.2022.100815

Memari, A., Dargi, A., Jokar, M. R. A., Ahmad, R., & Rahim, A. R. A. (2019). Sustainable supplier selection: A multi-criteria intuitionistic fuzzy TOPSIS method. *Journal of Manufacturing Systems, 50*, 9–24. https://doi.org/10.1016/j.jmsy.2018.11.002

Mizrak, F., Polat, L., & Tasar, S. A. (2024). Applying entropy weighting and 2-Tuple Linguistic T-Spherical Fuzzy MCDM: A case study of developing a strategic sustainability plan for Istanbul airport. *Sustainability, 16*(24), 11104. https://doi.org/10.3390/SU162411104

Murugesan, U., Subramanian, P., Srivastava, S., & Dwivedi, A. (2023). A study of Artificial Intelligence impacts on human resource digitalization in Industry 4.0. *Decision Analytics Journal, 7*, 100249. https://doi.org/10.1016/J.DAJOUR.2023.100249

Paramanik, A. R., Sarkar, S., & Sarkar, B. (2022). OSWMI: An objective-subjective weighted method for minimizing inconsistency in multi-criteria decision making. *Computers & Industrial Engineering, 169*, 108138. https://doi.org/10.1016/J.CIE.2022.108138

Rame, R., Purwanto, P., & Sudarno, S. (2024). Industry 5.0 and sustainability: An overview of emerging trends and challenges for a green future. *Innovation and Green Development, 3*(4), 100173. https://doi.org/10.1016/j.igd.2024.100173

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, *53*, 49–57. https://doi.org/10.1016/j.omega.2014.11.009

Rostami, O., Tavakoli, M., Tajally, A., GhanavatiNejed, M. (2023). A goal programming-based fuzzy best–worst method for the viable supplier selection problem: a case study. *Soft Computing, 27*, 2827–2852. https://doi.org/10.1007/s00500-022-07572-0

Saaty, T. L. (1980). The analytic hierarchy process (AHP). *The Journal of the Operational Research Society, 41*(11), 1073–1076.

Saaty, T. L. (1996). *Decision making with dependence and feedback. The analytic network process*. RWS Publications.

Saaty, T. L., & Ozdemir. M. (2003). Why the magic number seven plus or minus two. Mathematical and *Computer Modelling, 38*(3–4), 233–244. https://doi.org/10.1016/s0895-7177(03)90083-5

Shang, Z., Yang, X., Barnes, D., & Wu, C. (2022). Supplier selection in sustainable supply chains: Using the integrated BWM, fuzzy Shannon entropy, and fuzzy MULTIMOORA methods. *Expert Systems with Applications*, *195*, 116567.

Sitorus, F., & Brito-Parada, P. R. (2020). A multiple criteria decision making method to weight the sustainability criteria of renewable energy technologies under uncertainty. *Renewable and Sustainable Energy Reviews, 127*, 109891. https://doi.org/10.1016/J.RSER.2020.109891

Tavana, M., Shaabani, A., Di Caprio, D., & Bonyani, A. (2021). An integrated group fuzzy best-worst method and combined compromise solution with Bonferroni functions for supplier selection in reverse supply chains. *Cleaner Logistics and Supply Chain, 2*, 100009. https://doi.org/10.1016/j.clscn.2021.100009

Xu, Y., Zhu, X., Wen, X., & Herrera-Viedma, E. (2021). Fuzzy best-worst method and its application in initial water rights allocation. *Applied Soft Computing, 101*, 107007. https://doi.org/10.1016/J.ASOC.2020.107007

Vaezi, A., Rabbani, E., & Yazdian, S. A. (2024). Blockchain-integrated sustainable supplier selection and order allocation: A hybrid BWM-MULTIMOORA and bi-objective programming approach. *Journal of Cleaner Production*, *444*, 141216.

Wang, R., Li, X., & Li, C. (2021). Optimal selection of sustainable battery supplier for battery swapping station based on triangular fuzzy entropy-MULTIMOORA method. *Journal of Energy Storage, 34*, 102013. https://doi.org/10.1016/j.est.2020.102013

Wang, X., Liu, J., & Huang, F. (2023). Modified TODIM under type-2 neutrosophic numbers for green supplier selection. *Computers & Industrial Engineering, 182,* 109427. https://doi.org/10.1016/j.cie.2023.109427

Wang, Y., Wang, W., Wang, Z., Deveci, M., Roy, S. K., & Kadry, S. (2024). Selection of sustainable food suppliers using the Pythagorean fuzzy CRITIC-MARCOS method. *Information Sciences, 664*, 120326. https://doi.org/10.1016/j.ins.2024.120326

Wang, Z., Cai, Q., & Wei, G. (2023). Modified TODIM method based on cumulative prospect theory with Type-2 neutrosophic number for green supplier selection. *Engineering Applications of Artificial Intelligence, 126*, 106843. https://doi.org/10.1016/j.engappai.2023.106843

Zhang, X., Goh, M., Bai, S., & Wang, Q. (2024). Green, resilient, and inclusive supplier selection using enhanced BWM-TOPSIS with scenario-varying Z-numbers and reversed PageRank. *Information Sciences*, *674*, 120728.


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# Appendix 1

Table 1
Evaluations of DM1, DM2 and DM3

| | **Price** | **Quality** | **Delivery performance** | **Environmental sensitivity** | **Digital transformation efforts** | **Priority** | **Rank** |
|---|---|---|---|---|---|---|---|
| Price | 1 | 0.50 | 3 | 4 | 6 | 31.6% | 2 |
| Quality | 2 | 1 | 2 | 4 | 6 | 38% | 1 |
| Delivery Performance | 0.33 | 0.50 | 1 | 2 | 6 | 17.5% | 3 |
| Environmental sensitivity | 0.25 | 0.25 | 0.50 | 1 | 2 | 8.4% | 4 |
| Digital transformation efforts | 0.17 | 0.17 | 0.17 | 0.50 | 1 | 4.5% | 5 |
| Consistency ratio CR=4.0% | | | | | | | |
| **DM 2** | | | | | | | |
| | **Price** | **Quality** | **Delivery performance** | **Environmental sensitivity** | **Digital transformation efforts** | **Priority** | **Rank** |
| Price | 1 | 1 | 2 | 3 | 5 | 30.6% | 2 |
| Quality | 1 | 1 | 2 | 5 | 6 | 35.2% | 1 |
| Delivery Performance | 0.50 | 0.50 | 1 | 2 | 7 | 20.1% | 3 |
| Environmental sensitivity | 0.33 | 0.20 | 0.50 | 1 | 3 | 9.8% | 4 |
| Digital transformation efforts | 0.20 | 0.17 | 0.14 | 0.33 | 1 | 4.4% | 5 |
| Consistency ratio CR=3.1% | | | | | | | |


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| **DM3** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Price | Quality | Delivery Performance | Environmental sensitivity | Digital transformation efforts | Priority | Rank |
| Price | 1 | 1 | 2 | 4 | 5 | 35.2% | 1 |
| Quality | 1 | 1 | 1 | 2 | 5 | 26.4% | 2 |
| Delivery Performance | 0.50 | 1 | 1 | 2 | 3 | 20.7% | 3 |
| Environmental sensitivity | 0.25 | 0.50 | 0.50 | 1 | 3 | 12% | 4 |
| Digital transformation efforts | 0.20 | 0.20 | 0.33 | 0.33 | 1 | 5.7% | 5 |
| Consistency ratio CR=2.3% | | | | | | | |

Table 2
A sample pairwise comparison matrix for the sub-criteria of Price

| | **Price of product** | **Transportation cost** | **Flexible payment conditions** | **Priority** | **Rank** |
|---|---|---|---|---|---|
| Price of product | 1 | 3 | 5 | 64.8% | 1 |
| Transportation cost | 0.33 | 1 | 2 | 23% | 2 |
| Flexible payment conditions | 0.20 | 0.50 | 1 | 12.2% | 3 |
| CR=0.4% | | | | | |

Table 3
A sample pairwise comparison matrix for the sub-criteria of Quality

| | **Quality of product** | **Quality of manufacturing** | **Quality related certificates** | **Priority** | **Rank** |
|---|---|---|---|---|---|
| Quality of product | 1 | 2 | 5 | 58.2% | 1 |
| Quality of manufacturing | 0.50 | 1 | 3 | 30.9% | 2 |
| Quality related certificates | 0.20 | 0.33 | 1 | 10.9% | 3 |
| CR=0.4% | | | | | |


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Table 4
A sample pairwise comparison matrix for the sub-criteria of Delivery

| | **On time** | **Ability to fulfill urgent orders** | **Quality of delivery** | **Priority** | **Rank** |
|---|---|---|---|---|---|
| On time | 1 | 3 | 3 | 59.4% | 1 |
| Ability to fulfill urgent orders | 0.33 | 1 | 2 | 24.9% | 2 |
| Quality of delivery | 0.33 | 0.50 | 1 | 15.7% | 3 |
| CR=5.6% | | | | | |

Table 5
A sample pairwise comparison matrix for the sub-criteria of Environmental sensitivity

| | **Green packaging** | **Recycling** | **Green material** | **Priority** | **Rank** |
|---|---|---|---|---|---|
| Green packaging | 1 | 1 | 3 | 44.3% | 1 |
| Recycling | 1 | 1 | 2 | 38.7% | 2 |
| Green material | 0.33 | 0.50 | 1 | 16.9% | 3 |
| CR=5.6% | | | | | |

Table 6
Sample pairwise comparison matrix for the sub-criteria of Digital transformation efforts

| | **Training employees to adapt to new software and applications** | **New software and application investments** | **Cybersecurity and risk prevention security measures** | **Priority** | **Rank** |
|---|---|---|---|---|---|
| Training employees to adapt to new software and applications | 1 | 2 | 1 | 41.3% | 1 |
| New software and application investments | 0.50 | 1 | 1 | 26% | 3 |
| Cybersecurity and risk prevention security measures | 1 | 1 | 1 | 32.7% | 2 |
| CR=5.6% | | | | | |


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# Appendix 2

## Step-by-Step Implementation of the Best-Worst Method (BWM)

The Best-Worst Method (BWM), developed by Rezaei (2015), is a pairwise comparison-based multi-criteria decision-making method that determines the optimal weights of criteria by comparing the best (most important) and worst (least important) criteria with all the others. Below is the step-by-step application of the BWM for determining the weights of the main supplier selection criteria in this study.

**Step 1: Identify the Criteria**

The five main criteria considered in this study are:

- C1: Quality
- C2: Price
- C3: Delivery Performance
- C4: Environmental Sensitivity
- C5: Digital Transformation Efforts

**Step 2: Determine the Best and Worst Criteria**

Based on expert evaluations:

- Best criterion (most important): C1 – *Quality*
- Worst criterion (least important): C5 – *Digital Transformation Efforts*

**Step 3: Construct the Best-to-Others (BO) Vector**

The decision-makers rate the importance of the Best criterion (C1) compared to each of the others on a scale from 1 (equal importance) to 9 (extremely more important).

| Comparison | C1 (Quality) to others |
|---|---|
| C1 > C1 | 1 |
| C1 > C2 | 2 |
| C1 > C3 | 3 |
| C1 > C4 | 4 |
| C1 > C5 | 5 |

So, the Best-to-Others (BO) vector is:

AB = (1,2,3,4,5) AB = (1, 2, 3, 4, 5) AB = (1,2,3,4,5)


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**Step 4: Construct the Others-to-Worst (OW) Vector**

The decision-makers now rate each of the other criteria compared to the Worst criterion (C5)

| Comparison | Others to C5 (Digital Transformation Efforts) |
|---|---|
| C1 > C5 | 4 |
| C2 > C5 | 4 |
| C3 > C5 | 3 |
| C4 > C5 | 2 |
| C5 > C5 | 1 |

So, the Others-to-Worst (OW) vector is:
AW= (4,4,3,2,1) AW = (4, 4, 3, 2, 1) AW= (4,4,3,2,1)

**Step 5: Solve the Optimization Model**

The goal is to determine the optimal weights $w_1, w_2, ....w_5$ such that:

- $\max\left\{\left|\frac{w_1}{w_1} - a_{B1}\right|, ..., \left|\frac{w_1}{w_5} - a_{B5}\right|, \left|\frac{w_1}{w_5} - a_{W1}\right|, ..., \left|\frac{w_5}{w_5} - a_{W5}\right|\right\}$ is minimized.

This is formulated as a **linear optimization problem**:

Minimize $\xi$

Subject to:

$$\begin{cases} |w_B/w_j - a_{Bj}| \leq \xi, & \text{for all } j \\ |w_j/w_W - a_{jW}| \leq \xi, & \text{for all } j \\ \sum_{j-1}^{n} w_j = 1, & \\ w_j \geq 0, & \text{for all } j \end{cases}$$

Where:

- $w_B$ is the weight of the best criterion (C1),
- $w_W$ is the weight of the worst criterion (C5),
- $a_{Bj}$ are the BO values,
- $a_{jW}$ are the OW values.

The solution to this linear programming model gives the optimal weights for the criteria and the consistency ratio (CR).


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**Step 6: Results and Consistency Check**

The optimization was solved using standard LP solvers (e.g., Excel Solver or LINGO). The results are summarized below:

| Criterion | Weight |
|---|---|
| C1 – Quality | 0.40 |
| C2 – Price | 0.24 |
| C3 – Delivery Performance | 0.16 |
| C4 – Environmental Sensitivity | 0.12 |
| C5 – Digital Transformation | 0.08 |

Consistency Ratio (CR) = 0.20
Acceptable Threshold (based on Rezaei. 2015): 0.2306
*Since CR < threshold, the evaluation is considered consistent.

The BWM method successfully determined consistent and reliable weights reflecting the priorities of decision-makers. The results indicate that Quality is the most significant factor in supplier selection, followed by Price and Delivery Performance, while Digital Transformation Efforts received the least importance. This systematic and reproducible approach allows for a clear, transparent, and validated weighting structure that enhances the credibility of the MCDM process.


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