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Research Article

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A Novel Modified ARAS Approach for Evaluating Sustainable Green Supply Chains: A Case Study in the Food Industry

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Abstract
This paper introduces a novel framework for evaluating the performance of sustainable green supply chains using the Modified Additive Ratio Assessment (ARAS-M) method, an enhanced version of the traditional ARAS approach. The ARAS-M method addresses a critical gap in existing decision-making models by incorporating a linear programming technique to optimize the weighting process, which improves the robustness and flexibility of traditional models that often lack adaptability and precision. A comprehensive literature review identified key factors influencing green supply chain sustainability, such as environmental impact, energy efficiency, waste management, and resource optimization. These factors were integrated into the ARAS-M method, enabling a more accurate and dynamic evaluation of supply chain performance. The method was applied to assess six food industry companies' supply chains, with expert input to rank them based on sustainability attributes. Validation of the results was performed by comparing the rankings with real-world performance metrics, including environmental certifications and resource consumption reports. The findings revealed that companies excelling in environmental policies, energy efficiency, and waste reduction ranked highest, demonstrating the effectiveness and practical applicability of the ARAS-M method in evaluating green supply chain performance. This study highlights the critical role of sustainability practices in enhancing supply chain resilience and competitiveness.

Keywords: Multi-Criteria Decision-Making, Modified ARAS Method, Sustainable Supply Chain, Green Supply Chain Evaluation, Food Industry

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1. Introduction

Multi-Criteria Decision Making (MCDM) is a pivotal area within Operations Research that assists decision-makers in evaluating and prioritizing alternatives based on multiple, often conflicting criteria. The inherent complexity of real-world challenges, particularly in organizational contexts, necessitates the application of MCDM methodologies to effectively integrate various attributes and objectives into the decision-making process. These approaches play a crucial role across diverse industries, enhancing decision quality by enabling stakeholders to consider a broad spectrum of perspectives. MCDM can be categorized into two primary frameworks: Multiple Attribute Decision Making (MADM), which emphasizes the selection of the most suitable alternative from a set of options based on specific attributes, and Multiple Objective Decision Making (MODM), which focuses on optimizing multiple goals simultaneously. This classification lays the groundwork for understanding the distinct approaches within MCDM and sets the stage for exploring innovative techniques aimed at improving decision-making efficiency in complex scenarios.

MODM is a systematic decision-making process that empowers decision-makers to define their unique value systems, frame the context of their choices, and evaluate decisions methodically. By delineating decision options and relevant criteria, analysts can decompose complex decisions into manageable components. The primary goal of MODM is to solve optimization problems under specified constraints, addressing multiple, often conflicting objectives simultaneously. For instance, while one objective may aim to maximize profit, another might focus on minimizing labor costs, illustrating that the scale of measurement for each objective can differ without inherent conflict. This approach is particularly advantageous for design or planning scenarios, as it optimizes the allocation of limited resources amidst competing and sometimes contradictory constraints. In real-world environments characterized by multifaceted challenges, decision-makers often rely on MODM techniques to achieve several objectives concurrently. Various methods are employed in MODM, including Goal Programming and the Lexicographic method. Goal Programming facilitates the balance among conflicting objectives by prioritizing them based on importance, while the Lexicographic method simplifies the decision-making process by focusing on the most critical criteria first. These methodologies have been successfully applied in diverse contexts; for instance, Mousavi Janbehsarayi et al. [1] developed a framework that evaluates Low-Impact Development practices for urban stormwater management through cooperative game theory, aiming for effective resource allocation among stakeholders with conflicting interests. Similarly, Hwang et al. [2] proposed the TOPSIS method for MODM, allowing decision-makers to address multiple conflicting objectives by considering both positive and negative ideal solutions. By leveraging these advanced methodologies, MODM enhances decision-making efficiency in complex scenarios, ultimately leading to more informed and equitable outcomes. In recent studies, the breadth of MODM applications has been illustrated across various domains. For example, Soltanifar [3] emphasizes that many decisions in daily life involve multiple goals and factors, and advocates for enhanced interaction between decision-makers (DMs) and multi-objective methods through weight restrictions and discrimination intensity functions. Such improvements can lead to more effective decision support. Moallemi et al. [4] focus on acquisition planning for high-value assets, introducing a robust optimization approach to navigate uncertainties and develop effective strategies that align with multiple performance objectives throughout the asset life cycle. In construction, Groenia et al. [5] highlight the need to balance sustainability with conflicting objectives like structural safety and costs. Their interactive method for implementing multi-objective optimization models addresses diverse stakeholder needs, thereby supporting collaborative decision-making and fostering sustainable design solutions. Yalılı et al. [6] present a MODM model aimed at optimizing hybrid electricity generation systems in Türkiye, focusing on resource utilization and carbon emissions. Their work illustrates the substantial impact MODM techniques can have on energy system planning. Further, Zhou et al. [7] propose a framework that integrates multi-objective optimization with fuzzy multi-criteria decision-making for planning integrated energy systems (IES). Their approach effectively minimizes energy consumption, carbon emissions, and economic costs, showcasing the relevance of MODM in promoting sustainable energy solutions. Despite its benefits, MODM faces significant challenges. First, there is the issue of balancing conflicting objectives. Achieving a higher level of satisfaction for one objective often leads to decreased satisfaction for others, necessitating the identification of a balance among competing goals. This can involve weighting multiple objectives to simplify the primary problem into a single weighted goal. Second, temporal issues arise as the number of dimensions or criteria increases, leading to substantial computational costs. This challenge can hinder the efficiency of the decision-making process and limit the applicability of MODM in more complex scenarios.

MADM is a strategic approach for evaluating and selecting the best option among available alternatives based on diverse, conflicting attributes. In many decision-making scenarios, a choice must be made from multiple options, each influenced by various indicators, which complicates the decision-making process. MADM, a branch of MCDM, falls within the realm of operations research and encompasses methodologies specifically designed to address these complexities. MADM methods can be categorized into compensatory and non-compensatory approaches, allowing decision-makers to effectively navigate situations where different criteria exhibit varying characteristics and measurement units, often leading to conflict and trade-offs. These models are particularly valuable in real-world applications where the presence of competing criteria necessitates a structured decision-making framework. Recent studies illustrate advancements in MADM. Soltanifar [8] presents the Linear Assignment Voting (VLAM) method, enhancing traditional models by using Data Envelopment Analysis (DEA) to provide final weights for alternatives. This method was effectively applied in a case study on excavator procurement, improving decision-making capabilities. Tavana et al. [9] discuss the Analytical Hierarchy Process (AHP), emphasizing its robustness but also its challenges, such as extensive pairwise comparisons. They propose hybrid methods that integrate AHP with other weighting techniques, demonstrating greater efficiency and expert engagement while maintaining ranking accuracy. Further applications of MADM are evident in recent research. Soltanifar and Tavana [10] introduce a method that categorizes attributes to facilitate systematic expert comparisons without added computations, improving flexibility and precision while reducing complexity. Soltanifar [11] develops a hybrid method combining the COPRAS and MOORA techniques to determine attribute weights dynamically, ranking alternatives based on detailed interactions with decision-makers. In another study, Soltanifar et al. [12] propose an integrated MADM and DEA framework for heterogeneous attributes, effectively aggregating weights and scores for alternatives while simplifying decision-making processes, as applied to European countries' compliance with the Sustainable Development Goals. Additionally, they highlight that their model's independence from predetermined weights is a significant advantage. Moreover, Soltanifar et al. [13] enhance the WASPAS method by incorporating interaction with decision-makers to rank organizational leadership styles during the COVID-19 pandemic, demonstrating the method's applicability in crisis management. Soltanifar and Zargar [14] focus on cloud computing security risks, using pairwise comparisons to rank these risks based on expert opinions, with data privacy emerging as the top concern. El-Araby [15] addresses the Rank Reversal Phenomenon (RRP) in MCDM methods by proposing the MARCOS approach, which is tested against various engineering problems, showcasing its robustness and applicability. Kabgani [16] presents a two-stage MADM model for selecting Municipal Solid Waste (MSW) management facility locations, evaluating 15 attributes across economic, environmental, social, and technical categories. The study ranks technical attributes highest, contributing theoretical, practical, and technical insights for effective waste disposal location determination. Sheel et al. [17] focus on supplier selection, introducing a Relative Reliability Risk (R3I) assessment method that combines AHP, entropy, and alternative functionality charts, demonstrating improved accuracy over traditional approaches. Niyazi and Tavakkoli-Moghaddam [18] apply three MCDM methods for facility location selection, proposing a final ranking method based on REGIME to address ranking discrepancies. Nikjo et al. [19] tackle player selection in sports, presenting a model utilizing the WeFA framework and MCDM methods to effectively evaluate multiple criteria through expert votes and ranking alternatives. Soltanifar [20] investigates the integration of preferential voting with the Kemeny Median Indicator Ranks Accordance (KEMIRA) method, proposing an improved model that addresses inherent shortcomings through linear programming, demonstrated on real-world problems. In a subsequent study, Soltanifar et al. [21] introduce the Voting-KEMIRA method, which reformulates KEMIRA as a linear programming model to mitigate computational complexity in multi-category scenarios, successfully applied in hospital construction projects. Building on this, Soltanifar and Santos-Arteaga [22] present a hybrid approach that combines the Best Worst Method (BWM) and KEMIRA with Data Envelopment Analysis (DEA), enhancing flexibility in preference expression and improving attribute ranking accuracy via optimal weight selection. Additionally, Soltanifar et al. [23] propose the fuzzy KEMIRA method, which captures uncertainties in MADM, leveraging linear programming for optimal weight determination and illustrated through numerical examples and case studies, including innovation park location selection. Sabaei et al. [24] conduct a comprehensive review of Multi-Criteria Decision Making (MCDM) models pertinent to maintenance management in manufacturing, offering a comparative framework for selecting appropriate decision-making approaches. Recent developments in MADM techniques have introduced new models that address the challenges of uncertainty, subjectivity, and data aggregation. For instance, Lei et al. [25] proposed a three-way MADM model with objective risk avoidance coefficients based on q-rung orthopair fuzzy pre-order relations, which enhances decision-making by reducing subjective bias and improving the discrimination rate of distance measures. Liu et al. [26] introduced a multi-attribute group decision-making (MAGDM) method using single-valued neutrosophic credibility numbers (SvNCNs) and fairly weighted variable extended power average (VEPA) operators, providing a more flexible and objective aggregation method. Dai et al. [27] developed a stochastic consensus approach for uncertain MADM problems, integrating a stochastic belief distribution to measure uncertainty and proposing a consensus index for improved decision-making in uncertain environments. These advancements provide a broader context for the proposed ARAS-M method, highlighting its innovation in enhancing sustainability evaluation in green supply chains.

The Additive Ratio Assessment (ARAS) method, introduced by Zavadskas and Turskis [28], represents a cutting-edge approach for solving multi-criteria decision-making problems through compensatory mechanisms. This method quickly gained traction in various fields, including construction management, as demonstrated by Zavadskas et al. [29], who applied ARAS to assess foundation installation alternatives. The primary objective of the ARAS method is to facilitate the selection and ranking of options based on multiple criteria by determining the degree of preference for each alternative. Its adaptability has led to its

application in diverse scenarios, such as personnel selection [30], ranking factoring companies [31], and selecting internal safety auditors within construction organizations [32]. Moreover, the method has been employed in cost-benefit analyses [33], evaluating mobile models [34], and selecting software testing methods [35]. In a recent study, Idaman et al. [36] utilized the ARAS method to evaluate candidates for the position of Head of Production, demonstrating its effectiveness in integrating qualitative and quantitative criteria to ensure optimal decision-making. Furthermore, Fan et al. [37] extended the ARAS method to a picture fuzzy environment, addressing green supplier selection and showcasing its versatility in handling ambiguous information. Notably, Heidary Dahooie et al. [38] demonstrated its utility in oil and gas drilling project evaluations through an interval-valued fuzzy ARAS approach, underscoring the method's effectiveness across a broad spectrum of applications.
The evaluation of sustainable green supply chains in the food industry serves as an exemplary case for applying Multi-Criteria Decision-Making (MADM) methods. This issue has garnered attention due to the pressing need for organizations to adopt environmentally responsible practices. For instance, Soltanifar et al. [39] highlight the importance of supplier selection, emphasizing its direct impact on performance and profitability. Their study identifies essential criteria for green supplier selection—such as green design, purchasing, production, transportation, and pollution control—through a systematic review and expert engagement. They propose a new group voting analytical hierarchy process, demonstrating that valuable insights can be gained with minimal information, thereby enhancing decision-making efficiency. Similarly, Sharafi et al. [40] address the imperative of integrating green supply chain management (GSCM) to meet growing environmental concerns. They introduce a fuzzy Data Envelopment Analysis (DEA) model for green supplier selection, leveraging expert opinions and improving existing ranking methods to achieve comprehensive evaluations of suppliers. Building on these foundations, our research focuses on evaluating sustainable green supply chains specifically within the food industry. We present a significant advancement in decision-making methodologies by introducing the Modified Additive Ratio Assessment (ARAS-M), an innovative refinement of the traditional ARAS method. Unlike conventional approaches that often rely on static weighting schemes and limited engagement with decision-makers, ARAS-M incorporates a linear programming model to dynamically optimize weight allocation, addressing a critical gap in adaptability and precision. Additionally, ARAS-M enhances decision-making processes through improved interaction with experts, enabling the method to capture nuanced priorities effectively. This novel framework is specifically tailored to the sustainability challenges of the food industry, offering a robust and practical tool for evaluating suppliers based on comprehensive sustainability criteria. By bridging gaps in existing methods, ARAS-M not only contributes to advancing academic discourse but also delivers actionable insights for practitioners committed to enhancing sustainability in their supply chains.

The organization of this article is structured to facilitate a comprehensive understanding of our research on evaluating sustainable green supply chains in the food industry. We will begin with a methodology section, where we will provide an overview of the ARAS method and detail the design and explanation of our Modified Additive Ratio Assessment (ARAS-M). This section will include a structural comparison between the two methods to highlight the innovations introduced in ARAS-M. Following this, we will discuss sustainable GSCM in the food industry, defining the relevant attributes that pertain to this domain in a well-supported manner. We will then apply our proposed method to select a green supplier based on the defined attributes, demonstrating its practical utility. Finally, we will conclude with a summary of findings, further discussions, and suggestions for future research avenues to enhance sustainable practices in supply chain management.

2. Methodology

In this section, we aim to present the methodology for addressing the decision-making challenges related to sustainable green supply chains. As a foundational approach, the Additive Ratio Assessment (ARAS) method, known for its compensatory nature in multi-attribute decision-making (MADM), will first be introduced. ARAS, a well-established MADM technique, provides a structured mechanism for ranking alternatives based on multiple criteria. However, to enhance the robustness of the decision-making process, especially in scenarios where more nuanced judgments are required, we propose a modification. By integrating linear programming models and discrimination intensity functions, the improved method—Modified Additive Ratio Assessment (ARAS-M)—will offer more reasoned judgments and foster greater interaction with decision-makers. This enhancement ensures that decision-making becomes more aligned with the practical needs of complex, real-world applications, where flexibility and precision are crucial.

2.1.Overview of the ARAS Method

The Additive Ratio Assessment (ARAS) method is a multi-attribute decision-making (MADM) technique, which is designed to evaluate a set of alternatives based on multiple criteria, providing a structured way to rank the alternatives by determining their degree of utility. The key idea behind ARAS is to compare each alternative with an optimal one, often idealized, that possesses the best values for all criteria. The decision-making process starts with constructing a decision matrix that includes *m* alternatives and *n* criteria. This matrix not only captures the performance values of each alternative across all criteria but also includes an optimal alternative that either represents the best achievable values or is derived from predefined standards.

In this method, alternatives $\boldsymbol{A_1, A_2, \dots, A_m}$ are evaluated against criteria $\boldsymbol{C_1, C_2, \dots, C_n}$, forming a decision matrix as shown in Equation (1).

$$D = \begin{bmatrix} r_{01}, \dots, \dots, r_{0j}, \dots, \dots, r_{0n} \\ r_{11}, \dots, \dots, r_{1j}, \dots, \dots, r_{1n} \\ \vdots \ , \dots, \dots, \vdots, \dots, \dots, \vdots, \\ r_{i1}, \cdots, \dots, r_{ij}, \dots, \dots, r_{in} \\ \vdots \ , \dots, \dots, \vdots, \dots, \dots, \vdots \\ r_{m1}, \cdots, \dots, r_{mj}, \dots, \dots, r_{mn} \end{bmatrix}_{(m+1)\times n} \tag{1}$$

The entries r_{ij} represent the performance of the i^{th} alternative on the j^{th} criterion, while r_{0j} represents the optimal value for criterion *j*. When there are no predefined standards, an ideal alternative $\boldsymbol{A}^+$ is constructed, which holds the best possible values across all criteria based on Equation (2). It is important to note that this alternative is often hypothetical and may not exist in reality. Assuming J is the set of indices for benefit criteria (where higher values are better) and J' is the set of indices for cost criteria (where lower values are better).

$$A^{+}=\left\{\max_{i} r_{ij};\, j\in J\right\}\cup\left\{\min_{i} r_{ij};\, j\in J'\right\}=\left\{A_1^{+},A_2^{+},\ldots,A_n^{+}\right\} \tag{2}$$

The ARAS algorithm follows a systematic procedure:

1. *Normalization:* The decision matrix is normalized. For benefit criteria (positive), normalization is done using Equation (3), and for cost criteria (negative), it follows Equation (4). This step ensures comparability across different criteria.

$$\bar{r}_{ij}=\frac{r_{ij}}{\sum_{i=0}^{m} r_{ij}},\quad j\in J \tag{3}$$

$$r'_{ij}=\frac{1}{r_{ij}},\ \bar{r}_{ij}=\frac{r'_{ij}}{\sum_{i=0}^{m} r'_{ij}},\quad j\in J' \tag{4}$$

2. *Weighting:* The normalized matrix is weighted by multiplying each element by its corresponding criterion weight, $(w_1,w_2,\cdots,w_n);\sum_{j=1}^{n} w_j=1$ as determined by the decision-maker, yielding the weighted normalized matrix, calculated using Equation (5).

$$\hat{r}_{ij}=w_j\bar{r}_{ij},\qquad i=0,1,\ldots,m;\, j=1,2,\ldots,n \tag{5}$$

3. *Optimality Score:* The overall performance score S_i for each alternative is computed as the sum of the weighted normalized values across all criteria (Equation 6).

$$S_i=\sum_{j=1}^{n}\hat{r}_{ij},\ i=0,1,\ldots,m \tag{6}$$

4. *Degree of Utility:* The utility degree K_i for each alternative is obtained by comparing its performance score to that of the optimal alternative (Equation 7).

$$K_i=\frac{S_i}{S_0}, i=1,\ldots,m \tag{7}$$

5. *Ranking:* Finally, the alternatives are ranked based on their utility degrees. Higher utility values indicate better performance, guiding decision-makers to select the best alternative.

This stepwise procedure allows for a comprehensive and rational comparison of alternatives, making ARAS a powerful tool for solving decision problems in various domains.

2.2. Design and Explanation of the Modified Additive Ratio Assessment (ARAS-M)

One of the primary limitations of the ARAS method lies in its normalization process, which involves incorporating a "predefined optimal standard" or a “virtual ideal alternative” to normalize the decision matrix and subsequently weight it. The approach used in ARAS for normalization is linear and bears resemblance to the Simple Additive Weighting (SAW) method [41]. However, the linear normalization applied in ARAS is asymmetric, leading to certain challenges when evaluating criteria.

In research aiming to improve the weighting of criteria in ARAS, it was suggested that instead of linear normalization, the *min-max normalization* approach should be employed [42]. This modification addresses the asymmetry issue and provides a more robust framework for evaluation. Thus, in the first step, instead of Equations (3) and (4), the alternative formulas (8) and (9) will be used for normalization:

$$\bar{r}_{ij} = \frac{r_{ij} - \min\limits_{0\le i\le m} r_{ij}}{\max\limits_{0\le i\le m} r_{ij} - \min\limits_{0\le i\le m} r_{ij}}, \quad j \in J \tag{8}$$

$$\bar{r}_{ij} = \frac{\max\limits_{0\le i\le m} r_{ij} - r_{ij}}{\max\limits_{0\le i\le m} r_{ij} - \min\limits_{0\le i\le m} r_{ij}}, \quad j \in J' \tag{9}$$

In this section, we introduce the *Modified ARAS method (ARAS-M)*, which involves the following improvements:

1) *Normalization using min-max scaling* replaces the linear normalization used in the original ARAS method.
2) Instead of using predefined criteria weights, ARAS-M incorporates *criteria prioritization from experts* and uses *linear programming* models to determine the final weights, ensuring greater flexibility and decision-maker interaction.

Suppose we aim to evaluate m alternatives $\boldsymbol{A_1, A_2, \ldots, A_m}$ across n criteria $\boldsymbol{C_1, C_2, \ldots, C_n}$. The decision matrix takes the general form of Equation (10):

$$D = \begin{bmatrix} r_{01}, \ldots, \ldots, r_{0j}, \ldots, \ldots, r_{0n} \\ r_{11}, \ldots, \ldots, r_{1j}, \ldots, \ldots, r_{1n} \\ \vdots \; , \ldots, \ldots, \vdots, \ldots, \ldots, \vdots, \\ r_{i1}, \cdots, \ldots, r_{ij}, \ldots, \ldots, r_{in} \\ \vdots \; , \ldots, \ldots, \vdots, \ldots, \ldots, \vdots \\ r_{m1}, \cdots, \ldots, r_{mj}, \ldots, \ldots, r_{mn} \\ r_{(m+1)1}, \cdots, r_{(m+1)j}, \ldots, r_{(m+1)n} \end{bmatrix}_{(m+2)\times n} \tag{10}$$

Where r_{ij} is the value of alternative i under criterion j, r_{0j} is the best possible value, and $r_{(m+1)j}$ represents the worst possible value for criterion j. These values can either be based on predefined standards or, when no standard exists, the ideal positive and ideal negative alternatives ($\boldsymbol{A}^+$ and $\boldsymbol{A}^-$) are computed as follows:

- The ideal positive alternative ($\boldsymbol{A}^+$) is defined as the alternative with the best value across all criteria.
- The ideal negative alternative ($\boldsymbol{A}^-$) is defined as the alternative with the worst value across all criteria.

These can be computed via Equations (2) and (11), respectively, as:

$$A^- = \left\{ \min_i r_{ij};\, j \in J \right\} \cup \left\{ \max_i r_{ij};\, j \in J' \right\} = \left\{ A_1^-, A_2^-, \ldots, A_n^- \right\} \tag{11}$$

The modified algorithm of ARAS-M consists of the following steps:

Step 1: Normalize the decision matrix using the min-max normalization formula:

$$\overline{r}_{ij} = \frac{r_{ij} - r_{(m+1)j}}{r_{0j} - r_{(m+1)j}} \quad i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{12}$$

Let us assume that the weights of the criteria, which are to be obtained from the decision-maker (note that in the modified method, the actual weights are not extracted; rather, the criteria are prioritized by experts), are denoted as $\left(w_1, w_2, \cdots, w_n\right); \sum_{j=1}^{n} w_j = 1$.

By replacing the linear normalization process described in Equations (3) and (4) with the minimum-maximum normalization process from Equation (12), the utility degree can be recalculated according to Equation (13). Specifically, the utility ratio K_i for alternative $\boldsymbol{A_i}$ is computed as:

$$K_i = \frac{S_i}{S_0} = \frac{\sum_{j=1}^{n} \hat{r}_{ij}}{\sum_{j=1}^{n} \hat{r}_{0j}} = \frac{\sum_{j=1}^{n} w_j \overline{r}_{ij}}{\sum_{j=1}^{n} w_j \overline{r}_{0j}} = \frac{\sum_{j=1}^{n} w_j \left(\frac{r_{ij} - r_{(m+1)j}}{r_{0j} - r_{(m+1)j}} \right)}{\sum_{j=1}^{n} w_j \left(\frac{r_{0j} - r_{(m+1)j}}{r_{0j} - r_{(m+1)j}} \right)}, i = 1, \ldots, m \tag{13}$$

Since the weights of the criteria satisfy the condition $\sum_{j=1}^{n} w_j = 1$, the utility degree K_i can be calculated directly using the simplified formula in Equation (14):

$$K_i = \sum_{j=1}^{n} w_j \left(\frac{r_{ij} - r_{(m+1)j}}{r_{0j} - r_{(m+1)j}} \right), i = 1, \ldots, m \tag{14}$$

This modified formulation incorporates the new normalization technique and adjusts the utility calculation accordingly, reflecting the weights of the criteria derived from the expert prioritization process.

Step 3: Instead of directly assigning weights, we rank the criteria according to their importance as determined by experts. Assume K experts are involved, and $C_j^k, \left(j = 1, 2, \ldots, n; k = 1, 2, \ldots, K \right)$ represents the j^{th} priority criterion from expert k. This leads to constructing a *priority matrix* for each expert using Equation (15).

$$R_k = \left[a_{jj'}^k \right]_{n \times n}, a_{jj'}^k = \begin{cases} 0 & if\ C_j^k \preceq C_{j'}^k \\ 1 & if\ C_j^k \succ C_{j'}^k \end{cases}; j, j' = 1, 2, \ldots, n, k = 1, 2, \ldots, K \tag{15}$$

Step 4: The distance between the prioritizations of each expert and the others is calculated using Equation (16). The total distance ρ_k for each expert k is computed as:

$$\rho_k = \sum_{k'=1}^{K}\sum_{j=1}^{n}\sum_{j'=1}^{n}\left|a_{jj'}^{k} - a_{jj'}^{k'}\right|, \quad k = 1, 2, \ldots K \tag{16}$$

In this step, the expert with the minimum distance to all other experts is identified as the reference expert. The prioritization provided by this expert is selected as the "reference prioritization" and serves as the basis for determining the final weights of the criteria. Mathematically, this reference expert k^* is found by minimizing ρ_k (Equation (17)):

$$\rho_{k^*} = \min_{1\le k\le K} \rho_k \tag{17}$$

The prioritization of expert k^* is then considered the average prioritization for determining the criteria weights.

Step 5: A linear programming model is used to optimize the utility degree K_i for each alternative (Model (18)). This allows each alternative to select the best set of normalized criteria weights that optimally evaluate it.

$$\begin{aligned}
& K_i = max\sum_{j^*=1}^{n} w_{j^*}\left(\frac{r_{ij^*} - r_{(m+1)j^*}}{r_{0j^*} - r_{(m+1)j^*}}\right) \\
& s.t. \sum_{j^*=1}^{n} w_{j^*} = 1 \\
& w_{j^*} - w_{j^*+1} \ge d\left(j^*, \varepsilon\right), \quad j^* = 1, 2, \ldots, n-1 \\
& w_{n^*} \ge d\left(n^*, \varepsilon\right)
\end{aligned} \tag{18}$$

In Model (18), the weights $w_{j^*}, \left(j^* = 1, 2, \ldots, n\right)$, represent the re-indexed weights for the criteria based on the opinion of the reference expert.

Step 6: Finally, rank the alternatives based on their utility degrees. The higher the utility degree, the better the alternative ranks.

The modifications in ARAS-M, particularly the incorporation of criteria prioritization and linear programming, provide a more structured, justified, and interactive approach to decision-making. It not only allows for a better reflection of the decision-maker’s preferences but also improves the robustness and credibility of the final rankings.

2.3. Structural Comparison of ARAS and ARAS-M

The Modified Additive Ratio Assessment (ARAS-M) approach presents notable enhancements over the traditional ARAS method. These improvements primarily revolve around two key structural changes: normalization process and the way weights for the criteria are determined. In this section, we delve into these modifications and their implications for the decision-making process.

Normalization Process: In the ARAS method, a linear normalization process is used to transform the decision matrix values. This approach, while functional, has certain limitations, including the lack of symmetry and an over-reliance on predefined optimal and virtual ideal solutions. The normalization used in ARAS is similar to the Simple Additive Weighting (SAW) method, which can sometimes lead to biased rankings when criteria have significantly different ranges. In contrast, ARAS-M introduces the minimum-maximum normalization technique, which addresses these biases by adjusting the criteria values to a more balanced scale. This new normalization formula ensures that each criterion is rescaled within its actual minimum and maximum values, providing a more accurate reflection of performance across different criteria.

By adopting this approach, ARAS-M improves the fairness and objectivity in the comparison of alternatives, as each criterion contributes more evenly to the final ranking.

Criteria Weighting: Another significant structural difference between ARAS and ARAS-M is the method for determining criteria weights. In ARAS, these weights are typically provided directly by the decision-maker, who assigns fixed value based on their judgment of the importance of each criterion. This can sometimes lead to inconsistencies, especially when decision-makers have limited expertise in the criteria or struggle to assess their relative importance.

ARAS-M, on the other hand, enhances this process by utilizing expert prioritization instead of directly asking for weights. Through a more structured approach, the method derives weights by analyzing the relative prioritization provided by experts. This is achieved through the construction of a linear programming model that calculates the optimal weights for each criterion, taking into account the relative prioritizations.

This not only makes the weighting process more rigorous but also allows for greater interaction with the decision-makers, ensuring that the calculated weights reflect their true preferences without requiring them to provide precise values. This model also allows for a dynamic adjustment of weights, leading to a more flexible and tailored decision-making process.

Incorporation of Decision-Maker Interaction through Discrimination Intensity Functions: ARAS-M introduces a novel feature for improving decision-maker engagement by incorporating discrimination intensity functions. These functions enable a more interactive process for refining the weights of the criteria based on the decision-maker's preferences. Specifically, discrimination intensity functions allow the decision-maker to influence the difference between the weight of a given criterion and the next in line. This mechanism provides an additional level of control, enabling the decision-maker to express preferences not just for the criteria's importance but also for how significant the gap between criteria should be.

In cases where equal weights are acceptable, the discrimination intensity function, denoted as $d\left(.,\varepsilon\right)$, can take values close to zero. However, when criteria must be distinctly separated in importance, the function can be adjusted accordingly, making the model highly adaptive to various decision scenarios. This flexibility represents a key improvement, providing a richer dialogue between the decision-maker and the model and enabling more nuanced decision-making.

The origins of this approach can be traced back to Cook and Kress [43], who first proposed these weight control constraints in voting mechanisms. Their application has since been extended in several studies, including those by Noguchi et al. [44] and Llamazares and Pena [45]. The integration of these constraints allows ARAS-M to offer more robust solutions that reflect not only the rankings of the criteria but also the decision-makers' intensity of preferences.

Optimizing with Linear Programming: The final difference between ARAS and ARAS-M is the use of linear programming to calculate the optimal ranking for each alternative. The linear model ensures that the best possible weights are selected for each alternative, maximizing its performance within the bounds set by the decision-makers' prioritizations. In this way, ARAS-M allows for an optimally tailored evaluation of alternatives, ensuring that the results are both accurate and aligned with the decision-makers' objectives.

To summarize, ARAS-M represents a significant advancement over the traditional ARAS method by offering a more robust and interactive decision-making framework. The introduction of minimum-maximum normalization, the use of prioritization over fixed weights, and the inclusion of discrimination intensity functions make ARAS-M a highly adaptive and precise tool for multi-criteria decision analysis. These improvements not only lead to more accurate rankings but also provide greater flexibility for decision-makers to shape the decision-making process according to their specific preferences and needs.

The procedures for the ARAS and ARAS-M methods are summarized in Figure 1, which presents the flowchart comparison of both approaches.

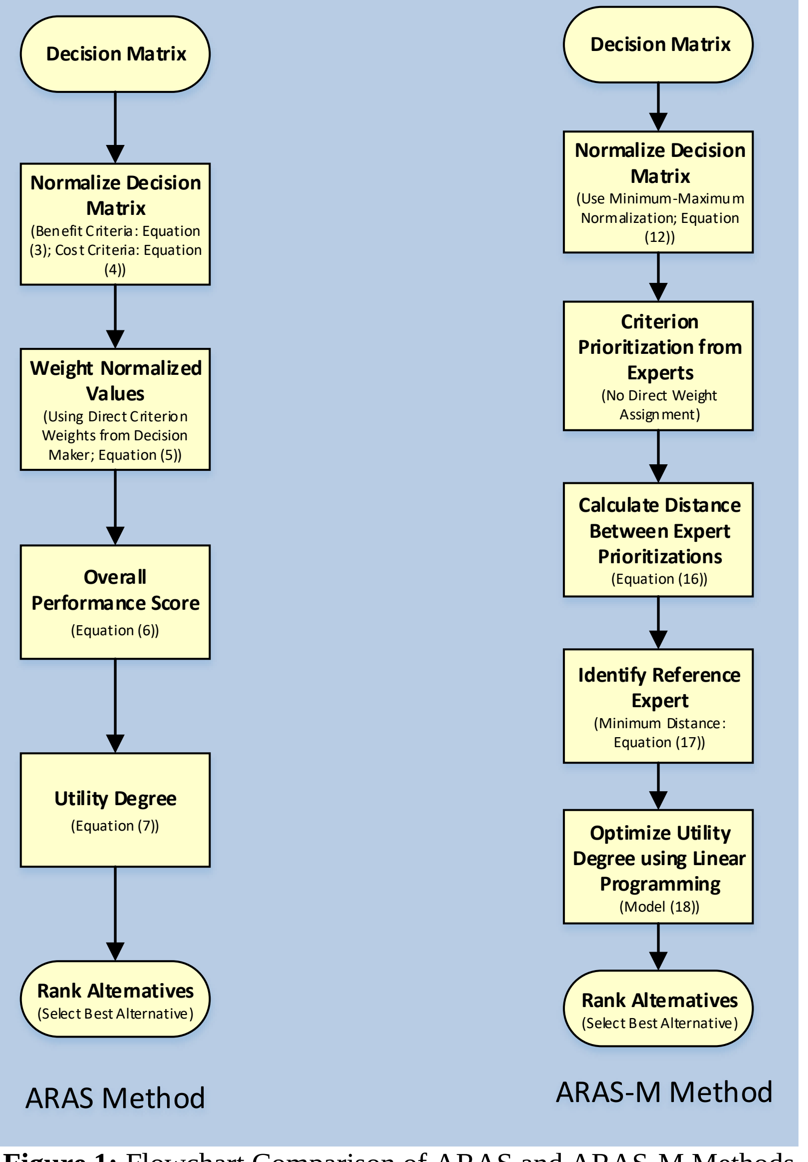

Figure 1: Flowchart Comparison of ARAS and ARAS-M Methods

3. Sustainable GSCM in the Food Industry

In today's increasingly environmentally conscious world, sustainable practices in supply chain management (SCM) have become essential, especially in industries like food production where environmental impacts are significant. The concept of a green supply chain integrates eco-friendly approaches throughout the entire lifecycle of a product, from sourcing raw materials to the final disposal. By incorporating sustainability, companies can reduce their environmental footprint, optimize resource efficiency, and enhance their competitive advantage in the market. The food industry, given its global reach and complex logistics, faces unique challenges and opportunities in adopting GSCM practices. This section is divided into two key subsections: first, we will explore the Importance of GSCM, highlighting its role in addressing environmental concerns, and then, we will examine the Relevant Attributes in the Food Industry, focusing on the specific factors that drive sustainability in this sector.

3.1. Importance of GSCM

GSCM plays a pivotal role in addressing environmental and sustainability challenges in the food industry. The integration of GSCM practices involves minimizing waste, reducing carbon footprints, and promoting eco-friendly packaging. In the food sector, such practices help mitigate resource depletion, waste management issues, and environmental contamination, which are critical concerns given the industry's heavy reliance on natural resources.

The importance of GSCM has been amplified by increasing regulatory pressures, consumer awareness, and the need for companies to align with global sustainability trends. These pressures compel firms to adopt sustainable procurement strategies, resource-efficient production methods, and eco-friendly logistics. GSCM also helps food companies maintain a competitive edge by complying with environmental regulations and satisfying the growing demand for sustainably produced food.

By implementing GSCM, food industry players not only contribute to environmental sustainability but also achieve economic benefits through cost savings in waste management and resource efficiency. Additionally, GSCM fosters innovation by encouraging the development of new, sustainable practices across the entire supply chain, from raw material sourcing to final product distribution [46].

3.2. Relevant Attributes in the Food Industry

To effectively evaluate the sustainability of green supply chain management (GSCM) in the food industry, certain key attributes must be considered. These attributes serve as critical factors influencing sustainability performance, encompassing environmental, social, and economic aspects. Below are the 11 relevant attributes, each essential to understanding GSCM's role within the food sector. The attributes presented in this section are not exhaustive, but they represent key factors critical for the sustainable green supply chain management (GSCM) of the food industry. These attributes were selected with the help of an expert panel consisting of eight specialists, including food industry professionals and GSCM experts. The Delphi method was employed to refine and prioritize these attributes, ensuring a well-rounded, expert-informed framework.

Energy Efficiency (C_1): Energy consumption is a critical factor in the food industry, particularly during production, transportation, and storage. Implementing energy-efficient technologies and practices reduces the carbon footprint of food products and contributes to sustainability goals. Several studies emphasize the importance of energy management as a core component of GSCM, with firms adopting renewable energy sources and energy-saving processes to cut costs and enhance environmental performance [46].

Waste Reduction (C_2): Waste generation, particularly food waste, is a significant concern within the food supply chain. Effective waste management strategies, including recycling and reusing waste by-products, are vital to improving sustainability. Waste reduction not only contributes to environmental goals but also enhances economic efficiency by reducing disposal costs and resource wastage [47].

Water Management (C_3): The food industry is one of the largest consumers of water resources, making sustainable water management an essential attribute. Practices such as water recycling and optimizing water usage throughout production and processing stages ensure that companies can mitigate water scarcity risks and reduce environmental impact. Proper water stewardship is now a critical part of GSCM strategies [48].

Sustainable Procurement (C_4): Sourcing raw materials sustainably ensures that environmental and social concerns are addressed from the very start of the supply chain. Sustainable procurement policies involve selecting suppliers based on their adherence to eco-friendly practices and labor standards, ensuring that the supply chain minimizes negative impacts on ecosystems and local communities [49].

Eco-Friendly Packaging (C_5): Packaging plays a crucial role in the food industry, but it often leads to significant environmental problems, especially with plastics. Sustainable packaging involves using biodegradable or recyclable materials and minimizing the overall volume of packaging to reduce waste. Many companies are innovating to adopt eco-friendly packaging solutions that align with GSCM practices [50].

Product Life Cycle (C_6): The entire life cycle of a product, from production to disposal, must be considered in evaluating its sustainability. Life Cycle Assessment (LCA) helps companies measure the environmental impact of food products across their entire life span, ensuring that GSCM efforts are comprehensive. The LCA approach is now integral to sustainability evaluations in the food industry [51].

Transportation Efficiency (C_7): Efficient transportation systems reduce fuel consumption and lower emissions. Logistics optimization, such as using energy-efficient vehicles, route planning, and load optimization, ensures that transportation activities in the food supply chain contribute to overall sustainability [52].

Supplier Collaboration (C_8): Collaborative relationships with suppliers foster better environmental performance across the supply chain. By engaging suppliers in sustainability initiatives, companies can extend their green practices and improve the overall sustainability of the chain. Supplier collaboration is particularly vital in ensuring the consistent supply of sustainably sourced materials [53].

Corporate Social Responsibility (CSR) (C_9): CSR initiatives in the food industry involve addressing social and environmental responsibilities, including fair labor practices, community engagement, and ethical sourcing. Companies are increasingly adopting CSR as a strategy to enhance their sustainability image and meet the growing demand for responsible business practices [54].

Carbon Footprint Reduction (C_{10}): Reducing the carbon footprint of food production, processing, and distribution is essential for mitigating climate change. Carbon management programs, such as carbon labeling and emission reduction targets, are common tools used to measure and reduce greenhouse gas emissions [54].

Product Traceability (C_{11}): Traceability allows companies to monitor the entire journey of food products through the supply chain, ensuring food safety, quality, and sustainability. With increasing consumer demand for transparency, traceability systems are becoming critical for proving the sustainability of products and for quick responses in case of contamination or recalls [55].

These attributes provide a comprehensive framework for assessing GSCM practices in the food industry, ensuring that sustainability is incorporated at every stage of the supply chain.

4. Case Study

In this case study, we evaluate six suppliers using the modified ARAS-M method within the context of sustainable green supply chain management (GSCM) for the food industry. The decision-making process incorporates expert judgment, translating qualitative linguistic inputs into quantitative values for analysis.

Table 1. Decision Matrix

	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6
C_1	10	9	9	8	8	8
C_2	9	8	8	8	7	7
C_3	10	9	10	9	5	6
C_4	10	10	9	10	8	8
C_5	10	9	9	9	8	9
C_6	9	9	8	8	7	7
C_7	10	10	9	8	8	8
C_8	10	10	9	9	5	6
C_9	10	9	9	8	6	7
C_{10}	10	9	9	9	7	8
C_{11}	10	10	10	10	8	9

First, the pairwise comparison matrix of the six suppliers is shown in Table 1. These qualitative inputs were aggregated from experts using a bipolar scale conversion. The attributes discussed in Section 3.2 were prioritized by five experts from the food industry and GSCM fields. Table 2 illustrates the outcome of this prioritization.

Table 2: Attribute Prioritization by Experts

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
C_1	2	1	2	4	2
C_2	11	10	11	11	11
C_3	8	9	8	1	8
C_4	3	3	3	8	4
C_5	5	5	5	5	6
C_6	10	11	10	10	9
C_7	6	7	6	6	5
C_8	9	8	9	9	10
C_9	7	6	7	7	7
C_{10}	4	4	4	3	3
C_{11}	1	2	1	2	1

Based on the expert rankings, the priority matrices for each expert are formed using Equation (15). This step is crucial as it captures the distinct preferences of each expert regarding the relevant attributes for supplier evaluation. Tables 3 through 7 present the priority matrices derived for each of the five experts. These matrices serve as the basis for further analysis, where the differences between individual expert preferences are quantified.

Table 3: Priority Matrix of Expert 1

Expert 1	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}

C_1	0	1	1	1	1	1	1	1	1	1	0
C_2	0	0	0	0	0	0	0	0	0	0	0
C_3	0	1	0	0	0	1	0	1	0	0	0
C_4	0	1	1	0	1	1	1	1	1	1	0
C_5	0	1	1	0	0	1	1	1	1	0	0
C_6	0	1	0	0	0	0	0	0	0	0	0
C_7	0	1	1	0	0	1	0	1	1	0	0
C_8	0	1	0	0	0	1	0	0	0	0	0
C_9	0	1	1	0	0	1	0	1	0	0	0
C_{10}	0	1	1	0	1	1	1	1	1	0	0
C_{11}	1	1	1	1	1	1	1	1	1	1	0

Table 4: Priority Matrix of Expert 2

Expert 2	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
C_1	0	1	1	1	1	1	1	1	1	1	1
C_2	0	0	0	0	0	1	0	0	0	0	0
C_3	0	1	0	0	0	1	0	1	0	0	0
C_4	0	1	1	0	1	1	1	1	1	1	0
C_5	0	1	1	0	0	1	1	1	1	0	0
C_6	0	0	0	0	0	0	0	0	0	0	0
C_7	0	1	1	0	0	1	0	1	0	0	0
C_8	0	1	1	0	0	1	0	0	0	0	0
C_9	0	1	1	0	0	1	1	1	0	0	0
C_{10}	0	1	1	0	1	1	1	1	1	0	0
C_{11}	0	1	1	1	1	1	1	1	1	1	0

Table 5: Priority Matrix of Expert 3

Expert 3	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
C_1	0	1	1	1	1	1	1	1	1	1	0
C_2	0	0	0	0	0	0	0	0	0	0	0
C_3	0	1	0	0	0	1	0	1	0	0	0
C_4	0	1	1	0	1	1	1	1	1	1	0
C_5	0	1	1	0	0	1	1	1	1	0	0
C_6	0	1	0	0	0	0	0	0	0	0	0
C_7	0	1	1	0	0	1	0	1	1	0	0
C_8	0	1	0	0	0	1	0	0	0	0	0
C_9	0	1	1	0	0	1	0	1	0	0	0
C_{10}	0	1	1	0	1	1	1	1	1	0	0
C_{11}	1	1	1	1	1	1	1	1	1	1	0

Table 6: Priority Matrix of Expert 4

Expert 4	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
C_1	0	1	0	1	1	1	1	1	1	0	0
C_2	0	0	0	0	0	0	0	0	0	0	0
C_3	1	1	0	1	1	1	1	1	1	1	1
C_4	0	1	0	0	0	1	0	1	0	0	0

C_5	0	1	0	1	0	1	1	1	1	0	0
C_6	0	1	0	0	0	0	0	0	0	0	0
C_7	0	1	0	1	0	1	0	1	1	0	0
C_8	0	1	0	0	0	1	0	0	0	0	0
C_9	0	1	0	1	0	1	0	1	0	0	0
C_{10}	1	1	0	1	1	1	1	1	1	0	0
C_{11}	1	1	1	0	1	1	1	1	1	1	0

Table 7: Priority Matrix of Expert 5

Expert 5	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
C_1	0	1	1	1	1	1	1	1	1	1	0
C_2	0	0	0	0	0	0	0	0	0	0	0
C_3	0	1	0	0	0	1	0	1	0	0	0
C_4	0	1	1	0	1	1	1	1	1	0	0
C_5	0	1	1	0	0	1	0	1	1	0	0
C_6	0	1	0	0	0	0	0	1	0	0	0
C_7	0	1	1	0	1	1	0	1	1	0	0
C_8	0	1	0	0	0	0	0	0	0	0	0
C_9	0	1	1	0	0	1	0	1	0	0	0
C_{10}	0	1	1	1	1	1	1	1	1	0	0
C_{11}	1	1	1	1	1	1	1	1	1	1	0

Using Equation (16), the distances between the priority rankings of each expert and others were calculated, resulting in the values shown in Table 8. This step allows us to identify consensus or divergence among the experts. From these calculations, it is evident that the first and third experts share the closest prioritization. Their alignment in preferences makes their combined prioritization the "reference prioritization," which will be used for determining the final weights of the attributes. Notably, these two experts provided identical rankings, simplifying the process of assigning reference values.

Table 8. Distance Between Each Expert's Prioritization and the Others

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
ρ_k	37	58	37	105	51

With the reference prioritization established, the decision matrix was rewritten, as shown in Table 9. This matrix not only reflects the revised ranking of the attributes but also identifies the best and worst possible values for each supplier using Equations (2) and (11). In this matrix, the attributes are re-indexed based on expert prioritization, with smaller indices representing higher priority.

Table 9: Rewritten Decision Matrix Based on Reference Prioritization

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
A^+	10	10	10	10	10	10	10	10	10	9	9
Supplier 1	10	10	10	10	10	10	10	10	10	9	9
Supplier 2	10	9	10	9	9	10	9	9	10	9	8
Supplier 3	10	9	9	9	9	9	9	10	9	8	8
Supplier 4	10	8	10	9	9	8	8	9	9	8	8
Supplier 5	8	8	8	7	8	8	6	5	5	7	7
Supplier 6	9	8	8	8	9	8	7	6	6	7	7
A^-	8	8	8	7	8	8	6	5	5	7	7

The next step involved normalizing the decision matrix using the min-max normalization technique described in Equation (12). Table 10 presents the normalized decision matrix, where the attributes have been scaled according to their priority-based rankings. This normalization ensures that all attributes are comparable, despite their varying units and scales.

Table 10: Normalized Decision Matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
Supplier 1	1	1	1	1	1	1	1	1	1	1	1
Supplier 2	1	0.5	1	0.7	0.5	1	0.75	0.8	1	1	0.5
Supplier 3	1	0.5	0.5	0.7	0.5	0.5	0.75	1	0.8	0.5	0.5
Supplier 4	1	0	1	0.7	0.5	0	0.5	0.8	0.8	0.5	0.5
Supplier 5	0	0	0	0	0	0	0	0	0	0	0
Supplier 6	0.5	0	0	0.3	0.5	0	0.25	0.2	0.2	0	0

To compute the utility degree *Ki* for each supplier, Model (18) was applied. This model is optimized to select the best set of normalized criteria weights for each supplier. Additionally, the interaction with the reference expert helped determine the recognition function, or intensity function, used to assess the distance between attributes. It was decided that the recognition function would be set to the maximum allowable value, ensuring that Model (18) remained feasible.

The final step in this process is the ranking of suppliers based on their utility degrees. The results of Model (18) and the ultimate ranking are shown in Table 11. Higher utility degrees indicate better supplier performance, and this ranking provides decision-makers with a clear and quantifiable basis for selecting the optimal supplier for sustainable practices in the food industry supply chain.

Table 11: Final Ranking of Suppliers Based on Utility Scores

ε_{max} =0.090909	**Supplier 1**	**Supplier 2**	**Supplier 3**	**Supplier 4**	**Supplier 5**	**Supplier 6**
K_i	1	0.808409	0.699439	0.622517	0	0.238405
Rank	1	2	3	4	6	5

This case study demonstrates the efficacy of the ARAS-M method in enhancing supplier evaluation, particularly within the complex and sustainability-driven context of GSCM. The integration of expert prioritization and advanced normalization techniques provides a more comprehensive and flexible framework for decision-making.

5. Conclusion

This study introduced the ARAS-M method as an innovative approach for evaluating sustainable GSCM in the food industry. By incorporating linear programming and expert prioritization, ARAS-M enhances the decision-making process compared to the traditional ARAS method. Through an extensive case study, we demonstrated the method's effectiveness in generating more reliable and robust rankings by utilizing normalized matrices and optimization techniques. This approach also improves the interaction with decision-makers through intensity detection functions, offering flexibility in adjusting the importance of criteria.

Our findings reinforce the significance of sustainable practices in GSCM, particularly in the food industry, where environmental, social, and economic factors play a crucial role in supply chain decision-making. The ARAS-M method, by minimizing subjective biases and enabling the prioritization of criteria, supports a holistic and adaptable approach to evaluating suppliers. Furthermore, its ability to evaluate suppliers based on both benefit and cost criteria makes it well-suited for dynamic and resilient supply chains.

While ARAS-M offers notable improvements, challenges remain, such as the inherent inaccuracy in determining the relative importance of criteria. Further refinement in this area is needed to enhance the model's robustness and reliability in diverse contexts.

Future studies could explore several key avenues for extending the ARAS-M method. One promising direction is the integration of fuzzy logic or interval-based data to better model uncertainty and handle imprecise information, which is common in real-world supply chain scenarios. Fuzzy ARAS-M could provide a more nuanced approach to expert judgments, addressing the vagueness that often arises in complex decision-making environments.

Another area for improvement is automating the expert prioritization process, which could make the method more scalable and applicable to a broader range of industries, beyond the food sector. Additionally, integrating ARAS-M with multi-objective optimization models could further enhance its flexibility, allowing it to address multiple conflicting objectives, a feature that would be highly beneficial for more complex and data-rich environments. Finally, the application of emerging technologies such as machine learning and big data analytics could enable the method to handle large datasets and dynamic supply chain environments more effectively.

By pursuing these directions, future research could significantly broaden the scope and impact of the ARAS-M method, contributing to its applicability in more diverse, complex, and uncertain supply chain contexts.

References

[1] Mousavi Janbehsarayi, S. F., Niksokhan, M. H., Hassani, M. R., & Ardestani, M. (2023). Multi-objective decision-making based on theories of cooperative game and social choice to incentivize implementation of low-impact development practices. *Journal of Environmental Management*, *330*, 117243. https://doi.org/10.1016/j.jenvman.2023.117243

[2] Hwang, C. L., Lai, Y. J., & Liu, T. Y. (1993). A new approach for multiple objective decision making. *Computers & Operations Research*, *20*(8), 889-899. https://doi.org/10.1016/0305-0548(93)90109-V

[3] Soltanifar, M. (2021). An investigation of the most common multi-objective optimization methods with propositions for improvement. *Decision Analytics Journal*, *1*, 100005. https://doi.org/10.1016/j.dajour.2021.100005

[4] Moallemi, E. A., Elsawah, S., Turan, H. H., & Ryan, M. J. (2018). Multi-objective decision making in multi-period acquisition planning under deep uncertainty. *Winter Simulation Conference (WSC), 2018*, 1334-1345. https://doi.org/10.1109/WSC.2018.8632316

[5] Groenia, S., van den Berg, M., Volker, L., Valcke, S., & Barros, E. (2024). Multi-objective decision-making for sustainable construction: Designing an interactive method for multi-actor project settings. Paper presented at *40th Annual ARCOM Conference 2024: Looking back to move forward*, London, United Kingdom.

[6] Yalılı, M., Menlik, T., & Boran, F. E. (2024). A novel multi-objective decision-making model to determine optimum resource and capacity configuration for hybrid electricity generation systems: A comparative case study in Türkiye. *Applied Energy, 376*, 124338. https://doi.org/10.1016/j.apenergy.2024.124338

[7] Zhou, X., Tan, W., Sun, Y., Huang, T., & Yang, C. (2024). Multi-objective optimization and decision making for integrated energy system using STA and fuzzy TOPSIS. *Expert Systems with Applications*, *240*, 122539. https://doi.org/10.1016/j.eswa.2023.122539

[8] Soltanifar, M. (2021). The voting linear assignment method for determining priority and weights in solving MADM problems. *Journal of Applied Research on Industrial Engineering*, *8*(Special Issue), 1-17. https://doi.org/10.22105/jarie.2021.268606.1240

[9] Tavana, M., Soltanifar, M., & Santos-Arteaga, F. J. (2023). Analytical hierarchy process: Revolution and evolution. *Annals of Operations Research*, *326*, 879–907. https://doi.org/10.1007/s10479-021-04432-2

[10] Soltanifar, M., & Tavana, M. (2024). A novel pairwise comparison method with linear programming for multi-attribute decision-making. *EURO Journal on Decision Processes*, *12*, 100051. https://doi.org/10.1016/j.ejdp.2024.100051

[11] Soltanifar, M. (2024). A new interval for ranking alternatives in multi attribute decision making problems. *Journal of Applied Research on Industrial Engineering*, *11*(1), 37-56. https://doi.org/10.22105/jarie.2022.339957.1467

[12] Soltanifar, M., Tavana, M., Santos-Arteaga, F. J., & Sharafi, H. (2023). A hybrid multi-attribute decision-making and data envelopment analysis model with heterogeneous attributes: The case of sustainable development goals. *Environmental Science & Policy*, *147*, 89-102. https://doi.org/10.1016/j.envsci.2023.06.004

[13] Soltanifar, M., Zargar, S. M., & Aman, M. (2023). Improved WASPAS method for determining criteria priority and weights in solving MADM problems: A case study to determine leadership style in Covid-19 pandemic. *Journal of Decisions and Operations Research*, *8*(3), 749-770. https://doi.org/10.22105/dmor.2023.345520.1616

[14] Soltanifar, M., & Zargar, S. M. (2021). Assessing and ranking cloud computing security risks based on a hybrid approach based on pairwise comparisons. *Iranian Journal of Information Processing and Management, 37*(1), 27-58. https://doi.org/10.52547/jipm.37.1.27

[15] El-Araby, A. (2023). The utilization of MARCOS method for different engineering applications: A comparative study. *International Journal of Research in Industrial Engineering, 12*(2), 155-164. https://doi.org/10.22105/riej.2023.395104.1379

[16] Kabgani, M. H. (2023). Measuring effective indicators for waste disposal in order to assess the sustainable environment: Application of fuzzy approach. *International Journal of Research in Industrial Engineering, 12*(3), 287-305. https://doi.org/10.22105/riej.2023.368774.1345

[17] Sheel, C. C., Rahman, S. M. A., & Bhowmick, T. (2024). A decision-making method for supplier selection in industrial manufacturing industry: A mathematical framework of integrating analytical hierarchical process and reliability risk evaluation in the field of industrial engineering sectors. *International Journal of Research in Industrial Engineering*. https://doi.org/10.22105/riej.2024.474342.1469

[18] Niyazi, M., & Tavakkoli-Moghaddam, R. (2014). Solving a facility location problem by three multi-criteria decision-making methods. *International Journal of Research in Industrial Engineering, 3*(4), 41-56. https://www.riejournal.com/article_48006.html

[19] Nikjo, B., Rezaeian, J., & Javadian, N. (2015). Decision making in best player selection: An integrated approach with AHP and extended TOPSIS methods based on WeFA framework in MAGDM problems. *International Journal of Research in Industrial Engineering, 4*(1(4)), 1-14. https://doi.org/10.22105/riej.2017.49166

[20] Soltanifar, M. (2023). Improved Kemeny median indicator ranks accordance method. *Asia-Pacific Journal of Operational Research, 40*(03), 2250024. https://doi.org/10.1142/S0217595922500245

[21] Soltanifar, M., Krylovas, A., & Kosareva, N. (2023). Voting-KEMIRA median indicator ranks accordance method for determining criteria priority and weights in solving multi-attribute decision-making problems. *Soft Computing, 27*, 6613–6628. https://doi.org/10.1007/s00500-022-07807-0

[22] Soltanifar, M., & Santos-Arteaga, F. J. (2024). Hybrid DEA-BWM-KEMIRA approach for multiple attribute decision-making: A weighted analysis perspective. *Soft Computing*. https://doi.org/10.1007/s00500-024-09933-3

[23] Soltanifar, M., Tavana, M., Santos-Arteaga, F. J., & Charles, V. (2024). A new fuzzy KEMIRA method with an application to innovation park location analysis and selection. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2024.3471876

[24] Sabaei, D., Erkoyuncu, J., & Roy, R. (2015). A review of multi-criteria decision-making methods for enhanced maintenance delivery. *Procedia CIRP*, *37*, 30-35. https://doi.org/10.1016/j.procir.2015.08.086

[25] Lei, S., Ma, X., Qin, H., Ren, D., & Niu, X. (2025). A new three-way multi-attribute decision-making with objective risk avoidance coefficients based on q-rung orthopair fuzzy pre-order relations, *Expert Systems with Applications*, 268, 126252, https://doi.org/10.1016/j.eswa.2024.126252.

[26] Liu, P., Shen, J., Zhang, P., & Ning, B. (2025). Multi-attribute group decision-making method using single-valued neutrosophic credibility numbers with fairly variable extended power average operators and GRA-MARCOS, *Expert Systems with Applications*, 263, 125703, https://doi.org/10.1016/j.eswa.2024.125703.

[27] Dai, X., Li, H., Zhou, L., Wu, Q. (2025). Stochastic consensus for uncertain multiple attribute group decision-making problem in belief distribution environment, *Applied Soft Computing*, 168, 112495, https://doi.org/10.1016/j.asoc.2024.112495.

[28] Zavadskas, E. K., & Turskis, Z. (2010). A new additive ratio assessment (ARAS) method in multi criteria decision-making. *Technological and Economic Development of Economy, 16*(2), 159-172. https://doi.org/10.3846/tede.2010.10

[29] Zavadskas, E. K., Turskis, Z., & Vilutiene, T. (2010). Multiple criteria analysis of foundation instalment alternatives by applying Additive Ratio Assessment (ARAS) method. *Archives of Civil and Mechanical Engineering, 10*(3), 123-141. https://doi.org/10.1016/S1644-9665(12)60141-1

[30] Karabasevic, D., Zavadskas, E. K., Turskis, Z., & Stanujkic, D. (2016). The framework for the selection of personnel based on the SWARA and ARAS methods under uncertainties. *Informatica*, *27*(1), 49-65. https://doi.org/10.15388/Informatica.2016.76

[31] Ozbek, A., & Erol, E. (2017). Ranking of factoring companies in accordance with ARAS and COPRAS methods. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, *7*(2), 105-116. https://doi.org/10.6007/IJARAFMS/v7-i2/2876

[32] Prasad, R. (2019). Selection of internal safety auditors in an Indian construction organization based on the SWARA and ARAS methods. *Journal of Occupational Health and Epidemiology, 8*(3), 134-140. https://doi.org/10.29252/johe.8.3.134

[33] Lee, J., Ozaki, I., Kishino, S., & Suzuki, K. (2021). Evaluation method of ARAS combining simulator experiment and computer simulation in terms of cost-benefit analysis. *International Journal of Intelligent Transportation Systems Research, 19*, 44-55. https://doi.org/10.1007/s13177-019-00215-z

[34] Goswami, S.S., & Mitra, S. (2020). Selecting the best mobile model by applying AHP-COPRAS and AHP-ARAS decision making methodology. *International Journal of Data and Network Science, 4*, 27–42. https://doi.org/10.5267/j.ijdns.2019.8.004

[35] Karabašević, D.M., Maksimović, M.V., Stanujkić, D.M., Jocić, G.B., & Rajčević, D.P. (2018). Selection of software testing method by using ARAS method. *Tehnika, 73*(5), 724-729. https://doi.org/10.5937/tehnika1805724K

[36] Idaman, A., Amrullah, & Rolanda, V. (2024). Analysis of the Additive Ratio Assessment Method in the selection of the best production head. *Jurnal Informasi Dan Teknologi*, *6*(2), 172-181. https://doi.org/10.60083/jidt.v6i2.546

[37] Fan, J., Han, D., & Wu, M. (2023). Picture fuzzy ARAS and VIKOR methods for multi-attribute decision problem and their application. *Complex & Intelligent Systems*, *9*, 5345–5357. https://doi.org/10.1007/s40747-023-01007-5

[38] Heidary Dahooie, J., Zavadskas, E.K., Abolhasani, M., Vanaki, A., & Turskis, Z. (2018). A novel approach for evaluation of projects using an interval-valued fuzzy ARAS method: A case study of oil and gas well drilling projects. *Symmetry, 10*(2), 45, 1-32. https://doi.org/10.3390/sym10020045

[39] Soltanifar, M., Zargar, S.M., & Homayounfar, M. (2022). Green supplier selection: A hybrid group voting AHP approach. *Journal of Operational Research and Its Applications*, *19*(2), 113-132. https://doi.org/10.52547/jamlu.19.2.113

[40] Sharafi, H., Soltanifar, M., & Hosseinzadeh Lotfi, F. (2022). Selecting a green supplier utilizing the new fuzzy voting model and the fuzzy combinative distance-based assessment method. *EURO Journal on Decision Processes*, *10*, 100010. https://doi.org/10.1016/j.ejdp.2021.100010

[41] Hwang, C. L., & Yoon, K. (1981). Multiple attribute decision making. Berlin: Springer. https://doi.org/10.1007/978-3-642-48318-9

[42] Ghram, M., & Frikha, H.M. (2018). A new procedure of criteria weight determination within the ARAS method. *Multiple Criteria Decision Making*, *13*, 56-73. https://doi.org/10.22367/mcdm.2018.13.03

[43] Cook, W.D., & Kress, M. (1990). A data envelopment model for aggregating preference rankings. *Management Science, 36*(11), 1302–1310. https://doi.org/10.1287/mnsc.36.11.1302

[44] Noguchi, H., Ogawa, M., & Ishii, H. (2002). The appropriate total ranking method using DEA for multiple categorized purposes. *Journal of Computational and Applied Mathematics*, *146*(1), 155–166. https://doi.org/10.1016/S0377-0427(02)00425-9

[45] Llamazares, B., & Pena, T. (2009). Preference aggregation and DEA: An analysis of the methods proposed to discriminate efficient candidates. *European Journal of Operational Research*, *197*, 714–721. https://doi.org/10.1016/j.ejor.2008.06.031

[46] Mastos, T., & Gotzamani, K. (2022). Sustainable supply chain management in the food industry: A conceptual model from a literature review and a case study. *Foods*, *11*(15), 2295. https://doi.org/10.3390/foods11152295

[47] Zhu, Q., Geng, Y., & Sarkis, J. (2020). Sustainable waste management in supply chains: Practices and implications. *International Journal of Production Economics*, *228*, 107652. https://doi.org/10.1016/j.ijpe.2020.107652

[48] Khalili-Damghani, K., Arab, A., & Jolai, F. (2021). Multi-objective decision making for sustainable water management in the food industry. *Sustainable Production and Consumption*, *27*, 10-27. https://doi.org/10.1016/j.spc.2021.07.006

[49] Gandhi, R., Govindan, K., & Jha, P. C. (2022). Sustainable procurement and supply chain practices in the food industry: A review. *Journal of Environmental Management*, *306*, 114415. https://doi.org/10.1016/j.jenvman.2022.114415

[50] Lau, K. H., Tang, C. S., & Wang, Y. (2022). Eco-friendly packaging innovations in the food industry. *Journal of Industrial Ecology*, *26*(1), 88-105. https://doi.org/10.1111/jiec.13092

[51] Kannan, G., & Govindan, K. (2020). A life cycle approach to food supply chain sustainability: A review. *Food Control*, *49*, 110-119. https://doi.org/10.1016/j.foodcont.2020.03.012

[52] Abdulrahman, M., Gunasekaran, A., & Subramanian, N. (2021). Logistics and transportation in sustainable supply chains: A systematic review. *Transportation Research Part E: Logistics and Transportation Review*, *140*, 102007. https://doi.org/10.1016/j.tre.2020.102007

[53] Gopal, P., & Thakkar, J. (2022). Collaboration in supply chains: A review of enablers and barriers. *International Journal of Production Research*, *58*(8), 2435-2456. https://doi.org/10.1080/00207543.2021.1874482

[54] Chkanikova, O., & Mont, O. (2020). Corporate social responsibility in the food sector: A focus on sustainability. *Journal of Cleaner Production*, *123*, 260-270. https://doi.org/10.1016/j.jclepro.2020.07.031

[55] Aung, M. M., & Chang, Y. S. (2020). Traceability in a food supply chain: Safety and quality perspectives. *Food Control*, *39*, 172-184. https://doi.org/10.1016/j.foodcont.2020.109256