

Comparative Evaluation of Ratio-Based MCDM Methods: Performance and Ranking Stability under DAM Weighting

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ABSTRACT

Keywords:

Ratio-Based MCDM;
DAM Weighting;
MOORA Method;
ARAS Method;
Ranking Stability;

Ratio-based Multi-Criteria Decision-Making (MCDM) methods provide practical approaches for ranking alternatives, but differences in normalization and aggregation mechanisms can produce different rankings and levels of stability. This study comparatively evaluates ratio-based MCDM methods under a common Data Assessment Method (DAM) weighting framework, focusing on MOORA and ARAS for logistics hub location selection. The study uses a dataset comprising 12 candidate logistics hub locations and six criteria. DAM is first applied to derive criterion weights, after which MOORA and ARAS are implemented using the same decision matrix and weighting configuration. Ranking performance is examined through baseline ranking comparison, while robustness is assessed using systematic criterion-weight perturbations of ± 0.05 and ± 0.10 . Kendall's Tau is employed to measure ranking consistency, and Mean Absolute Rank Change (MARC) is used to evaluate ranking stability. The DAM results show a relatively balanced criterion-weight distribution, with CLH02 receiving the highest weight of 0.1932. Both methods identify LH6 as the best alternative and LH9 as the least preferred, although several intermediate alternatives exchange positions. MOORA achieves a Kendall's Tau of 0.9163 and a MARC of 0.3715, whereas ARAS obtains 0.9674 and 0.1840, respectively. These results demonstrate that ARAS provides higher ranking consistency and substantially greater stability under weight perturbations. Therefore, ARAS is identified as the better-performing ratio-based MCDM method for the evaluated logistics hub location problem. The findings highlight the importance of assessing both ranking



consistency and stability when selecting MCDM methods for robust decision support.

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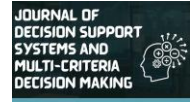
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I. Introduction

Multi-Criteria Decision-Making (MCDM) constitutes a fundamental component of Decision Support Systems (DSS), particularly in situations where decision-makers must evaluate and select alternatives based on multiple, often conflicting criteria[1], [2]. In practical decision environments, alternatives are rarely assessed using a single performance indicator because economic, technical, operational, environmental, and qualitative considerations frequently interact in determining the most appropriate decision. MCDM provides a structured framework for organizing these diverse criteria, processing heterogeneous evaluation data, and generating a priority order among competing alternatives[3], [4]. Its integration into DSS enables more systematic, transparent, and reproducible decision processes by transforming complex evaluation problems into analytical models that support informed decision-making. Consequently, the effectiveness of an MCDM-based DSS depends not only on the quality of the available data but also on the appropriateness of the weighting and ranking procedures employed.

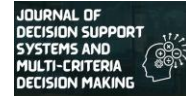
Within the MCDM framework, criteria weighting plays a decisive role because it determines the relative influence of each criterion on the final evaluation of alternatives[5], [6]. Inappropriate or excessively subjective weight assignments may introduce personal bias, distort the importance of decision criteria, and produce rankings that are highly dependent on individual preferences. Objective weighting methods address this issue by deriving criterion weights from the inherent characteristics of the decision matrix, such as data variation, information content, dispersion, or inter-criterion relationships. By reducing dependence on expert judgment, objective weighting can improve the consistency, transparency, and reproducibility of the decision-making process. However, the resulting weights may also exhibit considerable imbalance, particularly when certain criteria contain substantially greater variation or discriminatory information than others[7], [8]. Such imbalance can cause dominant criteria to disproportionately influence the final ranking, making the selection of



an appropriate weighting method an essential consideration in evaluating the reliability and fairness of MCDM outcomes.

Ratio-based MCDM methods provide an important approach for evaluating alternatives by expressing their performance through relative ratios across multiple criteria[9]. These methods generally transform the performance of alternatives into ratio-based measures and combine them with criterion weights to determine the overall preference of each alternative, thereby facilitating a ranking from the most to the least preferred option. Their relatively simple computational procedures, intuitive interpretation, and ability to handle benefit and cost criteria have contributed to their application in various decision-making contexts, including supplier selection, personnel evaluation, location selection, and resource allocation. Nevertheless, differences in ratio-based normalization procedures, aggregation mechanisms, and sensitivity to criterion weights may cause different methods to produce different rankings even when applied to the same dataset. Therefore, evaluating ratio-based MCDM methods requires more than comparing their final rankings[10]. Their performance should also be examined in terms of ranking consistency, sensitivity to weight variations, and robustness under alternative weighting configurations, particularly when objective weighting methods such as DAM are employed.

Comparing ratio-based MCDM methods presents several methodological challenges because differences in their computational procedures can directly influence the resulting alternative rankings. First, differences in normalization procedures may produce distinct relative performance values from the same decision matrix. The use of maximum-based, minimum-based, sum-based, ratio-based, or vector-based normalization can affect the relative position of alternatives and consequently influence their final scores. These differences become particularly relevant when datasets contain heterogeneous measurement scales, contrasting benefit and cost criteria, or substantial variations in criterion values[11], [12]. Second, differences in ratio-based aggregation mechanisms influence how normalized performances and criterion weights are combined to obtain an overall assessment. Although ratio-based methods generally evaluate alternatives through relative performance relationships, variations in additive ratios, weighted ratios, multiplicative formulations, or other ratio-based aggregation structures may generate different preference intensities among alternatives. As a result, two methods using identical criterion weights and input data may still produce different rankings because they establish different relationships between alternative performances and reference values. Third, ranking sensitivity to criterion weights represents a critical challenge in evaluating the reliability of ratio-based methods. Since criterion weights determine the relative contribution of each criterion to the final ratio-based assessment, even moderate changes in their values may alter the positions of competing alternatives, particularly when their performance levels are relatively close[13], [14]. This issue is especially important when objective weighting methods generate uneven weight distributions, as dominant



criteria may exert disproportionate influence on the resulting ranking. Therefore, a meaningful comparison should assess not only the baseline ranking performance of ratio-based MCDM methods but also their ranking consistency and stability under systematic weight perturbations.

Despite the extensive development and application of ratio-based MCDM methods, several research gaps remain in understanding their comparative behavior under a consistent weighting framework. Existing studies frequently evaluate ratio-based ranking methods using different weighting techniques or application-specific configurations, making it difficult to determine whether observed differences originate from the ranking mechanisms themselves or from variations in criterion weights. Furthermore, ranking stability under systematic weight perturbations has received insufficient attention, particularly in assessing how small changes in criterion importance affect the relative positions of alternatives. More importantly, the interaction between the Data Assessment Method (DAM) weighting and ratio-based ranking approaches has not been systematically investigated, leaving limited evidence regarding whether different ratio-based methods produce consistent, reliable, and robust rankings when operating under the same objective weighting scheme[15]. This gap highlights the need for a comprehensive comparative evaluation that examines both ranking performance and stability under controlled weight variations.

The objective of this study is to conduct a systematic comparative evaluation of ratio-based MCDM methods under a common DAM objective weighting scheme, focusing on their ranking performance, consistency, and stability across alternative evaluation scenarios. The study specifically examines how different ratio-based aggregation mechanisms respond to identical criterion weights and controlled weight perturbations, thereby identifying variations in ranking outcomes and the robustness of decision preferences. The main contributions of this research are threefold: first, it establishes a fair comparative framework by applying multiple ratio-based MCDM methods under the same DAM-derived weighting configuration; second, it provides a systematic assessment of ranking stability through controlled criterion-weight perturbations to evaluate the sensitivity and robustness of each method; and third, it offers empirical insights into the interaction between objective weighting and ratio-based ranking mechanisms, contributing to a clearer understanding of method reliability and supporting the selection of appropriate ratio-based ranking approaches for DSS applications.

II. Related Work

2.1. Multi-Criteria Decision-Making in Decision Support Systems

Multi-Criteria Decision-Making (MCDM) has become an important analytical approach in Decision Support Systems (DSS) because many real-world decisions involve several criteria that must be considered simultaneously. In practice, decision-makers often face alternatives



with different strengths and weaknesses, where improving one criterion may result in a reduction in another[16], [17]. MCDM provides a structured way to handle these situations by evaluating alternatives according to multiple criteria and combining the resulting information into an overall preference. Its integration into DSS helps transform complex evaluation problems into a more organized decision process, allowing users to compare alternatives and identify the most appropriate option based on defined evaluation criteria.

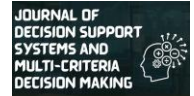
The role of MCDM in DSS extends beyond simply producing a ranking of alternatives. A typical MCDM process involves several stages, including the construction of a decision matrix, normalization of criterion values, determination of criterion weights, aggregation of criterion performance, and final ranking of alternatives[18], [19]. Each stage can influence the final decision, particularly the weighting and aggregation processes. Criterion weights determine how strongly each criterion contributes to the overall assessment, while the ranking method determines how the performance of alternatives is combined into a final score. Therefore, the selection of appropriate MCDM techniques is important to ensure that the resulting decisions are consistent with the characteristics of the decision problem.

The growing use of MCDM-based DSS has also created a need to examine the reliability and robustness of different decision-making methods[20], [21]. Two methods applied to the same dataset may produce different rankings because they use different normalization procedures, weighting interactions, or aggregation mechanisms. Such differences become more important when criterion weights are uneven or are subject to change. Consequently, evaluating an MCDM method should not be limited to its final ranking under a single configuration, but should also consider how stable the ranking remains when the decision conditions change. This perspective provides a stronger basis for assessing the suitability of MCDM methods within DSS and for determining whether the resulting decisions are sufficiently robust for practical applications.

2.2. Objective Criteria Weighting Methods

Objective criteria weighting methods are widely used in MCDM to determine the relative importance of evaluation criteria based on the information contained in the decision matrix rather than relying primarily on subjective judgments from decision-makers[22]–[24]. These methods are particularly useful when expert preferences are unavailable, inconsistent, or difficult to quantify. By examining the characteristics of the available data, objective weighting approaches can assign numerical weights that reflect the discriminatory information or variation associated with each criterion. Common approaches include Entropy, CRITIC, MEREC, LOPCOW, and other data-driven weighting techniques, each of which uses a different principle for measuring the importance of criteria.

The main advantage of objective weighting is its ability to provide a more reproducible and transparent basis for determining criterion importance[25], [26]. Entropy-based approaches generally



emphasize the amount of information or variation contained within each criterion, while CRITIC considers both criterion contrast and relationships among criteria. Other approaches, such as MEREC and LOPCOW, derive weights through different measures of criterion influence and data dispersion. Although these methods share the objective of reducing dependence on subjective judgments, they may generate substantially different weight distributions when applied to the same dataset. Consequently, the choice of an objective weighting method can have a direct effect on the subsequent evaluation and ranking of alternatives.

An important issue in objective weighting is the possibility of criterion weight imbalance, where a small number of criteria receive considerably larger weights than the remaining criteria[27], [28]. Such a distribution can cause dominant criteria to exert disproportionate influence on the final ranking, particularly when they are combined with utility-based MCDM methods. The resulting ranking may therefore reflect not only the actual performance of alternatives but also the characteristics of the weighting mechanism. For this reason, objective weighting methods should be evaluated not only according to the weights they generate but also according to how those weights affect ranking consistency and stability. Examining the interaction between objective weighting and alternative-ranking methods is consequently important for developing more reliable and robust MCDM-based decision support systems.

2.3. DAM Weighting

The DAM weighting is an objective criteria weighting approach designed to determine the relative importance of criteria directly from the information contained in the decision matrix[29]. Its fundamental concept is based on assessing the characteristics and distribution of criterion data to identify how strongly each criterion contributes to distinguishing the available alternatives. Rather than depending on subjective judgments or predefined preferences, DAM derives criterion weights through a mathematical assessment of the observed data. The weighting process therefore establishes a quantitative relationship between the information represented by each criterion and its resulting importance, providing a consistent basis for subsequent alternative evaluation.

The information extraction mechanism in DAM focuses on identifying the decision-relevant characteristics embedded in the criterion values. The observed performance of alternatives is processed to obtain an information measure for each criterion, which is then transformed into a relative weight after considering the contribution of all criteria. This mechanism allows criteria with stronger discriminatory information to be distinguished from criteria that provide relatively limited differentiation among alternatives. Because the calculation is performed directly from the decision matrix, the resulting weights are determined by the structure of the dataset rather than by individual preferences. This characteristic makes DAM suitable for decision problems involving multiple criteria with different performance patterns and levels of variation.



Compared with conventional subjective weighting methods, DAM offers several advantages, particularly in terms of objectivity, reproducibility, and reduced dependence on expert assessment. The method can generate criterion weights from available evaluation data without requiring decision-makers to assign importance values manually. In addition, the mathematical procedure provides a consistent weighting basis that can be reproduced when the same dataset is used. Compared with conventional objective methods, DAM also provides an alternative mechanism for extracting information from the decision matrix, which is useful for examining whether differences in weighting mechanisms influence subsequent ranking outcomes. This is particularly relevant because different objective weighting methods can produce different weight distributions even when applied to identical data.

In the proposed framework, DAM serves as the common objective weighting mechanism for evaluating the performance of utility-based MCDM methods. Applying the same DAM-derived weights to all selected ranking methods creates a controlled comparison in which differences in ranking outcomes can be primarily associated with the characteristics of the ranking methods rather than with changes in the weighting technique. The resulting framework subsequently examines the alternative rankings and their stability under controlled criterion-weight perturbations. In this way, DAM provides a consistent weighting foundation for investigating the interaction between objective criterion importance and utility-based aggregation, while the sensitivity analysis provides additional evidence regarding the robustness of the resulting decision rankings.

In the DAM framework, the weighting process consists of four main stages: (1) construction of the decision matrix, (2) normalization of the decision matrix, (3) calculation of preference values, and (4) determination of criterion weights. These stages establish a sequential relationship between the original performance data and the final criterion weights used in the subsequent MCDM ranking process.

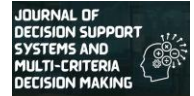
$$X = [x_{ij}]_{m \times n} \quad (1)$$

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (2)$$

$$PV_j = 100 * \left| \frac{\sqrt{\sum_{i=1}^m r_{ij}^2}}{\ln \frac{m}{\sigma_j}} \right|; \text{ where } \sigma_j = \sqrt{\frac{1}{m} \sum_{i=1}^m (s_{ij} - s_j)^2}; s_{ij} = r_{ij}^2 \quad (3)$$

$$w_j = \frac{PV_j}{\sum_{j=1}^n PV_j} \quad (4)$$

Overall, the DAM weighting procedure provides a consistent objective basis for determining criterion importance from the information contained in the decision matrix. Through the sequential stages of decision matrix construction, normalization, preference value calculation, and criterion weight determination, DAM converts the original evaluation data into a comparable set of criterion weights. These weights can then be applied consistently across different utility-based MCDM methods, enabling a fair assessment of their ranking behavior



without introducing variations caused by different weighting schemes. Consequently, DAM provides an appropriate foundation for examining differences in ranking performance, sensitivity, and stability among utility-based MCDM methods under a common objective weighting configuration.

2.4. Ratio-Based MCDM Methods

Ratio-based MCDM methods represent an important class of decision-making techniques that evaluate alternatives by establishing relative relationships among their performance values across multiple criteria[30], [31]. The underlying principle is that the relative desirability of an alternative can be determined by comparing its performance with a reference value, such as the maximum, minimum, sum, or another criterion-dependent benchmark. After the performance data are normalized or transformed into ratio-based measures, the resulting values are combined with the corresponding criterion weights to obtain an overall assessment score, which is subsequently used to rank the alternatives. This structure makes ratio-based methods relatively intuitive and computationally practical for integration into Decision Support Systems (DSS).

A major characteristic of ratio-based methods is their ability to represent the relative performance of alternatives while incorporating differences in criterion importance into the evaluation process. Criteria with higher weights contribute more strongly to the overall assessment, whereas criteria with lower weights have a smaller influence on the final ranking. However, the resulting ranking is also affected by the specific mathematical mechanism used to establish and aggregate performance ratios. Differences in reference values, ratio-based normalization, treatment of benefit and cost criteria, and aggregation procedures can therefore produce different rankings even when all methods use the same decision matrix and criterion weights. This makes the comparative evaluation of ratio-based methods important, particularly when the objective is to determine whether their ranking outcomes remain consistent and stable under identical decision conditions.

III. Material and Method

The materials and methods section describes the data, research materials, methodological procedures, and analytical techniques used to address the research objectives. This section explains how the study was conducted in a systematic and reproducible manner, including the source and characteristics of the dataset, data preparation, weighting procedure, application of MCDM methods, and evaluation techniques. In MCDM research, the section should clearly present the decision matrix, normalization process, criterion weighting, alternative ranking, and any comparative or sensitivity analysis applied in the study. A well-defined Materials and Methods section enables readers to understand the research



procedure and provides sufficient information to reproduce and validate the reported results.

3.1. Research Design

The research design refers to the overall framework developed to guide the study and ensure that the research objectives are addressed in a structured and consistent manner. In this study, the research design focuses on the comparative evaluation of utility-based MCDM methods using the DAM as a common objective weighting approach. The design emphasizes the relationship between objective criterion weighting, utility-based alternative ranking, comparative performance assessment, and ranking stability. It provides a clear framework for examining the behavior and reliability of different utility-based MCDM methods under the same weighting conditions and under variations in criterion weights. The overall research design adopted in this study is presented in Figure 1.

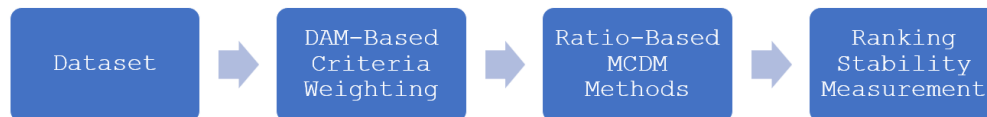
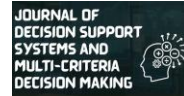


Figure 1. Research Design

The research consists of four main stages. First, the Dataset represents the data used as the basis for evaluating the selected alternatives and criteria. Second, DAM-Based Criteria Weighting determines the objective importance of each criterion using the DAM, producing a common weight configuration for all subsequent evaluations. Third, Ratio-Based MCDM Methods applies the selected ratio-based approaches to evaluate the alternatives using the same dataset and DAM-derived criterion weights, resulting in an overall assessment score and alternative ranking for each method. Fourth, Ranking Stability Measurement evaluates the consistency and robustness of the resulting rankings by examining changes in alternative positions under systematic variations in criterion weights, allowing the stability of each ratio-based MCDM method to be assessed comparatively.

3.2. Ratio-Based Multi-Criteria Decision Models

Ratio-based multi-criteria decision models are mathematical decision models that evaluate and rank alternatives by representing their performance across multiple criteria through relative ratios or comparative measures. The fundamental idea is to determine the relative desirability of each alternative by comparing its performance with an appropriate reference value while considering the relative importance of the evaluation criteria. Through this approach, alternatives with different performance characteristics can be assessed using comparable ratio-based measures, allowing their overall scores to be aggregated and ranked. Ratio-based models are widely used in decision support because they provide a relatively simple and interpretable framework for evaluating alternatives across multiple criteria, while their results



can be influenced by the normalization procedure, reference values, criterion weights, and aggregation mechanism adopted.

The multi-objective optimization on the basis of ratio analysis (MOORA) method is a ratio-based MCDM approach that evaluates alternatives by transforming their criterion performances into dimensionless relative values[32]–[34]. The method initially applies vector-based normalization to eliminate differences in measurement scales and obtain comparable performance ratios across criteria. The normalized values are then weighted according to the importance of each criterion and aggregated by maximizing the contributions of benefit criteria while minimizing those of cost criteria. The resulting assessment value represents the overall performance of each alternative and is used to establish the final ranking. The ratio-analysis structure of MOORA enables alternatives with heterogeneous performance measures to be evaluated within a common decision framework while explicitly considering both benefit and cost criteria.

The MOORA method consists of three main stages. First, the decision matrix is normalized using vector-based ratio normalization to transform the original criterion values into dimensionless measures, as presented in (1). Second, the normalized values are multiplied by the corresponding criterion weights and aggregated by maximizing benefit criteria and minimizing cost criteria, producing the MOORA optimization value as defined in (5). In this study, the criterion weights are obtained using DAM to provide a common objective weighting configuration. Third, the alternatives are ranked according to their optimization values, where a higher value indicates better overall performance, as expressed in (6).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (5)$$

$$y_i = \sum_{j \in B} u_{ij} \cdot w_j - \sum_{j \in C} u_{ij} \cdot w_j \quad (6)$$

Overall, MOORA provides a ratio-analysis-based framework for evaluating and ranking alternatives by transforming criterion performances into comparable normalized values and aggregating them according to their relative importance[35], [36]. By simultaneously maximizing benefit criteria and minimizing cost criteria, the method produces an overall optimization value that can be directly used to determine the preference order of alternatives.

The additive ratio assessment (ARAS) method is a multi-criteria decision-making approach that evaluates and ranks alternatives by comparing their overall performance with an optimal reference alternative[37], [38]. The method is based on the principle of additive ratio assessment, in which the performance values of alternatives are normalized to obtain comparable measures, multiplied by the corresponding criterion weights, and aggregated into an overall optimality value. The relative performance of each alternative is subsequently determined by comparing its optimality value with that of the optimal reference alternative through a utility degree. A higher



utility degree indicates a more preferable alternative. This structure enables ARAS to simultaneously consider multiple benefit and cost criteria while providing an interpretable basis for alternative ranking.

The ARAS method consists of three main stages. First, an optimal reference alternative is incorporated into the decision matrix using (1), followed by normalization of the criterion values to obtain comparable performance measures. Benefit and cost criteria are treated according to their respective normalization procedures, as presented in (7). Second, the normalized values are multiplied by the corresponding criterion weights and aggregated to obtain the optimality value of each alternative, as defined in (8). In this study, the criterion weights are derived from DAM to maintain a common objective weighting configuration across the evaluated MCDM methods. Third, the utility degree of each alternative is calculated relative to the optimal reference alternative using (9). The alternatives are then ranked in descending order of their utility degrees, with the highest value representing the most preferred alternative.

$$\bar{x}_{ij} = \begin{cases} \frac{x_{ij}}{\sum_{i=0}^m x_{ij}}; \text{benefit} \\ x_{ij}^- = \frac{1}{x_{ij}}; \frac{x_{ij}^-}{\sum_{i=0}^m x_{ij}^-}; \text{cost} \end{cases} \quad (7)$$

$$S_i = \sum_{j=0}^m \bar{x}_{ij} * w_j \quad (8)$$

$$K_i = \frac{S_i}{S_0} \quad (9)$$

Overall, ARAS provides an additive ratio assessment framework that evaluates alternatives relative to an optimal reference alternative[39]. By normalizing criterion performances, incorporating their corresponding weights, and calculating the utility degree relative to the optimal alternative, ARAS produces an interpretable measure of alternative preference. In this study, the use of DAM-derived weights provides a consistent objective weighting basis, allowing ARAS to be fairly compared with other MCDM methods in terms of ranking performance, consistency, and stability under controlled criterion-weight variations.

3.3. Dataset

The logistics hub location dataset represents a multi-criteria decision problem involving the selection of the most suitable location from a set of potential alternatives. Logistics hub location selection is a strategic decision because the selected location can influence the efficiency of distribution activities, transportation operations, service performance, and the overall effectiveness of the logistics network. The dataset provides performance information for several candidate locations that can be evaluated using an MCDM framework. In this study, the dataset is used as a common evaluation basis for the selected ratio-based MCDM methods, with the same objective criterion weights generated using the DAM method. The resulting rankings are subsequently analyzed to examine the comparative performance, consistency, and stability of the evaluated methods. The data used in



this study are presented in Table 1. The table contains the performance values of the candidate logistics hub locations across the evaluation criteria and serves as the primary decision matrix for the subsequent MCDM analysis.

Table 1. Logistics Hub Location Assessment Dataset

Alternatives	CLH01	CLH02	CLH03	CLH04	CLH05	CLH06
LH1	82	24	8.2	8.5	7.8	8.6
LH2	75	19	8.7	8.1	8.4	7.6
LH3	91	31	7.5	9.2	8.8	8.7
LH4	68	16	9.1	7.8	7.5	7.2
LH5	79	22	8.5	8.7	9.1	8.4
LH6	63	14	9.3	7.4	7.2	6.8
LH7	88	28	7.9	8.9	8.6	9.1
LH8	72	18	8.9	8.3	8.1	7.9
LH9	96	35	7.2	9.2	9.3	9.4
LH10	70	20	8.8	7.9	7.9	7.5
LH11	84	26	8.3	8.6	8.7	8.8
LH12	66	15	9.1	7.6	7.4	7.3

CLH01 (Transportation Cost) represents the estimated transportation expenditure associated with operating a logistics hub, where a lower value indicates a more favorable location. CLH02 (Distance to Customers) measures the distance between the candidate hub and the primary customer or demand areas, with shorter distances considered preferable. CLH03 (Accessibility) represents the ease of access to the location through major roads and transportation networks, where higher values indicate better accessibility. CLH04 (Infrastructure Quality) reflects the availability and quality of supporting infrastructure required for logistics operations, with higher values indicating better conditions. CLH05 (Labor Availability) represents the availability of an adequate workforce to support hub operations, where higher values indicate greater labor availability. CLH06 (Expansion Potential) reflects the potential for future expansion of the logistics hub in terms of available space and development capacity, with higher values indicating greater expansion potential.

The data presented in Table 1 are simulated data constructed to represent a logistics hub location selection problem for experimental evaluation. The dataset consists of 12 candidate locations, with each alternative assigned numerical performance values across six evaluation dimensions. The values were generated within plausible ranges to provide sufficient variation among alternatives while maintaining a realistic decision-making structure. The dataset includes both quantitative measurements and numerical assessment scores, allowing the selected MCDM methods to process heterogeneous performance values under a common decision matrix. The simulated dataset is used consistently across all methods to ensure that differences in the resulting rankings arise from the characteristics of the evaluated MCDM approaches rather than from differences in the input data.



IV. Result and Discussion

This section presents the comparative evaluation of ratio-based MCDM methods under a common DAM weighting framework. The analysis begins with the determination of objective criterion weights using DAM, which provides a consistent weighting configuration for all evaluated methods. The selected ratio-based MCDM methods are then applied to the same Logistics Hub Location dataset to obtain the alternative rankings and examine differences in their ranking performance. The analysis is subsequently extended through systematic criterion-weight perturbations to evaluate ranking stability and identify the sensitivity of each method to changes in criterion importance. The results are discussed comparatively to determine the consistency of the obtained rankings, the degree of ranking variation across evaluation scenarios, and the robustness of each method under the common objective weighting framework.

4.1. Criteria Weight Assessment Using the DAM Weighting Method

The determination of criteria weights is an essential stage in the multi-criteria decision-making process, as it reflects the relative importance of each criterion in evaluating competing alternatives. In this study, the DAM weighting method is employed to objectively assess the contribution of each criterion based on the information contained in the decision matrix. The resulting weights provide a consistent foundation for subsequent alternative evaluation and ranking, ensuring that the decision process considers the relative significance of all criteria in a systematic manner. The calculated criterion weights are presented and discussed to illustrate their distribution and influence on the overall decision-making framework.

The first stage involves constructing the decision matrix, which represents the performance of each alternative across the evaluated criteria. The original performance values are organized into a matrix according to the alternatives and criteria, as defined in (1). This matrix serves as the primary input for the subsequent normalization and weighting calculations. The resulting decision matrix is presented below.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} \\ x_{101} & x_{102} & x_{103} & x_{104} & x_{105} & x_{106} \\ x_{111} & x_{112} & x_{113} & x_{114} & x_{115} & x_{116} \\ x_{121} & x_{122} & x_{123} & x_{124} & x_{125} & x_{126} \end{bmatrix} \rightarrow X = \begin{bmatrix} 82 & 24 & 8.2 & 8.5 & 7.8 & 8.6 \\ 75 & 19 & 8.7 & 8.1 & 8.4 & 7.6 \\ 91 & 31 & 7.5 & 9.2 & 8.8 & 8.7 \\ 68 & 16 & 9.1 & 7.8 & 7.5 & 7.2 \\ 79 & 22 & 8.5 & 8.7 & 9.1 & 8.4 \\ 63 & 14 & 9.3 & 7.4 & 7.2 & 6.8 \\ 88 & 28 & 7.9 & 8.9 & 8.6 & 9.1 \\ 72 & 18 & 8.9 & 8.3 & 8.1 & 7.9 \\ 96 & 35 & 7.2 & 9.2 & 9.3 & 9.4 \\ 70 & 20 & 8.8 & 7.9 & 7.9 & 7.5 \\ 84 & 26 & 8.3 & 8.6 & 8.7 & 8.8 \\ 66 & 15 & 9.1 & 7.6 & 7.4 & 7.3 \end{bmatrix}$$

The second stage consists of normalizing the decision matrix to transform the original criterion values into a comparable scale. The



normalization process is performed using (2), ensuring that differences in measurement units and value ranges do not affect the consistency of the weighting procedure. The normalized values obtained for all alternatives and criteria are presented in Table 2.

Table 2. Normalization Result of DAM Weighting

Alternatives	CLH01	CLH02	CLH03	CLH04	CLH05	CLH06
LH1	0.0878	0.0896	0.0808	0.0848	0.0789	0.0884
LH2	0.0803	0.0709	0.0857	0.0808	0.0850	0.0781
LH3	0.0974	0.1157	0.0739	0.0918	0.0891	0.0894
LH4	0.0728	0.0597	0.0897	0.0778	0.0759	0.0740
LH5	0.0846	0.0821	0.0837	0.0868	0.0921	0.0863
LH6	0.0675	0.0522	0.0916	0.0739	0.0729	0.0699
LH7	0.0942	0.1045	0.0778	0.0888	0.0870	0.0935
LH8	0.0771	0.0672	0.0877	0.0828	0.0820	0.0812
LH9	0.1028	0.1306	0.0709	0.0918	0.0941	0.0966
LH10	0.0749	0.0746	0.0867	0.0788	0.0800	0.0771
LH11	0.0899	0.0970	0.0818	0.0858	0.0881	0.0904
LH12	0.0707	0.0560	0.0897	0.0758	0.0749	0.0750

The third stage involves calculating the preference values for each criterion based on the normalized decision matrix. This calculation is conducted using (3), producing preference values that reflect the relative contribution of each criterion within the DAM framework. The resulting preference values are presented in Table 3.

Table 3. Preference Score Results from DAM Weighting

CLH01	CLH02	CLH03	CLH04	CLH05	CLH06
3.3131	3.7783	3.0876	3.0668	3.1185	3.1954

The fourth stage determines the final criterion weights by converting the preference values into normalized weighting coefficients using (4). The resulting weights represent the relative importance of the criteria, with their total equal to one, and are subsequently used in the alternative ranking process. The complete results of the DAM weighting procedure, including the decision matrix, normalized values, preference values, and final criterion weights, are summarized in Table 4.

Table 4. Criteria Weight Results from DAM Weighting

CLH01	CLH02	CLH03	CLH04	CLH05	CLH06
0.1694	0.1932	0.1579	0.1568	0.1594	0.1634

The DAM weighting results show a relatively balanced distribution of importance across the six criteria. CLH02 obtains the highest weight at 0.1932, indicating that it has the greatest relative contribution to the decision-making process. It is followed by CLH01 with a weight of 0.1694, CLH06 with 0.1634, CLH05 with 0.1594, CLH03 with 0.1579, and CLH04 with 0.1568. Overall, the criterion weights sum to 1.0001 due to decimal rounding, which is practically equivalent to the required total weight of 1. The results indicate that DAM produces no extreme



differences in criterion importance, although CLH02 has the highest relative importance among the evaluated criteria.

4.2. Ranking Alternatives Using MOORA and ARAS

The alternative ranking process is conducted using the MOORA and ARAS methods to evaluate the performance of each alternative based on the criterion weights obtained from the DAM weighting method. Both methods transform the weighted criterion values into a comparable overall assessment, but they employ different evaluation mechanisms in determining the final ranking. MOORA evaluates alternatives through the aggregation of normalized beneficial and cost criteria, whereas ARAS determines the relative utility of each alternative by comparing its overall performance with an optimal reference alternative. The application of these two methods provides a comparative perspective on the resulting alternative rankings and enables the consistency of decision outcomes to be examined under the DAM-based weighting scheme.

The alternative ranking using the MOORA method consists of three main stages: normalization of the decision matrix, calculation of the MOORA optimization value, and ranking of alternatives based on their resulting optimization values.

The first stage involves normalizing the decision matrix to eliminate differences in measurement units and scales among the criteria. The normalized value for each alternative and criterion is calculated using the normalization procedure defined in (5), resulting in comparable performance values for all alternatives. The complete normalized decision matrix obtained at this stage is presented in Table 5.

Table 5. Normalization Result of MOORA Method

Alternatives	CLH01	CLH02	CLH03	CLH04	CLH05	CLH06
LH1	0.3016	0.2984	0.2791	0.2932	0.2726	0.3047
LH2	0.2759	0.2362	0.2961	0.2794	0.2936	0.2693
LH3	0.3347	0.3855	0.2553	0.3173	0.3076	0.3082
LH4	0.2501	0.1989	0.3097	0.2690	0.2621	0.2551
LH5	0.2906	0.2736	0.2893	0.3001	0.3180	0.2976
LH6	0.2317	0.1741	0.3165	0.2552	0.2516	0.2409
LH7	0.3237	0.3482	0.2689	0.3070	0.3006	0.3224
LH8	0.2648	0.2238	0.3029	0.2863	0.2831	0.2799
LH9	0.3531	0.4352	0.2450	0.3173	0.3250	0.3330
LH10	0.2575	0.2487	0.2995	0.2725	0.2761	0.2657
LH11	0.3090	0.3233	0.2825	0.2966	0.3041	0.3118
LH12	0.2428	0.1865	0.3097	0.2621	0.2586	0.2586

The second stage involves calculating the MOORA optimization value by multiplying the normalized values by their corresponding criterion weights obtained from the DAM weighting method. The weighted values are then aggregated by maximizing the performance of benefit criteria and minimizing the performance of cost criteria, as defined in (6). The resulting weighted values and MOORA optimization values for all alternatives are presented in Table 6.

**Table 6. Optimization Values Result of MOORA Method**

Alternatives	Optimization Values
LH1	0.0745
LH2	0.0890
LH3	0.0583
LH4	0.0937
LH5	0.0900
LH6	0.0966
LH7	0.0691
LH8	0.0955
LH9	0.0508
LH10	0.0858
LH11	0.0757
LH12	0.0963

The last stage involves ranking the alternatives according to their MOORA optimization values. A higher optimization value indicates better overall performance, meaning that the alternative with the highest value receives the first rank. The final ranking results obtained from the MOORA method are presented in Table 7.

Table 7. Ranking Result of MOORA Method

Alternatives	Optimization Values	Rank
LH6	0.0966	1
LH12	0.0963	2
LH8	0.0955	3
LH4	0.0937	4
LH5	0.0900	5
LH2	0.0890	6
LH10	0.0858	7
LH11	0.0757	8
LH1	0.0745	9
LH7	0.0691	10
LH3	0.0583	11
LH9	0.0508	12

The MOORA ranking results show that LH6 achieves the highest optimization value of 0.0966, placing it in first rank, followed closely by LH12 with 0.0963 in second place and LH8 with 0.0955 in third place. The subsequent positions are occupied by LH4 (0.0937), LH5 (0.0900), LH2 (0.0890), and LH10 (0.0858), ranked fourth through seventh, respectively. In the lower-ranking group, LH11 obtains 0.0757, followed by LH1 with 0.0745, LH7 with 0.0691, LH3 with 0.0583, and LH9 with 0.0508, which places last. Overall, the results indicate that LH6 is the best-performing alternative according to the MOORA method, while LH9 has the lowest overall performance among the evaluated alternatives.

The alternative ranking using the ARAS method consists of three main stages: normalization of the decision matrix, calculation of the optimality values, and determination of the utility degree of each alternative relative to the optimal reference alternative.

The first stage involves normalizing the decision matrix according to the characteristics of each criterion. Benefit and cost criteria are



processed using their respective normalization procedures, as defined in (7), to obtain comparable values across all alternatives. The complete normalized decision matrix obtained from this stage is presented in Table 2.

Table 8. Normalization Result of ARAS Method

Alternatives	CLH01	CLH02	CLH03	CLH04	CLH05	CLH06
A0	0.1013	0.1230	0.0916	0.0918	0.0941	0.0966
LH1	0.0778	0.0717	0.0808	0.0848	0.0789	0.0884
LH2	0.0851	0.0906	0.0857	0.0808	0.0850	0.0781
LH3	0.0701	0.0555	0.0739	0.0918	0.0891	0.0894
LH4	0.0938	0.1076	0.0897	0.0778	0.0759	0.0740
LH5	0.0807	0.0782	0.0837	0.0868	0.0921	0.0863
LH6	0.1013	0.1230	0.0916	0.0739	0.0729	0.0699
LH7	0.0725	0.0615	0.0778	0.0888	0.0870	0.0935
LH8	0.0886	0.0956	0.0877	0.0828	0.0820	0.0812
LH9	0.0664	0.0492	0.0709	0.0918	0.0941	0.0966
LH10	0.0911	0.0861	0.0867	0.0788	0.0800	0.0771
LH11	0.0759	0.0662	0.0818	0.0858	0.0881	0.0904
LH12	0.0967	0.1148	0.0897	0.0758	0.0749	0.0750

The second stage involves calculating the optimality value of each alternative by multiplying the normalized values by their corresponding criterion weights obtained from the DAM weighting method and aggregating the resulting weighted values, as defined in (8). The optimality values represent the overall performance of each alternative within the ARAS framework. The resulting weighted values and optimality values for all alternatives are presented in Table 9.

Table 9. Optimality Values Result of ARAS Method

Alternatives	Optimality Values
A0	0.1006
LH1	0.0801
LH2	0.0844
LH3	0.0775
LH4	0.0872
LH5	0.0844
LH6	0.0900
LH7	0.0795
LH8	0.0866
LH9	0.0771
LH10	0.0835
LH11	0.0808
LH12	0.0888

The third stage involves calculating the utility degree of each alternative relative to the optimal reference alternative using (9). The final utility degrees and ranking results obtained using the ARAS method are presented in Table 10.

Table 10. Final Utility Degrees Result of MOORA Method

Alternatives	Final Utility Degrees
LH1	0.7967



LH2	0.8397
LH3	0.7704
LH4	0.8674
LH5	0.8395
LH6	0.8949
LH7	0.7909
LH8	0.8617
LH9	0.7672
LH10	0.8299
LH11	0.8039
LH12	0.8829

The last stage involves ranking the alternatives according to their ARAS utility degrees. A higher utility degree indicates that an alternative is closer to the optimal reference alternative and therefore represents better overall performance. Accordingly, the alternative with the highest utility degree receives the first rank. The final ranking results obtained from the ARAS method are presented in Table 11.

Table 11. Ranking Result of ARAS Method

Alternatives	Final Utility Degrees	Rank
LH6	0.8949	1
LH12	0.8829	2
LH4	0.8674	3
LH8	0.8617	4
LH2	0.8397	5
LH5	0.8395	6
LH10	0.8299	7
LH11	0.8039	8
LH1	0.7967	9
LH7	0.7909	10
LH3	0.7704	11
LH9	0.7672	12

The ARAS ranking results indicate that LH6 achieves the highest final utility degree of 0.8949, placing it in first rank, followed by LH12 with 0.8829 in second place. LH4 and LH8 occupy the third and fourth positions with utility degrees of 0.8674 and 0.8617, respectively. The middle-ranking positions are held by LH2 (0.8397), LH5 (0.8395), LH10 (0.8299), LH11 (0.8039), and LH1 (0.7967), ranked fifth through ninth. Meanwhile, LH7 obtains a utility degree of 0.7909, followed by LH3 with 0.7704, while LH9 records the lowest utility degree of 0.7672 and ranks twelfth. Overall, the results show that LH6 is the most preferable alternative according to the ARAS method, whereas LH9 has the lowest overall utility among the evaluated alternatives.

4.3. Comparison of Alternative Rankings

The ranking results generated by the MOORA and ARAS methods provide an overall representation of the performance of the evaluated alternatives based on the criterion weights obtained from the DAM weighting method. Both methods use the same decision matrix and objective criterion weighting configuration, while applying different mathematical



procedures to process the normalized performance values. Through these procedures, each alternative receives a final evaluation value that reflects its performance across all considered criteria. The resulting values provide a structured representation of the decision outcomes and serve as the basis for arranging the alternatives according to their calculated performance.

The evaluation results obtained from MOORA and ARAS are subsequently organized to present the decision outcomes in a consistent manner. This presentation allows the performance patterns of all evaluated alternatives to be observed within the same analytical context while maintaining the characteristics of each respective MCDM method. At this stage, the focus is placed on presenting the resulting evaluation outcomes rather than interpreting the differences between the methods. Such an approach provides a clear foundation for the comparative analysis conducted in the subsequent discussion.

The graphical representation is particularly useful because it presents the evaluation outcomes of all alternatives in a concise and interpretable form. By displaying the results from MOORA and ARAS together, the figure provides an initial overview of the decision structure generated under the DAM weighting scheme. The visualization also supports the identification of the overall distribution of alternative performance before further statistical or comparative analysis is conducted. The complete visualization of the alternative evaluation results obtained from the MOORA and ARAS methods is presented in Figure 2.

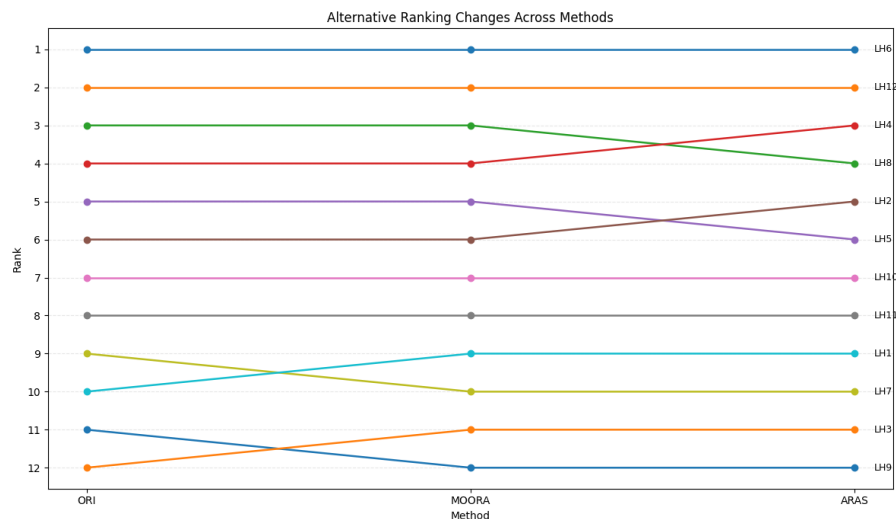
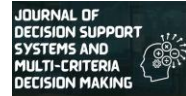


Figure 2. Comparison of Alternative Rankings

The ranking results show a high level of agreement among the ORI, MOORA, and ARAS methods. LH6 and LH12 consistently occupy the first and second positions, respectively, indicating that both alternatives are strongly preferred across all three approaches. LH8 and LH4 exchange positions between ORI and ARAS, with LH8 ranked third by ORI and MOORA but fourth by ARAS, while LH4 moves from fourth to third. A similar minor variation



occurs between LH5 and LH2, where ORI and MOORA assign ranks 5 and 6, whereas ARAS reverses their positions. The middle-ranked alternatives, LH10 and LH11, maintain identical positions across all methods at ranks 7 and 8. In the lower-ranking group, LH7 and LH1 show a small reversal, while LH9 and LH3 also exchange their positions between ORI and the two comparative methods. Overall, MOORA produces a ranking that is very close to ORI, differing only in the positions of LH7/LH1 and LH9/LH3, whereas ARAS exhibits several additional changes, particularly among the middle-ranked alternatives. These variations reflect differences in how each method processes normalized performance values, criterion weights, and aggregation principles. Therefore, the comparison emphasizes not only ranking agreement but also the extent to which each method produces a consistent decision preference under the same DAM-weighted decision environment.

4.4. Ranking Stability under Weight Perturbation

The ranking stability analysis evaluates the extent to which the decision outcomes produced by ORI, MOORA, and ARAS remain consistent when the DAM-derived criterion weights are subjected to controlled perturbations. In this analysis, the original weight vector is modified by increasing or decreasing selected criterion weights while maintaining the total weight equal to one, allowing the robustness of each method to be assessed under alternative weighting conditions. The resulting rankings are then compared with the original ranking to identify changes in alternative positions. A method that preserves the relative ordering of alternatives across a larger number of perturbation scenarios can be considered more stable because its decision outcome is less sensitive to moderate changes in the importance assigned to the criteria.

The ranking stability analysis is further conducted by applying weight perturbations of ± 0.05 and ± 0.10 to the original DAM-derived criterion weights. For the ± 0.05 scenario, each criterion weight is systematically increased and decreased by 0.05, followed by a proportional adjustment of the remaining criteria so that the total weight remains equal to one. This procedure represents a moderate change in the relative importance of the criteria and is used to examine whether the original ranking structure can be preserved under small variations in decision-maker preferences. The same procedure is subsequently applied with a larger perturbation of ± 0.10 , representing a more substantial change in criterion importance. For each scenario, the alternatives are re-evaluated using ORI, MOORA, and ARAS, and the resulting rankings are compared with the baseline configuration.

The comparison between the ± 0.05 and ± 0.10 perturbation scenarios provides a progressive assessment of ranking robustness. If an alternative retains its position or experiences only minor rank changes under both perturbation levels, its preference can be considered relatively insensitive to variations in criterion weights. In contrast, alternatives that exhibit larger positional changes, particularly under the ± 0.10 scenario, indicate greater dependence on the weighting configuration and closer competition with other alternatives. The



comparison also allows the stability of ORI, MOORA, and ARAS to be examined from a methodological perspective. A method that maintains a similar ranking structure across both perturbation levels demonstrates stronger resistance to changes in criterion importance, whereas frequent rank reversals indicate greater sensitivity. Thus, the ± 0.05 and ± 0.10 experiments complement the baseline ranking analysis by demonstrating whether the decision conclusions remain reliable when the DAM weights are subjected to increasingly stronger variations.

To further evaluate the consistency of the decision results, the rankings produced by MOORA were compared with the rankings obtained from the original MOORA method. The comparison focuses on the changes in alternative positions and the degree of agreement among the three methods, particularly for the highest, middle, and lowest-ranked alternatives. This analysis helps identify whether the methods produce a similar preference structure or whether differences in their aggregation mechanisms lead to rank reversals for particular alternatives. The overall comparison is presented in Figure 3, which provides a consolidated view of the ranking patterns and highlights the alternatives that maintain stable positions as well as those that experience changes in rank across the evaluated methods.

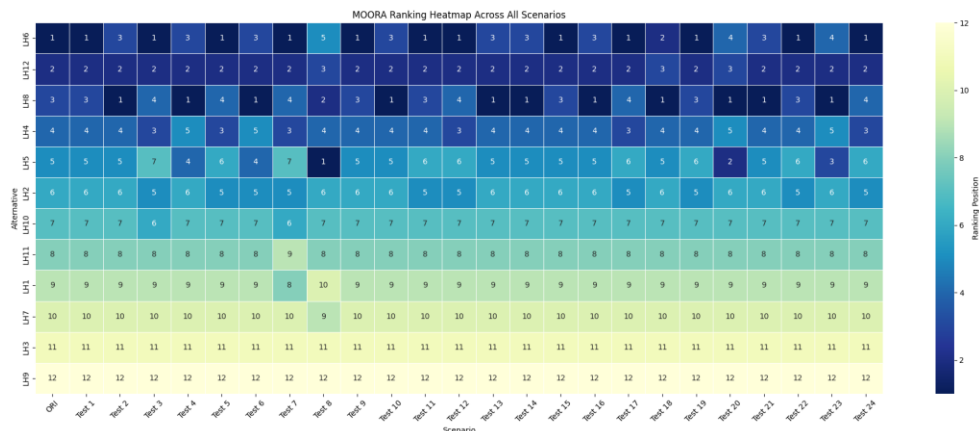


Figure 3. MOORA Ranking Heatmap Across All Scenarios

The MOORA ranking results across the original configuration and 24 test scenarios indicate that the ranking structure is generally stable, although several alternatives experience noticeable positional changes. LH6 remains the leading alternative in the original ranking but fluctuates between first and fifth positions, while LH8 shows the most substantial movement among the top alternatives, ranging from first to fourth position. LH12 demonstrates high stability, consistently occupying the second position in most scenarios and only declining to third in a few cases. LH4 remains within the third to fifth positions, whereas LH5 exhibits considerable variation, moving from first to seventh position depending on the scenario. LH2 is relatively stable within the fifth to sixth positions, while LH10 remains highly consistent around the sixth to seventh positions. The lower-ranked alternatives,



particularly LH3 and LH9, maintain their eleventh and twelfth positions throughout all scenarios, indicating strong ranking stability. Overall, the results suggest that weight variations primarily affect the ordering of the leading and middle-ranked alternatives, while the overall ranking structure and the positions of the lowest-ranked alternatives remain largely preserved.

To further evaluate the ranking consistency, the analysis is continued by examining the ARAS ranking and comparing its alternative positions with those obtained from ARAS ORI. The comparison focuses on how ARAS preserves or changes the relative order of alternatives and identifies the positions where differences emerge between the methods. Particular attention is given to the leading alternatives, the middle-ranking group, and the alternatives occupying the lower positions, since rank changes in these groups provide useful evidence of methodological sensitivity. The resulting comparison is summarized in Figure 4, which provides a consolidated view of the ranking patterns and highlights the alternatives that maintain stable positions as well as those that experience changes in rank across the evaluated methods.

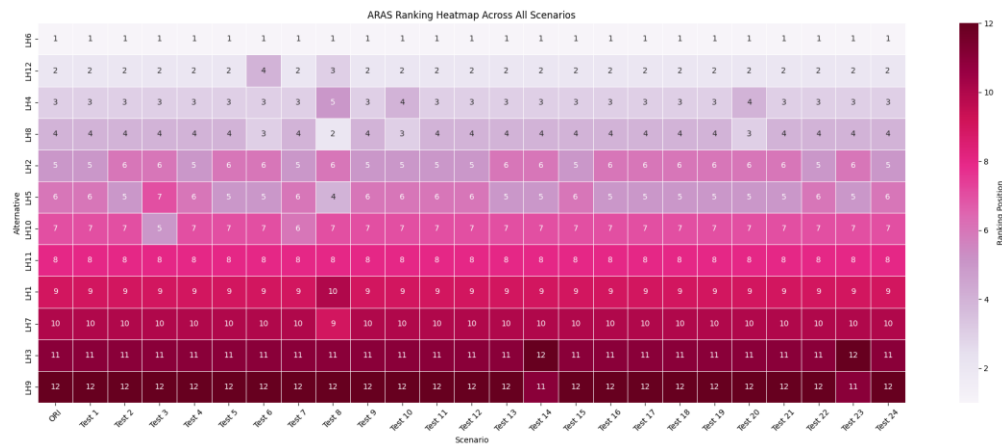
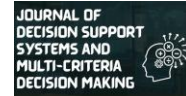


Figure 4. ARAS Ranking Heatmap Across All Scenarios

The ARAS ranking results demonstrate a highly stable decision structure across the original configuration and 24 test scenarios. LH6 consistently maintains the first position in every scenario, confirming its strong dominance and ranking robustness. LH12 also exhibits very high stability, remaining in second place throughout almost all tests, with only one decline to third position in Test 8. Among the next-ranked alternatives, LH4 generally occupies the third position but fluctuates between third and fifth, while LH8 primarily remains fourth but moves to second or third in several scenarios. LH2 and LH5 show moderate positional variation, with LH2 shifting between fifth and sixth positions and LH5 ranging from fourth to seventh. LH10 remains relatively stable around the fifth to seventh positions, whereas LH11 consistently retains the eighth position. The lower-ranked alternatives are particularly robust, with LH1 and LH7 only exchanging positions in Tests 8 and 23, while LH3 and LH9 experience limited reciprocal changes in Tests 13 and 23.



Overall, the ARAS results indicate stronger ranking stability than the MOORA evaluation, as the leading alternative remains completely unchanged and most ranking variations are restricted to adjacent positions or localized exchanges among middle- and lower-ranked alternatives.

4.5. Ranking Consistency and Stability Analysis

The ranking consistency and stability analysis is conducted to evaluate the reliability of the ranking results generated by the ratio-based MCDM methods under DAM weighting. The analysis considers two complementary aspects: the consistency of alternative rankings across different MCDM methods and the stability of rankings when criterion weights are subjected to controlled perturbations. Ranking consistency is assessed through rank correlation analysis to identify the degree of agreement among the evaluated methods, while ranking stability examines whether the relative positions of alternatives remain consistent when the criterion weights are increased or decreased. By integrating these two perspectives, the analysis provides a more comprehensive assessment of method robustness and determines whether the obtained decision rankings are strongly dependent on a particular weighting configuration or remain stable under changes in criterion importance.

The ranking correlation analysis is performed to examine the degree of agreement among the rankings produced by the evaluated ratio-based MCDM methods under DAM weighting. Kendall's Tau correlation coefficient is employed because it provides a non-parametric measure of rank association and is suitable for comparing the relative ordering of alternatives across different decision-making methods[40]. The analysis compares the ranking positions obtained from each method pair to identify whether the methods produce similar or substantially different decision preferences. A higher positive Kendall's Tau coefficient indicates stronger agreement between two ranking structures, whereas a coefficient close to zero reflects weak association and a negative coefficient indicates an inverse ranking relationship. This comparison is important because similar ranking patterns across different methods provide evidence that the decision outcomes are not strongly dependent on a single computational procedure, while lower correlations may indicate that differences in normalization, aggregation, or ranking mechanisms influence the final alternative positions. The pairwise Kendall's Tau coefficients are therefore used to identify the methods with the highest and lowest ranking consistency and to provide an overall view of the agreement among the evaluated approaches. The complete comparison of Kendall's Tau correlation values among the MCDM methods is presented in Figure 5.

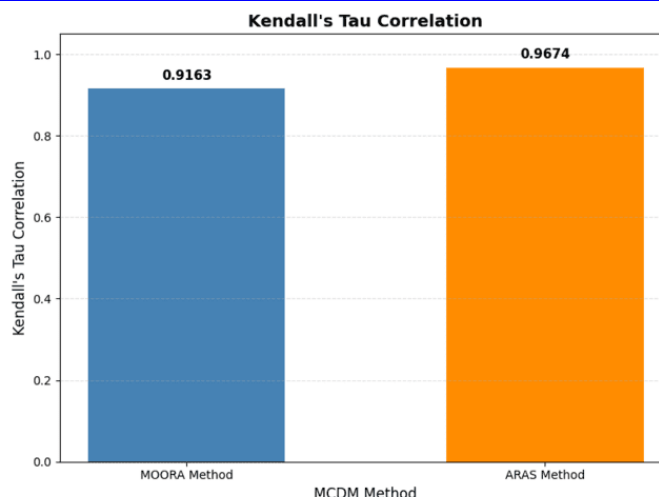


Figure 5. Comparison of Kendall's Tau Correlation Values

The Kendall's Tau analysis shows a high level of ranking agreement between the evaluated ratio-based MCDM methods under DAM weighting. The MOORA Method obtains a Kendall's Tau coefficient of 0.9163, indicating a very strong positive association with the reference ranking. In comparison, the ARAS Method achieves a higher coefficient of 0.9674, demonstrating a stronger degree of ranking consistency than MOORA. The difference of 0.0511 indicates that ARAS produces a ranking pattern that is more closely aligned with the evaluated reference ranking. Overall, both methods demonstrate high ranking consistency, as reflected by their coefficients being close to 1.0000, while the higher value obtained by ARAS suggests that its ranking outcomes are relatively more consistent and less divergent in comparison with MOORA.

The ranking stability analysis is conducted to evaluate the robustness of the MOORA and ARAS ranking results when the criterion weights are subjected to controlled perturbations. The Mean Absolute Rank Change (MARC) is employed as the primary measure to quantify the average magnitude of rank displacement experienced by the alternatives across the tested weight scenarios[41]. A lower MARC value indicates that the ranking positions undergo smaller changes from the original ranking, reflecting greater stability and robustness, whereas a higher value indicates that the ranking structure is more sensitive to changes in criterion importance. This measure provides a direct assessment of how consistently each MCDM method preserves its ranking structure when the relative importance of the criteria is modified. By comparing the MARC values of MOORA and ARAS, the analysis identifies which method is less affected by weight perturbations and therefore provides more stable decision outcomes under varying weighting conditions. The comparative MARC values obtained from the evaluated perturbation scenarios are presented in Figure 6.

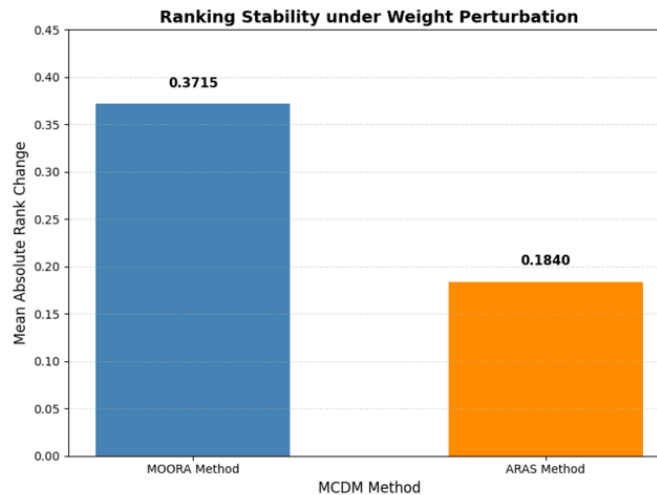
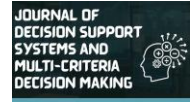


Figure 6. Comparison of Mean Absolute Rank Change

The ranking stability analysis based on the MARC demonstrates a clear difference in the robustness of the MOORA and ARAS methods under criterion weight perturbations. The MOORA Method records a MARC value of 0.3715, indicating that the average ranking position of alternatives changes by approximately 0.37 positions across the evaluated scenarios. In contrast, the ARAS Method produces a considerably lower MARC value of 0.1840, meaning that its ranking positions experience substantially smaller changes when the criterion weights are modified. The difference of 0.1875 between the two values indicates that ARAS exhibits a more stable ranking structure and is less sensitive to changes in criterion importance than MOORA. Therefore, although both methods can maintain relatively consistent decision structures, the lower MARC obtained by ARAS provides stronger evidence of ranking robustness under-weight perturbation.

4.6. Discussion

The DAM weighting results indicate that the decision problem is characterized by a relatively balanced distribution of criterion importance. Although CLH02 receives the highest weight of 0.1932, the remaining criteria range from 0.1568 to 0.1694, indicating that no single criterion dominates the evaluation. This balanced structure is important because the ranking outcomes are determined by the combined performance of logistics hub alternatives across multiple criteria rather than by excessive dependence on one criterion. The higher contribution of CLH02 provides additional influence to alternatives with strong performance on this criterion, while the relatively similar weights assigned to the other criteria ensure that their performance remains relevant. From a methodological perspective, DAM provides a suitable weighting configuration for comparative evaluation because MOORA and ARAS are applied using the same criterion importance structure. Consequently, differences in their ranking behavior can be interpreted primarily as



effects of the ranking mechanisms rather than differences in the underlying weight distribution.

The baseline ranking comparison demonstrates a strong agreement between MOORA and ARAS, particularly for the most and least preferred alternatives. Both methods identify LH6 as the best logistics hub location, LH12 as the second-ranked alternative, and LH9 as the least preferred alternative. This consistency suggests that the performance advantages and disadvantages of these alternatives are sufficiently pronounced to remain stable across different ratio-based evaluation mechanisms. Nevertheless, differences emerge among the intermediate alternatives, where MOORA places LH8 and LH4 in the third and fourth positions, respectively, while ARAS reverses these positions. A similar exchange occurs between LH5 and LH2. These variations indicate that the alternatives in the middle of the ranking have relatively competitive performance levels, making their positions more dependent on the mathematical treatment of normalized and weighted values. Therefore, although the detailed ordering differs slightly, the main decision structure remains consistent, particularly at the extreme positions where the practical decision implications are generally more important.

The observed ranking differences also highlight the complementary characteristics of MOORA and ARAS. Both methods use the same DAM-derived weights and decision matrix, but their aggregation procedures emphasize alternative performance differently. MOORA determines the optimization value by balancing beneficial and cost-related contributions, whereas ARAS evaluates alternatives according to their utility relative to an optimal reference alternative. These differences can affect alternatives whose overall performances are relatively close, explaining the rank exchanges observed in the middle group. However, the limited magnitude of these changes under the original weighting configuration demonstrates that both approaches are capable of capturing the general preference structure of the logistics hub problem. Thus, the comparison does not suggest that one method produces a fundamentally different decision outcome from the other; instead, it shows that ARAS and MOORA reach highly similar conclusions while differing in the degree to which individual alternatives are distinguished.

The weight perturbation analysis provides a more demanding assessment of method robustness because it examines whether the ranking structure can be maintained when the importance of individual criteria changes. Under the tested scenarios, MOORA exhibits greater movement among the leading and intermediate alternatives. LH6 and LH5 show relatively wider positional variations, whereas LH3 and LH9 remain consistently in the lower part of the ranking. ARAS, in contrast, maintains a more stable structure, with LH6 remaining in the first position and LH12 remaining almost unchanged across the evaluated scenarios. Most of the changes under ARAS are limited to neighboring alternatives, suggesting that moderate changes in criterion importance do not substantially disrupt the overall preference structure. These findings demonstrate that baseline agreement alone is insufficient to determine the superiority of an MCDM method. A method should also be



evaluated according to how reliably it preserves its ranking when the decision environment changes. In this respect, ARAS shows a stronger robustness profile than MOORA.

The statistical measures further confirm the advantage of ARAS. Kendall's Tau values of 0.9163 for MOORA and 0.9674 for ARAS indicate very strong ranking consistency for both methods, but the higher coefficient obtained by ARAS demonstrates closer agreement with the reference ranking. The distinction becomes more pronounced in the stability analysis, where MOORA produces a MARC value of 0.3715, while ARAS records only 0.1840. Because a lower MARC represents smaller average changes in alternative positions, ARAS exhibits substantially greater ranking stability under criterion-weight perturbations. The difference of 0.1875 between the two MARC values provides additional evidence that ARAS is less sensitive to changes in criterion importance. When these two indicators are considered jointly, ARAS achieves both higher ranking consistency and greater stability. Therefore, based on the empirical evidence obtained from this study, ARAS performs better overall than MOORA for the evaluated logistics hub location problem.

Overall, the findings demonstrate that both ratio-based MCDM methods can provide reliable decision support when combined with DAM weighting, but ARAS offers a more robust solution when ranking consistency and stability are considered simultaneously. The agreement in identifying LH6 as the most preferred alternative and LH9 as the least preferred alternative confirms that the main decision conclusion is not highly dependent on the selected ranking method. However, the superior Kendall's Tau value and substantially lower MARC obtained by ARAS indicate that its ranking structure is more resistant to changes in criterion importance. This makes ARAS the preferable method for the present case, particularly in decision environments where criterion priorities may be uncertain or subject to revision. The variations observed among middle-ranked alternatives should be viewed as an indication of competitive performance rather than as an inherent weakness of either method. Accordingly, the combined evaluation of baseline rankings, rank correlation, and weight-perturbation stability provides a more comprehensive basis for method selection and supports the use of ARAS when robustness is prioritized in logistics hub location decision-making.

V. Conclusion

This study comparatively evaluated Ratio-Based MCDM Methods, particularly MOORA and ARAS, under DAM weighting for logistics hub location selection. The DAM results produced a relatively balanced distribution of criterion importance, while the baseline rankings generated by both methods showed strong agreement, particularly in identifying LH6 as the best alternative and LH9 as the least preferred. Although several differences occurred among the intermediate alternatives, the overall decision structure remained consistent. These findings confirm that the evaluated ratio-based MCDM methods are capable



of providing reliable ranking results under the same objective weighting configuration.

The robustness analysis provides a clear distinction between the two Ratio-Based MCDM Methods. MOORA obtained a Kendall's Tau value of 0.9163 and a MARC value of 0.3715, whereas ARAS achieved a higher Kendall's Tau of 0.9674 and a lower MARC of 0.1840. These results demonstrate that ARAS provides stronger ranking consistency and greater stability when criterion weights are changed. Therefore, ARAS is considered the better-performing Ratio-Based MCDM Method than MOORA for the evaluated logistics hub location problem, particularly when robustness to changes in criterion importance is prioritized. The study also demonstrates that evaluating Ratio-Based MCDM Methods should consider not only the baseline ranking but also ranking consistency and stability. Future research can extend this framework by testing additional datasets, weighting approaches, and Ratio-Based MCDM Methods to further examine the generalizability of these findings.

CRediT Authorship Contribution Statement

Mahardika Inra Takaendengan: Conceptualization, Methodology, Supervision, Writing - Original Draft Preparation, Writing - Review & Editing. **Irma Anggraeni:** Conceptualization, Formal Analysis, Validation, Writing - Original Draft Preparation. **Febri Dwi Irawati:** Data Curation, Investigation, Validation, Writing - Original Draft Preparation. **Gde Brahupadhya Subiksa:** Conceptualization, Methodology, Resource, Visualization, Writing - Original Draft Preparation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

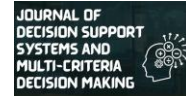
Declaration of Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

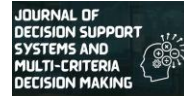


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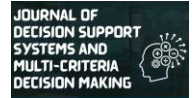
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