Journal of Information Technology, Software Engineering and Computer Science
Website : https://ejournal.techcart-press.com/index.php/itsecs
E-ISSN 2962-0635
P-ISSN 2962-0538
Volume 4, Number 4, October 2026
DOI : **https://doi.org/10.58602/itsecs.v4i4.377**
Page 119-138

Comprehensive Evaluation of Distance-Based MCDM Methods Using Response to Criteria Weighting: A Ranking Stability and Sensitivity Analysis

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Abstract: Selecting an appropriate new store location is a complex multi-criteria decision-making problem because potential locations must be evaluated using multiple criteria with different performance characteristics. This study proposes an integrated distance-based Multi-Criteria Decision-Making framework using RECA Weighting combined with TOPSIS, SPOTIS, and EDAS to determine objective criterion importance and evaluate the stability and robustness of alternative rankings. The dataset consists of eight potential store locations evaluated using six criteria: Rental Cost, Building Area, Accessibility, Consumer Traffic, Parking Availability, and Infrastructure. RECA Weighting is applied to determine objective criterion weights based on performance variation, while TOPSIS, SPOTIS, and EDAS are used to generate preference scores and rankings through different distance-based evaluation mechanisms. The results show that Consumer Traffic obtains the highest criterion weight of 0.1824, while Parking Availability receives the lowest weight of 0.1422. The ranking results identify LS5 as the best-performing alternative, followed by LS3, although several alternatives exhibit different ranking positions across the applied methods. Weight-variation analysis using Spearman rank correlation shows that SPOTIS achieves perfect ranking stability with a correlation of 1.0000, TOPSIS demonstrates very strong stability with a correlation of 0.9286, while EDAS produces a lower correlation of 0.1429, indicating greater ranking variation. These findings demonstrate that SPOTIS provides the highest robustness to criterion weight changes, followed by TOPSIS, whereas EDAS is more sensitive to weight variations due to its average-solution-based evaluation mechanism. Overall, the proposed framework provides a comprehensive approach for objective weighting, ranking stability assessment, sensitivity analysis, and robustness evaluation in new store location selection.
Keywords: Multi-Criteria Decision Making; RECA Weighting; Ranking Stability; Robustness Analysis; Store Location Selection;

1. INTRODUCING

Multi-Criteria Decision-Making (MCDM) plays an important role in supporting decision-making for problems that involve many alternatives and criteria with different characteristics, because it can systematically integrate various assessment aspects through weighting, normalization, and performance evaluation of alternatives[1]–[3]. The

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results of this evaluation are used to obtain preference values and create a ranking that shows the priority order of each alternative, so decision-makers can make choices based on more structured considerations. The ranking process becomes even more important when there are many alternatives with varying levels of achievement for each criterion[4], [5]. The situation gets more complex when several alternatives have relatively similar performance, as small differences in criteria values or weights can affect the preference values and the position of alternatives in the ranking.

The distance-based approach in MCDM evaluates alternatives based on how close they are to the ideal solution, which represents the best performance across all criteria[6], [7]. The distance between each alternative and the ideal solution is used as the basis for forming preference values, where alternatives with shorter distances generally indicate performance that is closer to the desired condition. This approach is advantageous because it can map the relationship between an alternative's position and the reference point in a more measurable way, so differences in performance between alternatives can be represented through closeness or deviation from the ideal condition. Even though they use a similar basic principle, each distance-based method can apply different mechanisms for measuring distance, normalization, and aggregation[8], [9]. These differences can lead to varying preference values and ranking orders, especially when the alternatives have relatively close performance. This situation shows that the distance calculation mechanism is one of the factors that can affect the consistency and characteristics of ranking results in distance based MCDM methods.

In this study, the technique for order preference by similarity to ideal solution (TOPSIS), Stable Preference Ordering Towards Ideal Solution (SPOTIS), and evaluation based on distance from average solution (EDAS) are used as MCDM methods that have evaluation characteristics based on closeness or distance to a reference condition. TOPSIS determines rankings based on the distance of alternatives from the positive ideal solution and the negative ideal solution, so alternatives that are closer to the positive ideal solution and further from the negative ideal solution get higher priority. SPOTIS uses the distance of each alternative from an ideal solution that's determined based on the best and worst limits of each criterion, so the position of the alternatives is evaluated based on how much they deviate from the ideal condition. Meanwhile, EDAS evaluates alternatives based on their distance from the average solution through Positive Distance from Average (PDA) and Negative Distance from Average (NDA), then combines both to get the final assessment score. The difference in reference points and measurement mechanisms allows the three methods to produce different ranking responses to changes in performance or criterion weights, making it interesting to compare in terms of ranking stability, sensitivity, and robustness.

The weight of criteria is one of the important components in MCDM because it determines the level of contribution of each criterion to the final value of each alternative. Changes in weight can alter the importance proportion of a criterion in the evaluation process, so increasing or decreasing a certain weight can potentially lead to changes in preference values and the ranking positions of alternatives. This situation also means that the weights generated by different weighting methods don't necessarily give the same order of alternatives, even if they use identical data and ranking methods. In this context, Response to Criteria Weighting (RECA) can be used as a weighting approach that takes into account data responses to changes or the importance characteristics of criteria in determining more representative weights[10], [11]. Applying RECA allows the weight distribution to be examined based on the response characteristics of each criterion, and then used in ranking methods to see its impact on decision outcomes. The response of the ranking method to RECA weights is important to analyze in order to understand ranking

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consistency, identify the most sensitive criteria, and evaluate the stability of results when there are changes in criteria weights[12], [13].

Previous studies have shown that criterion-weight sensitivity is important for evaluating the reliability and robustness of MCDM rankings. Variations in criterion weights can change ranking positions and identify criteria that strongly influence decision outcomes[14], [15]. In TOPSIS, weight sensitivity analysis has been used to assess the effects of parameter-weight changes on alternative rankings, while EDAS studies have applied weight variation scenarios to evaluate ranking consistency[16]. Recent research has further emphasized full-range weight sensitivity, rank reversal, and correlation analysis as tools for assessing ranking robustness and agreement among MCDM results[17], [18]. However, a systematic comparison of TOPSIS, SPOTIS, and EDAS using RECA-generated weight variations and integrating ranking stability, sensitivity, rank reversal, and correlation analysis remains limited. Therefore, this study addresses this gap by providing a comprehensive evaluation of the robustness and consistency of distance-based MCDM methods under changing criterion weights.

Even though various MCDM methods have been widely used to produce alternative rankings, most research still focuses on the final result of a single method or compares several methods based on the initial ranking without considering changes in criteria weights. This approach doesn’t fully reflect the consistency of the methods when the importance level of criteria changes. In distance based MCDM methods, differences in the mechanism for determining reference solutions and calculating distances can lead to different ranking responses to weight changes. Using RECA Weighting as a weighting approach also opens up a way to explore how the generated weights affect the behavior of the ranking methods. An evaluation that integrates ranking stability, weight sensitivity, ranking reversal, and robustness in the TOPSIS, SPOTIS, and EDAS methods still needs to be strengthened so that the comparison not only shows which method has the best ranking but also identifies which method can maintain ranking consistency when the criteria weights change.

This study aims to carry out a comprehensive evaluation of the performance of several distance based MCDM methods, namely TOPSIS, SPOTIS, and EDAS, using RECA as the approach for weighting criteria. The evaluation is done by comparing the ranking results produced by each method and analyzing how the rankings respond to changes in criteria weights. In particular, this study aims to compare the performance of TOPSIS, SPOTIS, and EDAS in generating alternative rankings, evaluate ranking changes in response to weight variations, measure the level of ranking stability for each method, identify the criteria that have the greatest impact on ranking changes, and determine which method has the highest robustness based on ranking consistency, sensitivity to weights, and the level of position changes for alternatives.

This study offers a comprehensive evaluation framework for distance based MCDM methods by integrating RECA into the analysis of weight changes and ranking results evaluation. The developed framework not only compares the initial rankings from TOPSIS, SPOTIS, and EDAS, but also tests how changes in criteria weights affect preference values and the position of each alternative. The evaluation is done simultaneously through measurements of ranking stability, sensitivity, and robustness, allowing the characteristics of each method to be analyzed more thoroughly. This approach makes it possible to identify methods that can maintain ranking consistency when criteria priorities change, while also showing which criteria have the most influence on changes in decision results. Thus, the contribution of this research is not only in comparing ranking results, but also in providing a basis for evaluating which distance based MCDM method has the best level of consistency and robustness against variations in criteria weights.

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2. RESEARCH METHODOLOGY

Research methodology is the part that systematically explains the stages, procedures, techniques, and approaches used in a study to achieve objectives and address the formulated problems. The research stages include preparing a decision matrix, determining criteria weights using RECA, applying each MCDM method to get the initial ranking, varying the criteria weights, and recalculating the ranking for each weight change scenario. The results are then analyzed using ranking stability, sensitivity, ranking reversal, and robustness indicators to see how each method responds to changes in criteria priorities and to determine which method produces the most consistent ranking.

2.1. Research Stages

The research stages describe the systematic sequence of activities carried out to achieve the research objectives, beginning with data preparation and criteria weighting, followed by the application of distance based MCDM methods and evaluation of the resulting rankings. This structured process ensures that each stage produces the required input for the subsequent stage and allows the evaluation to be conducted consistently across the methods being compared. The main advantage of using a structured research-stage framework is that it provides a clear and reproducible research procedure, facilitates comparison between TOPSIS, SPOTIS, and EDAS, and enables the effects of criteria-weight changes to be evaluated through stability, sensitivity, and robustness measures. The research consists of four main stages: Data Collection, Criteria Weighting Using RECA, Ranking Using Distance-Based MCDM, and Comprehensive Stability and Robustness Analysis, as illustrated in Figure 1.

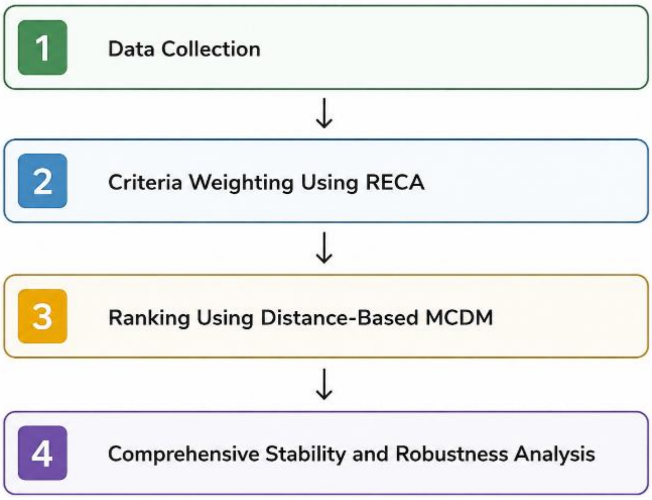

Figure 1. Research Stages

The research framework consists of four sequential stages. The first stage, Data Collection, involves collecting the data of alternatives and criteria required to construct the decision matrix. The second stage, Criteria Weighting Using RECA, determines the relative importance of each criterion based on the RECA approach, producing the criteria weights used in subsequent calculations. The third stage, Ranking Using Distance-Based MCDM, applies TOPSIS, SPOTIS, and EDAS to evaluate the alternatives and generate their respective preference values and rankings. The final stage, Comprehensive Stability and Robustness Analysis, examines the response of each method to changes in criteria weights by simultaneously evaluating ranking stability, sensitivity, and robustness, allowing the most consistent method and the criteria with the greatest influence on ranking changes to be identified.

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2.2. RECA Weighting

RECA Weighting is a weighting method that determines the importance level of each criterion based on responses and performance variations of alternatives in each criterion[13]. The RECA steps start with creating a decision matrix that contains the performance values of each alternative against all criteria using (1), then continue with calculating preference values to obtain the relative preference value of each alternative using (2). These values are then normalized so that they are on a comparable scale using (3), and afterward used to determine the standard value as a reference value for each criterion using (4). The next step is to calculate preference variation to measure the level of performance variation of alternatives against the reference value using (5), then determine preference deviation as the basis to know the contribution of each criterion using (6). At the final stage, the criterion weights are calculated based on the relative deviation values of each criterion compared to all the criteria using (7), so we get the weights used in the ranking process.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{n1} \\ \vdots & \ddots & \vdots \\ x_{1m} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

$$PV_{ij} = \frac{x_{ij}}{\sqrt[n]{\prod_{j=1}^{n} x_{ij}}} \quad (2)$$

$$R_{ij} = \frac{PV_{ij}}{PV_j^{max}} \quad (3)$$

$$N_j = \frac{1}{N} \sum R_{ij} \quad (4)$$

$$\emptyset_j = \sum_{i=1}^{m} \left[R_{ij} - N_j\right]^2 \quad (5)$$

$$\Omega_j = \left|1 - \emptyset_j\right| \quad (6)$$

$$w_j = \frac{\Omega_j}{\sum_{j=1}^{n} \Omega_j} \quad (7)$$

The results of RECA Weighting is the objective weight for each criterion, reflecting the level of contribution and the variation of information present in the alternative data. Using RECA weights allows the ranking process to take the data's characteristics into account more objectively and serves as a basis for evaluating changes in rankings, stability, sensitivity, and robustness of each method when there are changes in the criteria weights.

2.3. Distance-Based MCDM Methods

Distance Based MCDM Methods are a group of methods in MCDM that determine the preference or ranking of alternatives based on the distance between each alternative's performance and a reference point, such as an ideal solution, anti-ideal solution, or a specific reference point. These methods work by converting the decision matrix into comparable values, identifying a reference point or ideal solution, and then calculating the distance of each alternative to that point. Alternatives that have the smallest distance to the ideal solution, or the most favorable distance to the reference point, usually get a higher preference ranking.

The TOPSIS method is one of the MCDM methods used to rank alternatives based on how close they are to the positive ideal solution and how far they are from the negative ideal solution[19]–[21]. The main principle of TOPSIS is that the best alternative is the one that is closest to the positive ideal condition while being farthest from the negative ideal condition. This method can be used for both benefit and cost criteria by considering the importance weight of each criterion. The TOPSIS steps involve creating and normalizing the decision matrix using (8), then multiplying it by the criteria weights to get the weighted normalized matrix in Equation (9). Next, the positive and negative ideal solutions are determined using (10) and (11), then the distance of each alternative to both solutions is calculated using (12) and (13). Preference values are calculated using (14), and then the

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alternatives are ranked based on the preference values, with the highest value being the best rank.

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\left[\sum_{i=1}^{j} x_{ij}^{2}\right]}} \quad (8)$$

$$v_{ij} = w_j * x_{ij}^{*} \quad (9)$$

$$y_j^{+} = \begin{cases} max_i y_{ij} \; ; if\ j\ is\ a\ benefit\ attribute \\ min_i y_{ij} \; ; if\ j\ is\ a\ cost\ attribute \end{cases} \quad (10)$$

$$y_j^{-} = \begin{cases} min_i y_{ij} \; ; if\ j\ is\ a\ benefit\ attribute \\ max_i y_{ij} \; ; if\ j\ is\ a\ cost\ attribute \end{cases} \quad (11)$$

$$D_i^{+} = \sqrt{\sum_{j=1}^{n} \left(y_i^{+} - y_{ij}\right)^2} \quad (12)$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_i^{-}\right)^2} \quad (13)$$

$$V_i = \frac{D_i^{-}}{D_i^{-} + D_i^{+}} \quad (14)$$

The SPOTIS method is a distance based MCDM method that evaluates and ranks alternatives based on their distance from the ideal solution point (optimal point). SPOTIS determines the optimal point for each criterion by considering benefit and cost characteristics, then calculates the relative distance of each alternative to that point[22]–[24]. The alternative with the smallest total distance value is considered to perform closest to the ideal solution, thus getting the best ranking. The steps of the SPOTIS method start with determining the optimal point for each criterion based on the benefit and cost characteristics using (15). Next, the distance of each alternative to the optimal point is normalized based on the criteria value range using (16). These distance values are then multiplied by the criteria weights and summed to get the preference value of each alternative using (17).

$$x_j^{*} = \begin{cases} \max_j x_{ij} \; ; if\ j\ is\ a\ benefit\ attribute \\ \min_j x_{ij} \; ; if\ j\ is\ a\ cost\ attribute \end{cases} \quad (15)$$

$$d_{ij} = \frac{\left|x_{ij} - x_j^{*}\right|}{\left|x_j{}^{max} - x_j^{min}\right|} \quad (16)$$

$$y_i = \sum_{j=1}^{n} w_j * d_{ij} \quad (17)$$

The EDAS method is an MCDM method that evaluates alternatives based on their distance from the Average Solution. Unlike methods that use the ideal solution as a reference point, EDAS uses the average value of each criterion as a reference[25]–[27]. The performance of each alternative is assessed based on the Positive Distance from Average (PDA) and Negative Distance from Average (NDA), and then these two measures are combined to get the final evaluation score. The EDAS method starts by calculating the average solution (AV) for each criterion using (18). Next, the Positive Distance from Average (PDA) and Negative Distance from Average (NDA) are calculated based on whether the criterion is a benefit or cost using (19) and (20). The PDA and NDA values are then multiplied by the criteria weights to get the SP and SN values using (21) and (22). Next, the values are normalized into NSP and NSN using (23) and (24). The final Appraisal Score (AS) is calculated using (25), and then the alternatives are ranked based on the AS value.

$$AV_j = \frac{\sum_{i=1}^{j} x_{ij}}{n} \quad (18)$$

$$PDA_{ij} = \begin{cases} \frac{\max(0,(x_{ij} - AV_j))}{AV_j} ; if\ j\ is\ a\ benefit\ attribute \\ \frac{\max(0,(AV_j - x_{ij}))}{AV_j} ; if\ j\ is\ a\ cost\ attribute \end{cases} \quad (19)$$

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$$NDA_{ij} = \begin{cases} \frac{\max(0,(AV_j - x_{ij}))}{AV_j}; if\ j\ is\ a\ benefit\ attribute \\ \frac{\max(0,(x_{ij} - AV_j))}{AV_j}; if\ j\ is\ a\ cost\ attribute \end{cases} \quad (20)$$

$$SP_i = \sum_{j=1}^{n} w_j * PDA_{ij} \quad (21)$$

$$SN_i = \sum_{j=1}^{n} w_j * NDA_{ij} \quad (22)$$

$$NSP_i = \frac{SP_i}{\max SP_i} \quad (23)$$

$$NSN_i = \frac{SN_i}{\max SN_i} \quad (24)$$

$$AS_i = \frac{1}{2} * (NSP_i + NSn_i) \quad (25)$$

The three methods, TOPSIS, SPOTIS, and EDAS, are distance based MCDM approaches that evaluate alternatives by measuring their relative distance from a defined reference point. TOPSIS considers both positive and negative ideal solutions, SPOTIS evaluates alternatives based on their distance from an optimal point, while EDAS measures performance relative to the average solution. These differences in reference points and distance measurement mechanisms provide distinct perspectives for evaluating alternatives, making the three methods suitable for comparative analysis to assess ranking robustness and decision consistency.

3. RESULT AND DISCUSSIONS

This study presents a comprehensive evaluation of distance based MCDM methods by integrating RECA Weighting with TOPSIS, SPOTIS, and EDAS to investigate the influence of objective criteria weighting on the resulting alternative rankings. The proposed framework applies RECA to determine the relative importance of criteria based on the performance variation of alternatives, while TOPSIS, SPOTIS, and EDAS provide different distance-based mechanisms for evaluating and ranking alternatives. TOPSIS determines preferences according to the distance from positive and negative ideal solutions, SPOTIS evaluates the distance of alternatives from an optimal point, and EDAS measures the positive and negative deviations from the average solution. The resulting rankings are then examined through ranking stability analysis to identify the consistency of alternative positions across the three methods. In addition, sensitivity analysis is employed to assess how changes in criterion weights affect the ranking results and to identify criteria that have a substantial influence on decision outcomes. Through the integration of objective weighting, comparative distance-based ranking, stability assessment, and sensitivity analysis, the study aims to provide a more reliable evaluation of alternative performance and strengthen the robustness of DSS decision-making under different methodological and weighting conditions.

3.1. Dataset

The dataset used in this study is a dataset for selecting new store locations, consisting of eight alternatives, namely LS1 to LS8, with each alternative representing a different store location. Each alternative is evaluated based on six criteria: Rental Cost (C1), Building Area (C2), Accessibility (C3), Consumer Traffic (C4), Parking Availability (C5), and Infrastructure (C6). Rental Cost represents the cost of renting the location, Building Area shows the available building space, Accessibility reflects how easy it is to get to the location, Consumer Traffic indicates the level of traffic or potential customer visits, Parking Availability represents the availability of parking facilities, and Infrastructure shows the condition of supporting infrastructure at each location. The variation in values across these six criteria shows differences in characteristics and performance levels among the alternatives, which forms the basis for the multi-criteria decision-making process. This dataset is then used as a decision matrix to determine objective weights using RECA

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Weighting, and each alternative is evaluated using the TOPSIS, SPOTIS, and EDAS methods to produce rankings and analyze the consistency, stability, and sensitivity of the decision results. The dataset used in this study is shown in Table 1.

Table 1. Dataset New Location Store[28]

Alternative Name	C1	C2	C3	C4	C5	C6
LS1	45	120	8	550	10	9
LS2	40	100	7	500	8	8
LS3	55	150	9	600	12	9
LS4	38	90	6	480	6	7
LS5	60	160	8	620	15	10
LS6	42	130	9	570	11	8
LS7	36	110	7	510	9	7
LS8	48	140	8	590	13	9

The dataset used shows that there are variations in performance values for each criterion used in the decision-making process. These differences serve as the basis for determining the importance level of each criterion through RECA Weighting. Then, the weights obtained are used in the TOPSIS, SPOTIS, and EDAS methods to generate preference values, rank options, and evaluate the stability and sensitivity of the decision results.

3.2. Calculating Criteria Weights Using RECA Weighting

The calculation of criteria weights using RECA Weighting is done to get the objective importance level of each criterion based on responses and data performance variations. The process starts by using a decision matrix as the input for the calculation, then the relative preference value of each data is calculated to show performance responses to each criterion using (1) and (2). These preference values are then normalized so that they are on a comparable scale using (3). The normalization results are used to determine the standard value as a reference point for each criterion using (4). Next, the preference variation is calculated to measure the level of performance deviation from the standard value using (5), then the preference deviation value is determined as a basis for identifying the relative contribution of each criterion using (6). The final stage is carried out by calculating the weight of each criterion based on the proportion of its deviation value to the total deviation of all criteria using (7). The criterion weights obtained from this process are presented in Table 2.

Table 2. Criteria Weight Results Using RECA Weighting

C1	C2	C3	C4	C5	C6
0.1651	0.1601	0.1738	0.1824	0.1422	0.1764

Based on the RECA Weighting results, the weights show that Consumer Traffic C4 has the highest weight at 0.1824, followed by Infrastructure C6 at 0.1764 and Accessibility C3 at 0.1738. Next, Rental Cost C1 has a weight of 0.1651, while Building Area C2 gets a weight of 0.1601. Meanwhile, Parking Availability C5 has the lowest weight at 0.1422. These results indicate that Consumer Traffic C4 contributes the most in the evaluation process, while Parking Availability C5 contributes the least. Overall, the differences in weights between criteria are relatively small, so all criteria are fairly balanced in terms of importance in the decision-making process.

Based on the weighting results, each criterion has a different contribution in the decision-making process, with Consumer Traffic C4 being the most dominant criterion and Parking Availability C5 having the lowest contribution. The obtained weights are then used as parameters in the evaluation process using the TOPSIS, SPOTIS, and EDAS methods to

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DOI : https://doi.org/10.58602/itsecs.v4i4.377
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generate preference scores and rankings, allowing for comparisons of the stability and sensitivity of the decision results.

3.3. Final Scores Calculation of Distance-Based MCDM Methods

The final score calculation is done by applying the criteria weights obtained through RECA Weighting into the TOPSIS, SPOTIS, and EDAS methods. Each method processes the decision matrix and criteria weights using different distance-based evaluation mechanisms to produce a final value for each alternative. These values represent the relative performance level based on the characteristics of each method and serve as the basis for determining the preference ranking. Using the same weights across all three methods allows for a more consistent comparison of evaluation results, so any differences in scores can be linked to the calculation characteristics of each method. Then, the final scores obtained from TOPSIS, SPOTIS, and EDAS are used to compare evaluation results, identify the best-performing alternatives, and serve as a basis for ranking stability and sensitivity analysis.

The final score calculation using the TOPSIS method is done through several steps, starting with determining the weighted normalized decision matrix based on normalization values and criteria weights using (9). Next, the positive ideal solution and negative ideal solution are determined by considering the characteristics of benefits and costs using (10) and (11). After that, the distance of each alternative to the positive ideal solution and negative ideal solution is calculated using (12) and (13). Based on these two distance values, the preference value or final TOPSIS score is then calculated using (14). The preference value obtained shows the relative closeness of each alternative to the ideal solution, so it can be used as a basis for evaluation and ranking. The results of the final TOPSIS score calculation is presented in Table 3.

Table 3. Final Scores of Alternatives Using the TOPSIS Method

Alternative Name	Final Score
LS1	0,5240
LS2	0,3728
LS3	0,6315
LS4	0,3046
LS5	0,6605
LS6	0,6133
LS7	0,4330
LS8	0,6819

Based on Table 3, the final TOPSIS scores show variations in the evaluation results across the alternatives. LS8 obtained a final score of 0.6819, followed by LS5 with 0.6605, LS3 with 0.6315, and LS6 with 0.6133. Meanwhile, LS1 obtained a score of 0.5240, followed by LS7 at 0.4330, LS2 at 0.3728, and LS4 at 0.3046. These values represent the relative closeness of each alternative to the ideal solution based on the TOPSIS calculation using the RECA-derived criteria weights. The differences in final scores indicate varying levels of overall performance among the evaluated alternatives and provide the numerical basis for subsequent comparative analysis with other distance based MCDM methods.

The final score calculation using the SPOTIS method starts by determining the optimal point for each criterion based on benefit and cost characteristics using (15). Next, the distance of each alternative to the optimal point is calculated through a normalization process using (16) to get distance values that can be compared across criteria. These distance values are then multiplied by the weight of each criterion and summed up to get the final SPOTIS score using (17). The resulting score shows how close each alternative is to the optimal point, so a smaller score indicates a closer distance to the optimal condition. The results of the SPOTIS final score calculation are shown in Table 4.

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Journal of Information Technology, Software Engineering and Computer Science
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E-ISSN 2962-0635
P-ISSN 2962-0538
Volume 4, Number 4, October 2026
DOI : https://doi.org/10.58602/itsecs.v4i4.377
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Table 4. Final Scores of Alternatives Using the SPOTIS Method

Alternative Name	Final Score
LS1	0,4403
LS2	0,6651
LS3	0,2859
LS4	0,8486
LS5	0,2231
LS6	0,3558
LS7	0,6447
LS8	0,3157

Based on the final scores presented in Table 4, the SPOTIS method produces different distance values for each alternative. LS5 has a final score of 0.2231, followed by LS3 with 0.2859, LS8 with 0.3157, and LS6 with 0.3558. Meanwhile, LS1 obtains a score of 0.4403, LS7 obtains 0.6447, LS2 obtains 0.6651, and LS4 obtains 0.8486. These values represent the distance of each alternative from the optimal point based on the criteria weights obtained through RECA Weighting. The differences in scores indicate varying degrees of proximity to the optimal condition and provide a basis for further comparison with the final scores generated by other distance based MCDM methods.

The final score calculation of the EDAS method starts with determining the average solution based on the value of each criterion in Equation (18). Next, the Positive Distance from Average (PDA) and Negative Distance from Average (NDA) are calculated to measure the deviation of each alternative's performance from the average solution in Equations (19) and (20). The PDA and NDA values are then multiplied by the criteria weights to get the respective aggregate values in Equations (21) and (22). These results are then normalized to obtain the Normalized Positive Distance (NPD) and Normalized Negative Distance (NND) in Equations (23) and (24). The final step is to calculate the Appraisal Score (AS) as the final EDAS score in Equation (25). The AS value shows the relative performance level of each alternative based on its closeness and deviation from the average solution. The final score calculation results of the EDAS method are shown in Table 5.

Table 5. Final Scores of Alternatives Using the EDAS Method

Alternative Name	Final Score
LS1	0,0967
LS2	0,3321
LS3	0,4124
LS4	0,5811
LS5	0,6330
LS6	0,1977
LS7	0,3537
LS8	0,2737

Based on the final scores presented in Table 5, the EDAS method produces different appraisal scores for each alternative. LS5 obtains the highest final score of 0.6330, followed by LS4 with 0.5811 and LS3 with 0.4124. The other alternatives obtain scores of 0.3537 for LS7, 0.3321 for LS2, 0.2737 for LS8, 0.1977 for LS6, and 0.0967 for LS1. These scores represent the overall performance of each alternative based on its positive and negative deviations from the average solution, after incorporating the criteria weights obtained through RECA Weighting. The variation in appraisal scores reflects differences in the relative performance of the alternatives and provides a basis for comparing the evaluation results obtained from EDAS with those generated by TOPSIS and SPOTIS.

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Journal of Information Technology, Software Engineering and Computer Science
Website : https://ejournal.techcart-press.com/index.php/itsecs
E-ISSN 2962-0635
P-ISSN 2962-0538
Volume 4, Number 4, October 2026
DOI : https://doi.org/10.58602/itsecs.v4i4.377
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3.4. Ranking Results Using Distance-Based MCDM Methods

The ranking results are obtained by ordering the final scores generated by TOPSIS, SPOTIS, and EDAS according to the preference direction of each method. The three methods use the same decision matrix and criteria weights obtained from RECA Weighting, but apply different distance-based evaluation mechanisms, which may lead to differences in the position of alternatives. Comparing the rankings allows the consistency of alternative positions across methods to be observed and provides an initial indication of the robustness of the decision outcomes. The comparison also serves as a basis for subsequent ranking stability and sensitivity analysis to determine the extent to which methodological differences influence the final decision. The comparison results of the rankings obtained from TOPSIS, SPOTIS, and EDAS are presented in Table 6.

Table 6. Comparison Results of Alternative Rankings

Alternative Name	Rank ORI	Rank TOPSIS	Rank SPOTIS	Rank EDAS
LS5	1	2	1	1
LS3	2	3	2	3
LS8	3	1	3	6
LS6	4	4	4	7
LS1	5	5	5	8
LS7	6	6	6	4
LS2	7	7	7	5
LS4	8	8	8	2

Based on Table 6, the comparison shows that LS5 maintains a highly consistent position, occupying rank 1 in the ORI, SPOTIS, and EDAS results, while obtaining rank 2 with TOPSIS. LS3 also demonstrates relatively stable performance with ranks 2, 3, 2, and 3 across ORI, TOPSIS, SPOTIS, and EDAS, respectively. LS8 shows greater variation, moving from rank 3 in ORI and SPOTIS to rank 1 in TOPSIS and rank 6 in EDAS. LS6 remains at rank 4 in ORI, TOPSIS, and SPOTIS but shifts to rank 7 in EDAS, whereas LS1 consistently occupies rank 5 in the first three results and moves to rank 8 in EDAS. LS7 records rank 6 in ORI, TOPSIS, and SPOTIS and improves to rank 4 in EDAS, while LS2 remains relatively stable around ranks 7 and 5. LS4 consistently occupies rank 8 in ORI, TOPSIS, and SPOTIS but changes substantially to rank 2 in EDAS. Overall, the results indicate that TOPSIS and SPOTIS produce relatively similar ranking patterns, while EDAS shows greater variation for several alternatives, particularly LS8, LS6, and LS4.

To evaluate how well the ranking results obtained from TOPSIS, SPOTIS, and EDAS match, Spearman's rank correlation is used as a measure of the relationship between the ranking results. This analysis helps to see to what extent the change in position of an alternative in one method follows a consistent pattern with the other methods. The Spearman coefficient ranges from −1 to 1, with values closer to 1 indicating stronger rank agreement, while lower values show differences in ranking patterns between methods. In this study, rank correlation is used to compare the results of TOPSIS, SPOTIS, and EDAS to determine the consistency level of the evaluation results. The Spearman rank correlation results between methods are shown in Figure 2.

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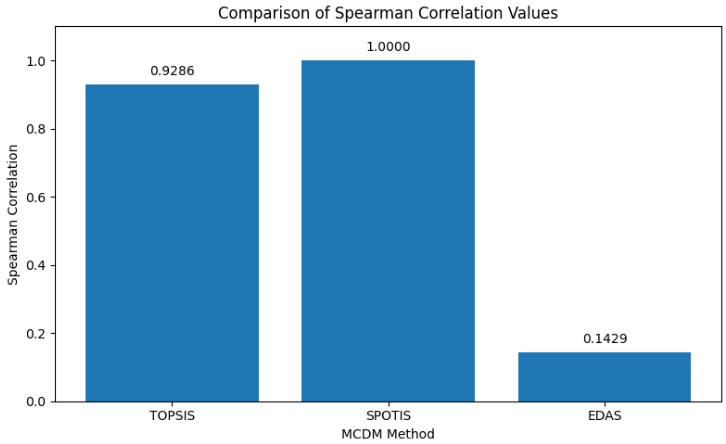

Figure 2. Comparison of Correlation Values

Based on the Spearman correlation results, SPOTIS shows the highest correlation value of 1.0000, indicating a perfect match with the reference ranking. TOPSIS has a correlation value of 0.9286, showing a very strong ranking agreement. Meanwhile, EDAS has a correlation value of 0.1429, indicating a relatively weak ranking relationship compared to the other two methods. These results suggest that the ranking pattern produced by SPOTIS is the most consistent with the reference ranking, while EDAS produces a ranking pattern that is more different.

3.5. Comprehensive Stability and Robustness Analysis

The comprehensive stability analysis demonstrates that the integration of RECA Weighting with distance based MCDM methods produces generally consistent decision patterns, although the degree of stability varies according to the evaluation mechanism applied by each method. The ranking comparison shows that LS5 is the most stable alternative because it occupies the first position in the reference ranking, SPOTIS, and EDAS, while remaining in the second position under TOPSIS. LS3 also demonstrates a relatively stable position, with ranks of 2, 3, 2, and 3 across the reference ranking, TOPSIS, SPOTIS, and EDAS, respectively. Similarly, LS6, LS1, LS7, and LS2 experience only moderate changes in their ranking positions across the evaluated methods. These results indicate that several alternatives maintain their relative performance despite being evaluated using different distance-based mechanisms. The consistency is further supported by the Spearman correlation analysis, where SPOTIS achieves a perfect correlation value of 1.0000 with the reference ranking and TOPSIS reaches 0.9286, indicating a very strong agreement. These high correlation values demonstrate that the decision outcomes generated by TOPSIS and SPOTIS are relatively stable and are not substantially affected by the methodological differences in distance calculation. Therefore, the dominant alternatives identified through the proposed framework can be considered to have a relatively strong performance profile because their positions remain consistent under different distance-based evaluation mechanisms.

The robustness analysis further considers the differences observed among TOPSIS, SPOTIS, and EDAS to determine whether methodological changes can substantially alter the decision conclusion. The results show that TOPSIS and SPOTIS provide highly comparable ranking patterns, particularly for LS5, LS3, LS6, LS1, LS7, LS2, and LS4. The most notable difference occurs for LS8, which achieves the first position in TOPSIS but falls to the sixth position in EDAS. LS4 also demonstrates a considerable shift, moving from the eighth position in TOPSIS and SPOTIS to the second position in EDAS. These changes can be explained by the different evaluation principles employed by the methods. TOPSIS

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evaluates alternatives according to their relative distance from positive and negative ideal solutions, while SPOTIS measures distance from a predefined optimal point. EDAS, in contrast, evaluates alternatives according to their positive and negative deviations from the average solution. Consequently, an alternative that performs strongly relative to an ideal solution may not necessarily obtain an equivalent position when its performance is assessed in relation to the average solution. Despite these methodological differences, the leading alternatives remain relatively recognizable, particularly LS5 and LS3, which consistently occupy high positions across the evaluated methods. This indicates that the decision framework possesses a reasonable level of robustness because the main recommendation is not completely altered by the selection of a distance-based ranking method.

The stability of the decision results is also closely related to the objective criteria weights generated by RECA Weighting. The obtained weights are relatively balanced, ranging from 0.1422 for Parking Availability to 0.1824 for Consumer Traffic, indicating that no single criterion dominates the decision process excessively. Consumer Traffic receives the highest weight, followed by Infrastructure, Accessibility, Rental Cost, Building Area, and Parking Availability. The relatively narrow difference between the highest and lowest weights suggests that the final ranking is influenced by the combined performance of alternatives across multiple criteria rather than by an isolated criterion. This characteristic strengthens the robustness of the evaluation because moderate changes in one criterion are less likely to completely determine the final position of an alternative. At the same time, the higher weight assigned to Consumer Traffic indicates that this criterion should receive greater attention in sensitivity testing because changes in its relative importance may have a more noticeable effect on the ranking outcomes. The same consideration applies to Infrastructure and Accessibility because their weights are also relatively high. Therefore, a comprehensive robustness assessment should examine whether increasing or decreasing the weights of these influential criteria results in major changes in the ranking order. If the leading alternatives remain in comparable positions under these weight perturbations, the resulting decision can be regarded as more stable and reliable. Conversely, substantial rank reversals under small weight changes would indicate that the decision is sensitive to criterion importance and should therefore be interpreted with greater caution.

To assess the robustness of the proposed decision-making method, a sensitivity analysis was performed by systematically modifying the criterion weights. As the weights indicate the relative importance assigned to each criterion, changes in their values may lead to variations in the final ranking of alternatives. Accordingly, several testing scenarios were developed by increasing and decreasing the initial weights while ensuring that the sum of all criterion weights remained equal to 1. The rankings obtained from each scenario were subsequently compared with the original ranking to examine the influence of weight changes on the decision results and to evaluate the stability of the proposed method. The weight modification scenarios used in the sensitivity analysis are presented in Table 1.

Table 7. Sensitivity Analysis Test Scenario with Changes in Criterion Weights

Test Scenario	C1	C2	C3	C4	C5	C6
Initial Weight	0.1651	0.1601	0.1738	0.1824	0.1422	0.1764
Test 1: C1 increases by 0.05	0.2049	0.1525	0.1655	0.1737	0.1354	0.1680
Test 2: C2 increases by 0.05	0.1572	0.2001	0.1655	0.1737	0.1354	0.1680
Test 3: C3 increases by 0.05	0.1572	0.1525	0.2131	0.1737	0.1354	0.1680
Test 4: C4 increases by 0.05	0.1572	0.1525	0.1655	0.2213	0.1354	0.1680
Test 5: C5 increases by 0.05	0.1572	0.1525	0.1655	0.1737	0.1830	0.1680
Test 6: C6 increases by 0.05	0.1572	0.1525	0.1655	0.1737	0.1354	0.2156
Test 7: C1 decreased by 0.05	0.1212	0.1685	0.1829	0.1920	0.1497	0.1857
Test 8: C2 decreased by 0.05	0.1738	0.1159	0.1829	0.1920	0.1497	0.1857

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Test 9: C3 decreased by 0.05	0.1738	0.1685	0.1303	0.1920	0.1497	0.1857
Test 10: C4 decreased by 0.05	0.1738	0.1685	0.1829	0.1394	0.1497	0.1857
Test 11: C5 decreased by 0.05	0.1738	0.1685	0.1829	0.1920	0.0971	0.1857
Test 12: C6 decreased by 0.05	0.1738	0.1685	0.1829	0.1920	0.1497	0.1331

Based on the weight variation scenarios, the ranking of each alternative was recalculated using the TOPSIS method. For each scenario, changes in the criterion weights resulted in different preference values based on the relative closeness of each alternative to the positive and negative ideal solutions, which consequently affected the ranking positions. The results of all weight variation scenarios were then compared to evaluate the stability of the alternative rankings. Overall, the ranking changes resulting from each scenario are presented in Figure 3, illustrating how variations in criterion weights influence the ranking positions of the alternatives.

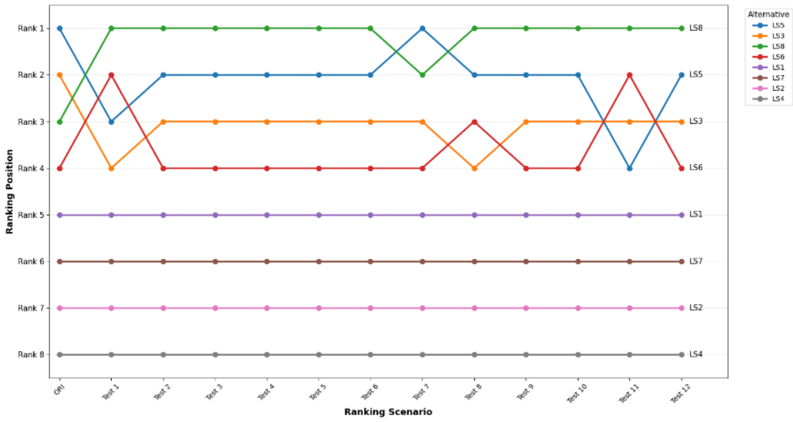

Figure 3. Comparison Results of TOPSIS Method Rankings Based on Sensitivity Analysis

The TOPSIS ranking results show that LS5 consistently achieved the highest position, starting from rank 1 in the original scenario and remaining in the top three across all 12 test scenarios, although its ranking fluctuated between first and fourth place. LS8, which was ranked third in the original scenario, demonstrated the strongest performance under most weight variation scenarios, achieving rank 1 in Tests 1–6 and Tests 8–12, while dropping slightly to second place in Test 7. LS3 showed relatively stable performance, with rankings ranging from second to fourth, whereas LS6 generally occupied fourth place but improved to second in Test 11 and third in Test 8. Meanwhile, LS1 consistently maintained fifth place across all scenarios, while LS7, LS2, and LS4 remained unchanged at sixth, seventh, and eighth place, respectively. These results indicate that the upper-ranked alternatives, particularly LS5, LS8, LS3, and LS6, are more sensitive to changes in criterion weights, whereas the lower-ranked alternatives exhibit highly stable rankings throughout the weight variation scenarios.

Based on the weight variation scenarios, the ranking of each alternative was recalculated using the SPOTIS method. For each scenario, changes in the criterion weights resulted in variations in the SPOTIS preference values and, consequently, affected the ranking positions of the alternatives. The results obtained from all weight variation scenarios were then compared to assess the stability and robustness of the alternative rankings under different weight configurations. Overall, the ranking changes across the scenarios are presented in Figure 4, illustrating the influence of criterion weight variations on the ranking order of the alternatives using the SPOTIS method.

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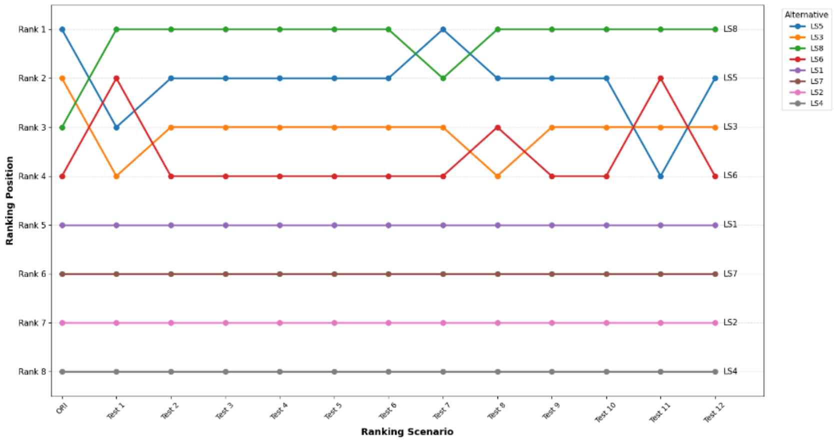

Figure 4. Comparison Results of SPOTIS Method Rankings Based on Sensitivity Analysis

The SPOTIS ranking results demonstrate a completely stable ranking pattern across all weight variation scenarios. LS5 consistently maintained the first position from the original ranking through Tests 1–12, indicating that it remained the best-performing alternative regardless of changes in criterion weights. Similarly, LS3, LS8, and LS6 consistently occupied the second, third, and fourth positions, respectively, throughout all scenarios. The lower-ranked alternatives also showed no changes in their positions, with LS1 remaining fifth, LS7 sixth, LS2 seventh, and LS4 eighth in every test. This consistent ranking pattern indicates that the SPOTIS method is highly robust and insensitive to the applied weight variations, as none of the alternatives experienced a change in ranking position across the 12 test scenarios. Therefore, the SPOTIS results provide strong evidence of ranking stability and demonstrate that the original ranking is highly reliable under different criterion weight configurations.

Based on the weight variation scenarios, the ranking of each alternative was recalculated using the EDAS method. For each scenario, changes in the criterion weights resulted in variations in the appraisal scores of the alternatives, which consequently affected their ranking positions. The results obtained from all weight variation scenarios were then compared to evaluate the stability and robustness of the alternative rankings under different weight configurations. Overall, the ranking changes across the scenarios are presented in Figure 5, illustrating the influence of criterion weight variations on the ranking order of the alternatives using the EDAS method.

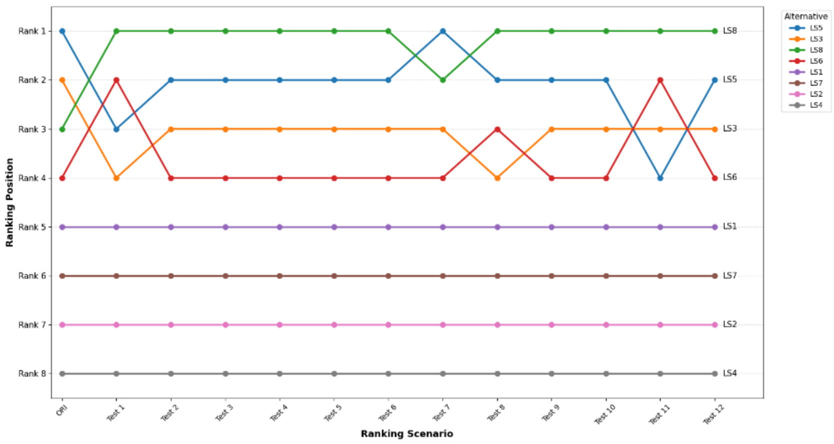

Figure 5. Comparison Results of EDAS Method Rankings Based on Sensitivity Analysis

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P-ISSN 2962-0538
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DOI : **https://doi.org/10.58602/itsecs.v4i4.377**
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The EDAS ranking results show a highly stable ranking pattern across all 12 weight variation scenarios, although several alternatives experienced substantial changes compared with the original ranking. LS5 consistently maintained the first position in the original ranking and all test scenarios, indicating that it is the most robust alternative under different criterion weight configurations. In contrast, LS4 improved substantially from eighth place in the original ranking to second place in all test scenarios, followed by LS3, which moved from second to third place, and LS7, which improved from sixth to fourth place. LS2 also improved from seventh to fifth place, while LS8 declined from third to sixth place, LS6 from fourth to seventh place, and LS1 from fifth to eighth place. Notably, although these changes occurred between the original ranking and the test scenarios, the rankings remained completely unchanged across Tests 1–12. This indicates that the EDAS method produces a stable ranking under the applied weight variations, while the differences between the original and test rankings suggest that the initial weighting configuration has a substantial influence on the relative ordering of the alternatives.

Based on the ranking results obtained from the TOPSIS, SPOTIS, and EDAS methods, a correlation analysis was performed to evaluate the degree of similarity and consistency among the alternative rankings generated by each method and across the different weight variation scenarios. The correlation values were calculated by comparing the ranking positions of the alternatives, allowing the relationships between the methods and the stability of their rankings to be quantitatively assessed. The resulting correlation coefficients are presented in Figure 6, which illustrates the level of agreement among the ranking results and provides further evidence of the consistency and robustness of the decision-making outcomes under different weight configurations.

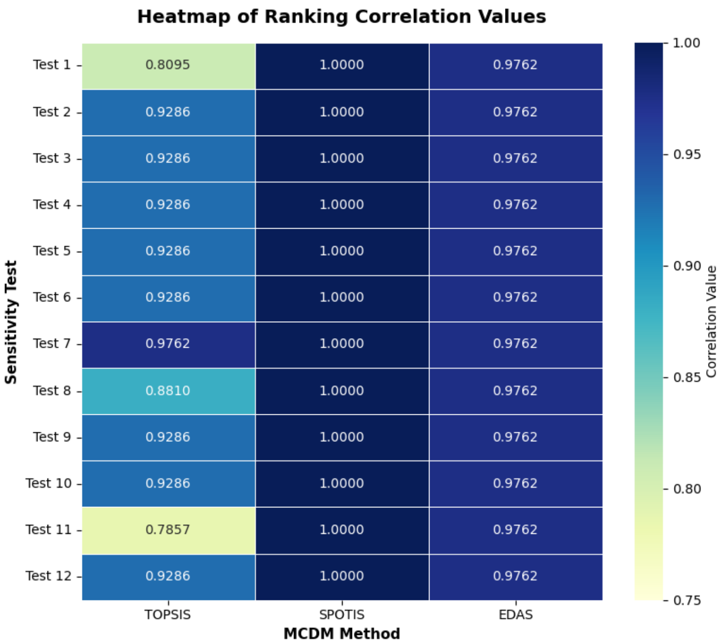

Figure 6. Comparison of Spearman Correlation Values from Sensitivity Analysis

Based on the heatmap results, the SPOTIS method demonstrates the highest-ranking stability, achieving a correlation value of 1.0000 across all 12 tests, indicating that changes in the criterion weights do not affect the ranking order of the alternatives. The EDAS method also exhibits very high stability, with a consistent correlation value of 0.9762 across all tests. In contrast, TOPSIS shows greater variation in its correlation values, ranging from 0.7857 to 0.9762, with the lowest value occurring in Test 11 and the highest

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in Test 7. Overall, these results indicate that SPOTIS provides the highest level of ranking robustness and consistency, followed by EDAS, while TOPSIS is relatively more sensitive to changes in criterion weights.

Overall, the combined findings from ranking comparison, Spearman correlation, RECA-based weighting, and cross-method evaluation indicate that the proposed framework provides a meaningful level of stability and robustness for new store location selection. SPOTIS demonstrates the strongest agreement with the reference ranking, as reflected by its perfect Spearman correlation of 1.0000, while TOPSIS also provides a highly consistent result with a correlation of 0.9286. EDAS produces a considerably different ranking pattern, reflected by its lower correlation value of 0.1429, demonstrating that its average-solution-based evaluation mechanism is more sensitive to the distribution of alternative performance. Nevertheless, the presence of consistently high-ranking alternatives, particularly LS5 and LS3, provides evidence that the core decision pattern remains identifiable across multiple evaluation approaches. The differences observed for LS8 and LS4 also provide important information rather than simply indicating inconsistency, because they reveal alternatives whose positions are more dependent on the underlying evaluation mechanism. From a decision-support perspective, these alternatives should therefore receive additional attention when final recommendations are formulated. The overall analysis confirms that combining objective RECA Weighting with multiple distance-based MCDM methods enables the decision maker to distinguish between stable alternatives and method-sensitive alternatives, thereby reducing dependence on a single computational approach. This comprehensive stability and robustness analysis strengthens the reliability of the resulting decision process by demonstrating not only which alternatives perform well, but also how consistently their performance is maintained under different ranking mechanisms and weighting considerations. Furthermore, the sensitivity analysis based on 12 weight-variation tests provides additional evidence of the robustness of the ranking results. SPOTIS demonstrates the strongest stability, achieving a correlation value of 1.0000 in all 12 tests, indicating that changes in criterion weights do not alter the ranking structure. EDAS also exhibits a highly stable ranking pattern, consistently obtaining a correlation value of 0.9762 across all 12 tests. In comparison, TOPSIS shows greater variation, with correlation values ranging from 0.7857 to 0.9762. The lowest TOPSIS correlation occurs in Test 11 at 0.7857, while the highest value of 0.9762 is obtained in Test 7. Nevertheless, TOPSIS maintains high correlation values in most of the sensitivity tests, including 0.9286 in Tests 2–6 and 9–12, 0.8095 in Test 1, and 0.8810 in Test 8. These findings demonstrate that although TOPSIS is comparatively more sensitive to changes in criterion weights, its ranking results remain generally consistent. Therefore, the sensitivity analysis complements the initial Spearman correlation results by demonstrating that the proposed framework remains robust not only under the original weighting configuration but also under systematic variations in criterion weights.

4. CONCLUSION

This study concludes that the integration of RECA Weighting with distance-based MCDM methods, namely TOPSIS, SPOTIS, and EDAS, provides a comprehensive framework for evaluating and selecting new store locations while considering objective criteria importance and ranking stability. RECA Weighting produced relatively balanced criterion weights, with Consumer Traffic (C4) obtaining the highest weight of 0.1824 and Parking Availability (C5) the lowest weight of 0.1422, indicating that all criteria contribute meaningfully to the decision process. The ranking results show that LS5 consistently demonstrates strong performance, achieving the first position in the reference ranking, SPOTIS, and EDAS, while obtaining second position with TOPSIS, followed by LS3 as another relatively stable alternative. The stability analysis further confirms strong

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agreement between the reference ranking and TOPSIS and perfect agreement with SPOTIS, with Spearman correlation values of 0.9286 and 1.0000, respectively, whereas EDAS produces a substantially different ranking pattern with a correlation of 0.1429. These findings demonstrate that TOPSIS and SPOTIS provide more consistent ranking outcomes, while EDAS reveals greater sensitivity to the distribution of alternatives relative to the average solution. Overall, the integration of objective RECA Weighting, comparative distance-based MCDM methods, ranking correlation, and stability analysis enhances the reliability and robustness of the decision-making process by identifying both consistently high-performing alternatives and alternatives whose rankings are more sensitive to the evaluation mechanism. Future research may extend the proposed framework by incorporating larger and more diverse datasets, additional objective weighting techniques, and alternative MCDM methods to further evaluate ranking consistency and robustness. Further studies could also explore broader sensitivity analyses and real-time decision criteria to improve the practical applicability and reliability of new store location selection.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Sumanto: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Ryan Randy Suryono**: Writing – original draft, Conceptualization. **Riska Aryanti**: Writing – original draft, Visualization. **Hetty Rohayani**: Writing – review & editing, Validation. **Setiawansyah**: Supervision, Writing – review & editing. **Desyanti**: Writing – original draft, Software, Investigation.

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.

FUNDING STATEMENTS

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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.

REFERENCES

[1] T. Van Dua and D. D. Trung, “MEPSI (Mutriss Enhanced Preference Selection Index): a novel method for ranking alternatives,” *EUREKA Phys. Eng.*, vol. 2024, no. 6, pp. 169–178, Nov. 2024, doi: 10.21303/2461-4262.2024.003408.

[2] J. Wang, S. Setiawansyah, and S. Sumanto, “Comparison of Objective Weighting Methods in SAW and Their Effect on Alternative Ranking Results,” *J. Masy. Inform.*, vol. 17, no. 1, pp. 89–112, Feb. 2026, doi: 10.14710/jmasif.17.1.78414.

[3] M. Krstić, G. P. Agnusdei, P. P. Miglietta, S. Tadić, and V. Roso, “Applicability of Industry 4.0 Technologies in the Reverse Logistics: A Circular Economy Approach Based on COmprehensive Distance Based RAnking (COBRA) Method,” *Sustainability*, vol. 14, no. 9. 2022. doi: 10.3390/su14095632.

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Journal of Information Technology, Software Engineering and Computer Science
Website : https://ejournal.techcart-press.com/index.php/itsecs
E-ISSN 2962-0635
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Volume 4, Number 4, October 2026
DOI : https://doi.org/10.58602/itsecs.v4i4.377
Page 119-138

[4] E. Roszkowska and T. Wachowicz, "Impact of Normalization on Entropy-Based Weights in Hellwig's Method: A Case Study on Evaluating Sustainable Development in the Education Area," *Entropy*, vol. 26, no. 5. 2024. doi: 10.3390/e26050365.
[5] A. Yudhistira, S. Setiawansyah, T. Ardiansah, S. Maryana, Y. Yadin, and R. Oktaviani, "Development of Multi-Attribute Utility Theory Methods in Dynamic Decision Models Using Change-Data Driven," *Evergreen*, vol. 11, no. 4, pp. 3279–3289, Dec. 2024, doi: 10.5109/7326962.
[6] V. R. R. Mota, C. F. S. Gomes, D. F. de Lima Silva, and M. dos Santos, "The novel hybrid multiple criteria decision method BWM-Moora-N applied for investment funds prioritization," *Oper. Res.*, vol. 24, no. 3, p. 36, 2024, doi: 10.1007/s12351-024-00817-w.
[7] A. Puška, D. Božanić, Z. Mastilo, and D. Pamučar, "Extension of MEREC-CRADIS methods with double normalization-case study selection of electric cars," *Soft Comput.*, vol. 27, no. 11, pp. 7097–7113, 2023, doi: 10.1007/s00500-023-08054-7.
[8] V. Simić, B. Milovanović, S. Pantelić, D. Pamučar, and E. B. Tirkolaee, "Sustainable route selection of petroleum transportation using a type-2 neutrosophic number based ITARA-EDAS model," *Inf. Sci. (Ny).*, vol. 622, pp. 732–754, 2023, doi: https://doi.org/10.1016/j.ins.2022.11.105.
[9] S. Dündar, "Prioritizing the Regional Preferences of Turkish Investors Regarding Foreign Direct Investment by ARLON Method," *Konya J. Eng. Sci.*, vol. 13, no. 3, pp. 927–946, 2025, doi: 10.36306/konjes.1648279.
[10] A. Asistyasari, M. W. Arshad, I. Chandra, Y. Nuryaman, and V. H. Saputra, "Integration of RECA Weighting and MARCOS Methods in Decision Support Systems for the Selection of the Best Customer Recommendations," *J. Inform. dan Rekayasa Perangkat Lunak*, vol. 6, no. 2, pp. 122–136, Jun. 2025, doi: 10.33365/jatika.v6i2.219.
[11] D. A. Megawaty, D. Damayanti, S. Sumanto, P. Permata, D. Setiawan, and S. Setiawansyah, "Development of a Decision Support System Based on New Approach Respond to Criteria Weighting Method and Grey Relational Analysis: Case Study of Employee Recruitment Selection," *JOIV Int. J. Informatics Vis.*, vol. 9, no. 1, pp. 314–323, 2025, doi: 10.62527/joiv.9.1.2744.
[12] A. Asistyasari, I. Chandra, S. H. Hadad, Y. Nuryaman, and J. Wang, "Decision Support System Based on RECA and COPRAS Methods in Performance Evaluation of Non-Permanent Employees," *J. Inform. dan Rekayasa Perangkat Lunak*, vol. 6, no. 3 SE-Articles, pp. 236–251, Sep. 2025, doi: 10.33365/jatika.v6i3.848.
[13] S. Setiawansyah and I. Chandra, "Objective Approach in Supplier Selection: Integration of RECA Weighting and Combinative Distance-based Assessment Method," *Chain J. Comput. Technol. Comput. Eng. Informatics*, vol. 4, no. 3, pp. 138–159, Jul. 2026, doi: 10.58602/chain.v4i3.264.
[14] E. Triantaphyllou and A. Sánchez, "A Sensitivity Analysis Approach for Some Deterministic Multi-Criteria Decision-Making Methods," *Decis. Sci.*, vol. 28, no. 1, pp. 151–194, Jan. 1997, doi: 10.1111/j.1540-5915.1997.tb01306.x.
[15] V. Maliene, R. Dixon-Gough, and N. Malys, "Dispersion of relative importance values contributes to the ranking uncertainty: Sensitivity analysis of Multiple Criteria Decision-Making methods," *Appl. Soft Comput.*, vol. 67, pp. 286–298, 2018, doi: 10.1016/j.asoc.2018.03.003.
[16] T. Rashid, A. Ali, and Y.-M. Chu, "Hybrid BW-EDAS MCDM methodology for optimal industrial robot selection.," *PLoS One*, vol. 16, no. 2, p. e0246738, 2021, doi: 10.1371/journal.pone.0246738.
[17] À. Gaona, A. Guisasola, and J. A. Baeza, "An integrated TOPSIS framework with Full-

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Journal of Information Technology, Software Engineering and Computer Science
Website : https://ejournal.techcart-press.com/index.php/itsecs
E-ISSN 2962-0635
P-ISSN 2962-0538
Volume 4, Number 4, October 2026
DOI : **https://doi.org/10.58602/itsecs.v4i4.377**
Page 119-138

Range Weight Sensitivity Analysis for robust decision analysis," *Decis. Anal. J.*, vol. 17, p. 100642, 2025, doi: 10.1016/j.dajour.2025.100642.
[18] G. Demir and R. Arslan, "Sensitivity Analysis in Multi-Criterion Decision-Making Problems," *Ankara Hacı Bayram Veli Üniversitesi İktisadi ve İdari Bilim. Fakültesi Derg.*, vol. 24, no. 3, pp. 1025–1056, 2022, doi: 10.26745/ahbvuibfd.1103531.
[19] B. Yagmahan and H. Yılmaz, "An integrated ranking approach based on group multi-criteria decision making and sensitivity analysis to evaluate charging stations under sustainability," *Environ. Dev. Sustain.*, vol. 25, no. 1, pp. 96–121, 2023, doi: 10.1007/s10668-021-02044-1.
[20] B. Deta and S. M. I. Bedanaen, "Comparison of SAW, AHP, and TOPSIS Methods in a Decision Support System for Teacher Performance Evaluation," *Res. Horiz.*, vol. 5, no. 5 SE-Articles, pp. 1995–2008, Oct. 2025, doi: 10.54518/rh.5.5.2025.798.
[21] J. Liu, X. Bao, and L. Chen, "Artificial intelligence in educational technology and transformative approaches to English language using fuzzy framework with CRITIC-TOPSIS method," *Sci. Rep.*, vol. 15, no. 1, p. 25542, 2025, doi: 10.1038/s41598-025-09844-9.
[22] P. L. de Oliveira, M. Â. L. Moreira, I. P. de Araújo Costa, D. A. de Moura Pereira, C. F. S. Gomes, and M. dos Santos, "Human Resources Selection Through the PSI-SPOTIS Hybrid Modelling: Multi-criteria Analysis of Sellers for Technological Market BT - Proceedings of International Conference on Information Technology and Applications," 2025, pp. 445–459. doi: 10.1007/978-981-96-1758-6_37.
[23] A. Shekhovtsov, J. Więckowski, B. Paradowski, B. Kizielewicz, J. Watróbski, and W. Sałabun, "A Novel Approach Utilizing Local Criteria Weights for Multi-criteria Evaluation Within the SPOTIS Method BT - Intelligent Information and Database Systems," 2024, pp. 276–287.
[24] T. Ali, A. Aytekin, and M. Demidionov, "Optimal siting of wind powered green hydrogen production in Bangladesh using interval-valued T-spherical fuzzy multi-criteria decision-making method," *Int. J. Hydrogen Energy*, vol. 217, p. 153931, 2026, doi: https://doi.org/10.1016/j.ijhydene.2026.153931.
[25] S. Bektaş, "Financial Performance Ranking With A New Hybrid Decision Making Model: Application Of The CRISUS-RAWEC Hybrid Model For The Reinsurance Industry," *Gümüşhane Univ. J. Soc. Sci.*, vol. 17, no. 1, pp. 233–249, 2026, [Online]. Available: https://dergipark.org.tr/en/pub/gumus/article/1721934
[26] M. A. Al-Gerafi *et al.*, "Designing of an effective e-learning website using inter-valued fuzzy hybrid MCDM concept: A pedagogical approach," *Alexandria Eng. J.*, vol. 97, pp. 61–87, 2024, doi: https://doi.org/10.1016/j.aej.2024.04.012.
[27] P. Liu, X. Wang, Y. Fu, and P. Wang, "Graph model for conflict resolution based on the combination of probabilistic uncertain linguistic and EDAS method," *Inf. Sci. (Ny).*, vol. 660, no. 3, pp. 120–136, 2024, doi: 10.1016/j.ins.2024.120116.
[28] R. D. Gunawan, M. W. Arshad, A. D. Wahyudi, R. R. Suryono, T. Widodo, and F. Ulum, "Modification of Additive Ratio Assessment Method through Distance-Based Weighting Approach for Optimizing Assessment Accuracy," *Paradig. - J. Komput. dan Inform.*, vol. 27, no. 2, pp. 55–64, 2025, doi: 10.31294/p.v27i2.8810.

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