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Comparison of Objective Weighting Methods in SAW and Their Effect on Alternative Ranking Results

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Abstract
Determining criterion weights is a vital step in multi-criteria decision making, yet it often suffers from evaluator subjectivity and unstable results when relying on expert judgment. Dependence on human perception may also lead to inconsistencies across criteria, underscoring the need for objective, data-driven approaches to derive rational, measurable weights. This study analyzes and compares six objective weighting methods: Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, in the selection of new store locations. Each method applies distinct mathematical principles but shares a common foundation in objective data analysis, free from subjective bias. The findings reveal that criterion S5 consistently receives the highest weight, emphasizing its dominant role in decision outcomes. Using the Simple Additive Weighting (SAW) method, New Store Location 5 ranks first across all weighting techniques, followed by Locations 3 and 8. The Spearman correlation test confirms a high level of consistency among methods, with coefficients of 1 for RECA, G2M, and LOPCOW, and 0.9879 for Entropy, MEREC, and CRITIC. These results demonstrate that objective weighting methods produce stable and reliable evaluations, effectively supporting data-based strategic decision making in multi-criteria contexts. These findings reinforce the view that a data-driven, systematic approach to weighting criteria is more effective than a subjective one, as it can yield consistent, measurable, and replicable results.

Keywords: *objective weighting, multi-criteria decision making, Entropy, MEREC, SAW*

1 Introduction

Decision support systems (DSS) play a very important role in the context of multi-criteria decision-making, especially when decisions must be made based on a number of interacting and often conflicting factors[1]–[3]. In complex situations such as selecting a business location, evaluating supplier performance, or determining investment strategies, relying solely on intuition is no longer sufficient because it risks producing biased and inconsistent decisions. DSS enables decision-makers to integrate quantitative and qualitative data, process it systematically using analytical methods, and present results that are more objective and accountable. In addition, DSS supports the implementation of the Multi-criteria decision making (MCDM) method, which can balance various criteria based on different importance weights, making decision outcomes more rational and transparent [4]–[7]. The presence of DSS also helps reduce uncertainty by providing alternative scenarios and sensitivity analyses, offering a more comprehensive view of potential risks. Thus, DSS not only speeds up the

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decision-making process but also improves the accuracy, efficiency, and legitimacy of decision outcomes across various application domains.

The simple additive weighting (SAW) method plays an important role as one of the most popular and widely used MCDM methods due to its simplicity and effectiveness in solving decision-making problems[8]–[10]. The basic principle of this method is to normalize the performance values of each alternative across all criteria, then multiply them by the predetermined weights for each criterion, thereby producing a total score that can be used to rank the alternatives. The main advantage of SAW is its ability to deliver results that are easy to understand, transparent, and directly interpretable by decision-makers, without requiring complex mathematical calculations. Moreover, this method is flexible in accommodating various types of data, both quantitative and qualitative, that have been transformed into numerical scales. Its role becomes increasingly significant when used in situations that require quick ranking while still maintaining the rationality of evaluation, such as employee selection, supplier selection, or project performance evaluation. Thus, SAW not only provides a practical solution but also strengthens the foundation of systematic and objective decision-making within the MADM framework[11]–[13].

Accurate weighting of criteria is highly significant in producing valid alternative rankings within the MCDM framework. The weighting process determines the extent to which each criterion contributes to the overall evaluation, so errors in assigning weights can lead to distorted results and incorrect recommendations[14]–[16]. Accurate weights reflect the relative importance of the criteria, whether objective (based on data) or subjective (based on decision-makers' preferences), making the final ranking more representative of the decision objectives to be achieved. In addition, proper weighting ensures a balance between dominant and supporting factors, so that decisions do not focus solely on a single aspect but consider all dimensions comprehensively. In practice, accurate weighting also supports transparency and consistency, as each alternative's ranking can be logically explained by the measurable contributions of the criteria. Therefore, accurate criteria weighting is not merely a technical stage, but a foundation that determines the validity, reliability, and credibility of multi-criteria decision-making outcomes.

A common issue in multi-criteria decision-making is the difference in results produced by various objective weighting methods, which in turn can affect the final ranking of alternatives. Each method, such as Entropy, CRITIC, or LOPCOW, has different calculation principles and focuses in assessing data variation and the importance of a criterion, resulting in weight distributions that are not always consistent with one another. These differences in weights can lead to changes in the ranking order of alternatives, raising questions about the reliability and validity of the decisions produced. The situation becomes increasingly critical when decisions are related to strategic areas where the consequences of ranking differences can be highly significant. Furthermore, the variability in results from objective weighting methods also has the potential to create uncertainty and doubt for decision-makers in selecting the best alternative. Therefore, understanding the impact of different weighting methods on the final outcomes is crucial for enhancing transparency, justification, and reliability in the multi-criteria decision-making process.

Although previous research has extensively discussed the use of objective weighting methods and their application to various MCDM techniques such as TOPSIS, VIKOR, and other distance-based methods, most of these studies still focus on comparing the performance of ranking methods, rather than on a deep comparative analysis of the behaviour of objective weights and their direct impact on changes in alternative ranking results. From this perspective, previous research has not systematically explored how differences in statistical principles in objective weighting methods result in different patterns of criteria dominance when integrated into a consistent ranking framework. This study examines the comparison of various objective weighting methods within the SAW framework, chosen not merely for their popularity, but for their linear, transparent, easily interpretable nature, and high sensitivity to variations in criterion weights, so that any change in weight can be directly observed on the scores and rankings of alternatives. Unlike TOPSIS or VIKOR, which involve ideal solutions and compromise mechanisms, SAW allows for a more pure evaluation of the impact of weights, making it a superior framework for comparative weighting studies and providing new insights into the relationship between objective weighting methods and decision-making outcomes.

The aim of this study is to analyze the differences arising from the application of various objective weighting methods within the SAW framework, which is known as one of the simplest and most widely used MCDM methods. This analysis is important because each objective weighting method has different principles and calculation mechanisms, which can potentially result in different weight distributions and affect the ranking outcomes of alternatives. This study also aims to systematically evaluate how these differences in weights impact the ranking order of alternatives, both in terms of result consistency and decision validity. The evaluation is conducted by considering the reliability of the methods, sensitivity to data, and the extent to which the weights represent the importance of the analyzed criteria. Furthermore, this research is aimed at providing recommendations regarding a more consistent and suitable objective weighting method aligned with the characteristics of SAW applications, thereby strengthening the legitimacy of decision outcomes. The resulting recommendations are expected to assist decision-makers in selecting the appropriate weighting approach, particularly in cases involving multiple criteria with varying levels of importance. Thus, this research not only focuses on the comparative aspect of methods but also offers practical contributions in enhancing the reliability and transparency of SAW usage. Ultimately, the main goal of this study is to ensure that SAW-based decision-making processes can produce alternative rankings that are more valid, objective, and scientifically as well as practically accountable.

The main contribution of this research is its effort to provide a deeper understanding of how various objective weighting methods influence the ranking results of alternatives within the SAW framework. This study not only compares weighting methods such as Entropy, CRITIC, MEREC, G2M, RECA, and LOPCOW, but also evaluates the sensitivity and stability of the ranking results produced by each approach. Thus, this research contributes to identifying the most consistent weighting methods that are adaptive to data characteristics and capable of producing more objective and representative decisions. Furthermore, this study strengthens the literature on MCDM by providing an empirical basis for researchers and practitioners to select the appropriate weighting method for various decision-making contexts, whether in management, industry, or data-driven decision support systems.

The six objective weighting methods used in this study, namely Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, were chosen because each represents a different statistical and structural approach to objectively extracting criterion weights, ranging from measuring information uncertainty (Entropy), the impact of criterion removal (MEREC), evaluating relative contribution and balance (RECA and G2M), sensitivity to range-based and skewed data changes (LOPCOW), to variability and correlations among criteria (CRITIC). This diversity of characteristics makes them highly relevant for comparative analysis within the SAW framework, which is additive, linear, and transparent, so that changes in weights across methods can be directly reflected and easily interpreted in alternative scores and rankings. Moreover, although previous studies have widely applied objective weighting methods in DS, their implementation is generally fragmented and combined with various ranking methods, without an integrated analysis of the consistency and relative impact among weighting methods within the same calculation framework. This study emphasises the relevance of all six methods and makes a new contribution by systematically evaluating their compatibility and effects in SAW-based DSS.

2 Research Methods

This study uses a quantitative approach based on the MCDM method, focusing on the application of SAW to analyze differences in objective weighting methods, as shown in Figure 1. The research data were obtained from Gunawan's study [17], which included several alternatives and criteria relevant to the decision-making context. The research stages began with the identification of criteria and alternatives to be evaluated, followed by data normalization to ensure uniformity of scales among the criteria. After that, the criteria weights were determined using several objective weighting methods, such as Entropy, CRITIC, MEREC, G2M, RECA, and LOPCOW, each reflecting a different approach to assessing the variation and importance of the criteria. The weights obtained are then integrated into the SAW calculation to produce the total score for each alternative, which is subsequently used to rank the alternatives. The ranking results are compared to assess consistency and differences arising from different weighting methods. Comparison of alternative rankings was also conducted to test the stability of the results across the weighting methods used for the criteria. Thus, this research method is systematically designed to achieve the research objectives: to evaluate the effects of weighting variations on SAW results and to provide recommendations for the most consistent method.

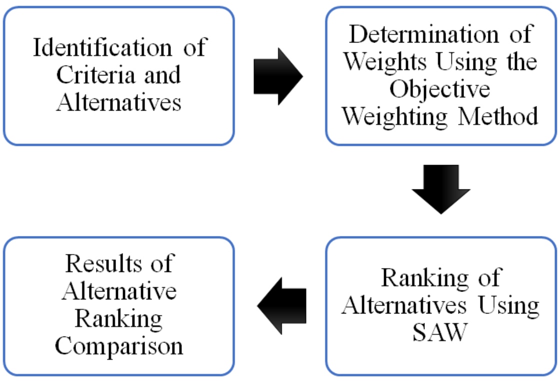


Figure 1 Research stages

2.1 Entropy Method

The entropy method is an objective approach to determining the weights of criteria in the MCDM. Its basic principle is based on the concept of information theory, where the level of uncertainty or variation in data is used as a basis to determine the importance of a criterion[18], [19]. The Entropy Method can reduce subjectivity in weighting by determining criterion weights entirely from the existing data distribution, resulting in outcomes that are more objective, consistent, and scientifically accountable. The main formula used in the entropy method is as follows:

$$k_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{1}$$

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{n} k_{ij} \ln(k_{ij}) \tag{2}$$

$$D_j = 1 - E_j \tag{3}$$

$$w_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{4}$$

Where x_{ij} is the value of the ii-th alternative with respect to the j^{th} criterion, while k_{ij} is the normalized ratio that indicates the proportion of an alternative's value contribution to the total value for that criterion. The value E_j represents the entropy level or uncertainty of the j^{th} criterion, with k being a normalization constant equal to $1/\ln(m)$ so that the calculation results remain within the range [0,1]. Furthermore, D_j is called the degree of divergence, which indicates the variation in the information about a criterion. A criterion with a high divergence value plays a more significant role in differentiating alternatives. The final weight of each criterion (w_j) is obtained by dividing the divergence value of a criterion by the total sum of all divergences. In this way, the Entropy method ensures that weights are determined solely by the data distribution, thereby guaranteeing greater objectivity than traditional subjective approaches.

2.2 Method Based on the Removal Effects of Criteria (MEREC)

The MEREC method is one of the objective weighting approaches in MCDM that emphasizes analyzing the impact of removing a criterion on the overall evaluation results[20], [21]. Its basic concept is that the greater the change in the aggregated value when a criterion is removed, the more important that criterion is in the decision-making process. Thus, the criterion weights are determined by their actual contributions to the stability and accuracy of the alternative evaluation results. This approach is considered fairer and more consistent because the resulting weights do not depend on the decision maker's subjective perception, but rather on the sensitivity of the criteria to changes in the results. The main advantage of MEREC is its ability to provide a more rational assessment of the importance of criteria, especially in cases with many interacting attributes, thereby improving the quality and reliability of decision support systems. The main formula used in the MEREC method is as follows:

$$n_{ij} = \begin{cases} \frac{\min x_{kj}}{x_{ij}} & (for\ benefical\ criteria) \\ \frac{x_{ij}}{\max x_{kj}} & (for\ non-benefical\ criteria) \end{cases} \tag{5}$$

$$S_i = \ln\left(1 + \left(\frac{1}{m}\sum\left|\ln\left(n_{ij}\right)\right|\right)\right) \tag{6}$$

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j}\left|\ln\left(n_{ij}\right)\right|\right)\right) \tag{7}$$

$$E_j = \sum\left|S'_{ij} - S_i\right| \tag{8}$$

$$w_j = \frac{E_j}{\sum_k E_k} \tag{9}$$

Where n_{ij} indicates the normalized value of the i^{th} alternative with respect to the j^{th} criterion, which is used to standardize the evaluation scale across criteria. The value x_{ij} represents the performance or original value of the i^{th} alternative on the j^{th} criterion, while min(x_{kj}) and max(x_{kj}) respectively denote the smallest and largest values among all alternatives for the j^{th} criterion. The symbol m represents the total number of alternatives evaluated in the decision-making process. The value S_i represents the overall performance level of the i^{th} alternative after all criteria are considered, whereas S'_{ij} indicates the performance value of the i^{th} alternative when the j^{th} criterion is removed from the calculation. The symbol E_j indicates the magnitude of the influence or deletion effect of the j^{th} criterion on the total evaluation of alternatives. Finally, w_j is the final weight of the j^{th} criterion obtained through the normalization process of all deletion effect values, thereby representing the relative importance level of each criterion objectively in decision-making.

2.3 Respond to Criteria Weighting (RECA) Method

The RECA method is an approach to criteria weighting developed to produce more adaptive and objective weights based on the responsiveness of data to variations among criteria[22]–[24]. The main concept of RECA is to measure the extent to which each criterion significantly contributes to differentiating among alternatives in the decision-making process. The higher the level of response or sensitivity of a criterion to changes in alternative values, the greater the weight assigned to that criterion. The main formula used in the RECA method is as follows:

$$PV_{ij} = \frac{x_{ij}}{\sqrt[n]{\prod_{j=1}^{n} x_{ij}}} \tag{10}$$

$$R_{ij} = \frac{PV_{ij}}{PV_j^{max}} \tag{11}$$

$$N = \frac{1}{N} \sum R_{ij} \tag{12}$$

$$\emptyset_j = \sum_{i=1}^{m} \left[R_{ij} - N\right]^2 \tag{13}$$

$$\Omega_j = \left|1 - \emptyset_j\right| \tag{14}$$

$$w_j = \frac{\Omega_j}{\sum_{k=1}^{n} \Omega_k} \tag{15}$$

Where PV_{ij} represents the proportional value of the i^{th} alternative with respect to the j^{th} criterion, obtained by comparing the initial value x_{ij} with the geometric mean of all alternative values across all criteria, where n denotes the total number of criteria evaluated. The symbol R_{ij} is the standardized ratio value of each alternative against a specific criterion. It is calculated by dividing PV_{ij} by the maximum PV_j value for the same criterion to ensure all values are within a comparable range. The symbol N denotes the average R_{ij} value of all alternatives, serving as a central measure or reference value of the resulting ratio distribution. The symbol $\emptyset_j$ indicates the variability or dispersion of values in the j^{th} criterion, calculated as the sum of the squared differences between R_{ij} and its average N for all alternatives. The value Ω_j is a measure of the stability of a criterion, obtained from the absolute difference between 1 and $\emptyset_j$; the larger this value, the more important the criterion because it indicates high consistency with the evaluation results. Finally, the symbol w_j represents the final weight of the j^{th} criterion, obtained by normalizing all Ω_j values against their total, thereby producing the relative importance proportion of each criterion in the decision-making process.

2.4 Grey Geometric Mean (G2M) Weighting Method

The G2M weighting method is an objective weighting approach that integrates grey system theory with the concept of geometric mean to address uncertainty and inaccuracy of data in the multi-criteria decision-making process[25], [26]. This method serves to determine the weights of criteria more rationally by considering the grey degree of each criterion, which reflects the level of information and data variability available. The main formula used in the G2M weighting method is as follows:

$$GM_j = \left(\prod_{i=1}^{n} x_{ij}\right)^{1/n} \tag{16}$$

$$R_{ij} = \frac{x_{ij}}{GM_j} \tag{17}$$

$$GRG_j = \frac{1}{n}\sum_{j=1}^{n} R_{ij} \tag{18}$$

$$w_j = \frac{GRG_j}{\sum_{k=1}^{n} GRG_k} \tag{19}$$

Where GM_j represents the geometric mean of the values of the jth criterion, calculated based on the product of all alternative values for that criterion, and raised to the power of $1/n$, where n is the total number of evaluated alternatives. The symbol R_{ij} represents the ratio between the performance value of the i^{th} alternative (x_{ij}) and the geometric mean value GM_j, which is used to assess to what extent the performance of the alternative compares to the geometric midpoint of the related criterion. Furthermore, the symbol GRG_j represents the grey relational grade of the j^{th} criterion, which is the average value of all R_{ij} ratios indicating the degree of relationship or relative contribution between alternatives and criteria in the decision-making system. Finally, the symbol w_j represents the final weight of the j^{th} criterion, obtained by normalizing the GRG_j value against the total GRG_k values of all criteria. This weight reflects the relative importance of each criterion based on the strength of the relationship indicated by the grey relational grade value.

2.5 Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW) Method

The LOPCOW method is an objective weighting approach used to assess the relative importance level among criteria based on the logarithmic variation of percentage value changes of attributes for each alternative[27]–[29]. This approach is based on the idea that the sensitivity of a criterion to data changes can be measured more accurately using a logarithmic function, which can capture nonlinear dynamics in the distribution of decision values. In LOPCOW, criterion weights are calculated by considering the ratio of normalized value changes and the logarithmic influence of data variability, thereby producing a weight distribution that is more stable and better adapted to differences in scale among criteria. The main formula used in the LOPCOW method is as follows:

$$n_{ij} = \frac{x_{ij}}{m+\sum_{i=1}^{m} {x_{ij}}^2} \tag{20}$$

$$PV_j = 100 * \left| \frac{\sqrt{\sum_{i=1}^{m} {n_{ij}}^2}}{\ln \frac{m}{\sigma_j}} \right| \tag{21}$$

$$w_j = \frac{PV_j}{\sum_{k=1}^{n} PV_k} \tag{22}$$

Where n_{ij} represents the normalization value of the i-th alternative with respect to the j^{th} criterion, obtained by dividing the original value x_{ij} by the sum of the total number of alternatives m and the total square of all x_{ij}values for that criterion. This value is used to balance differences in scale across the data so that all criteria can be compared proportionally. The symbol PV_j indicates the parameter value or influence value of the j^{th} criterion, which is calculated by multiplying 100 by the absolute value of the square root of the sum of $n_{ij}{}^2$ of all alternatives, then divided by the natural logarithm of the ratio between the number of alternatives m and the standard deviation σ_j. This value represents the sensitivity and strength of a criterion's influence within the overall evaluation system. Finally, the symbol w_j denotes the final weight of the j-th criterion, obtained by normalizing the PV_j value against the total of all PV_k values from all criteria. This weight serves as a proportional measure of each criterion's relative importance in the objective decision-making process.

2.6 Criteria Importance Through Inter-criteria Correlation (CRITIC) Method

The CRITIC method is an objective weighting approach used to determine the relative importance level among criteria based on two main aspects: the level of data variation and the correlation among criteria[30]–[32]. The basic concept of this method is that a criterion is considered more important if it has a high level of dispersion (standard deviation) and low correlation with other criteria, as this indicates a greater ability to provide unique information for the decision-making process. The calculation procedure involves data normalization, calculation of standard deviations, correlation analysis among criteria, and determination of the final weights based on each criterion's total information contribution. The main formula used in the CRITIC method is as follows:

$$d_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{23}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_j\right)^2}{n}} \tag{24}$$

$$R_{ij} = \frac{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_j\right) * \left(d_{ij} - \bar{d}_h\right)}{\sqrt{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_j\right)^2} * \sqrt{\sum_{i=1}^{n}\left(d_{ij} - \bar{d}_h\right)^2}} \tag{25}$$

$$C_j = \sigma_j \sum_{j=1}^{n}\left(1 - R_{ij}\right) \tag{26}$$

$$w_j = \frac{c_j}{\sum_{k=1}^{n} c_k} \tag{27}$$

Where d_{ij} represents the normalized value of the i^{th} alternative with respect to the j[th] criterion, calculated by comparing the difference between the actual value x_{ij} and the minimum value x_{ij} against the range of that criterion, which is the difference between the maximum value max x_{ij} and the minimum value $\min x_{ij}$. This value is used to convert data into the [0,1] scale so that it can be compared fairly. The symbol σ_j denotes the standard deviation of the j[th] criterion, obtained from the square root of the mean of the squared differences between each d_{ij} normalization value and the average d_j, with n being the number of alternatives. The symbol R_{ij} represents the correlation coefficient between the j^{th} criterion and the h^{th} criterion, calculated from the ratio of the covariance of the two criteria to the product of the standard deviations of each criterion. The value C_j represents the magnitude of the contribution of the j[th] criterion, obtained by multiplying the standard deviation σ_j by the sum of $(1 -$

R_{ij}), which assesses the extent of variation and independence of a criterion from other criteria. Finally, the symbol w_j denotes the final weight of the *j-th* criterion, calculated by normalizing the value of C_j against the total of all C_k. This weight reflects the relative importance of each criterion based on a combination of data diversity and inter-criteria relationships.

2.7 Simple Additive Weighting (SAW) Method

The SAW method is one of the most basic and popular techniques in MCDM, based on the principle of weighted summation of each alternative's value across all criteria[33]–[35]. The advantage of the SAW method lies in its simplicity, ease of implementation, and its ability to provide results that are intuitive and easy to interpret. However, SAW is also sensitive to the determination of weights and normalization scales, making the results' accuracy highly dependent on the objectivity of the weighting process and the accuracy of the data used. The main formula used in the SAW method is as follows:

$$r_{ij} \begin{cases} \dfrac{x_{ij}}{\max x_{ij}} \; ; if\ j\ for\ benefical\ criteria \\ \dfrac{min\ x_{ij}}{x_{ij}} ; if\ j\ for\ non-benefical\ criteria \end{cases} \tag{28}$$

$$V_i = \textstyle\sum_{j=1}^{n} w_j . r_{ij} \tag{29}$$

Where r_{ij} represents the normalization value of the i^{th} alternative with respect to the j^{th} criterion, which is determined based on the type of criterion. For beneficial criteria, the normalization value is obtained by dividing the actual value x_{ij} by the maximum value $\max x_{ij}$, so that the alternative with the highest value will have the highest normalization value. Conversely, for cost criteria (non-beneficial criteria), normalization is done by comparing the minimum value $\min x_{ij}$ with the actual value x_{ij}, so that alternatives with lower costs receive higher values. This r_{ij} value is used to standardize the scale of all criteria so they can be compared objectively. The symbol V_i represents the total preference value or aggregate score of the i^{th} alternative, obtained by summing the results of multiplying the criterion weight w_j by the normalization value r_{ij} for all n criteria. The value of V_i serves as the basis for ranking alternatives, with the alternative with the highest value considered the best choice according to the evaluation method.

2.8 Sensitivity Analysis

Sensitivity analysis is an important stage in the multi-criteria decision-making process, aimed at evaluating the extent to which the ranking of alternatives is affected by changes in the weights or values of the criteria. Through this analysis, the stability of the decision model can be determined, as well as the criteria that most influence the final outcome. The process is carried out by systematically varying the weight values or certain parameters, then observing changes in the ranking positions of each alternative. If the ranking results remain stable despite changes in the weights, the model is considered robust or highly reliable. Conversely, if small changes in weights cause significant shifts in rankings, then the model is sensitive, and a reassessment of the weighting or criteria structure is necessary. Thus, sensitivity analysis plays an important role in ensuring the validity, consistency, and reliability of the decision results produced by a multi-criteria decision support system.

3 Results and Discussions

A comparison of various objective weighting methods within the SAW framework shows that differences in approaches to determining criterion weights have a significant impact on the final ranking of alternatives. Each method has a different calculation basis for determining the importance level of criteria. The Entropy method assigns weights based on the level of uncertainty or information in the data, so criteria with greater variation receive higher weights. In contrast, CRITIC considers both data dispersion (standard deviation) and criterion correlation, so the resulting weights reflect a balance between diversity and independence among factors. The MEREC method measures the impact of removing each criterion on the overall outcome, making it more sensitive to changes in the contribution of criteria to the performance of alternatives. Meanwhile, G2M uses the geometric mean to capture proportional relationships between values, emphasizing the natural balance among data. The RECA method evaluates weights based on the effects of correlation and criterion deviation, identifying criteria that have a strong influence but are not mutually redundant. On the other hand, LOPCOW uses logarithmic percentage changes to assess data sensitivity, resulting in weights that are adaptive to the scale and distribution of values. When these six methods are applied to SAW, it is observed that although the main ranking patterns tend to be consistent for the extremes (best and worst), there are significant differences in the middle positions due to variations in weight distribution. This shows that the weighting method directly influences the sensitivity of the final SAW results.

3.1 Dataset

The dataset used in this study consists of several alternatives representing the evaluation objects, which are assessed against several quantitative and qualitative criteria in the study context. Each alternative has numerical values for each criterion that reflect the level of performance or the characteristics being measured. The dataset's criteria are divided into two types: beneficial, where higher values indicate better performance, and non-beneficial, where lower values are more desirable. Table 1 is the dataset used in this study.

Table 1 Dataset (Source:[17])

Alternative	Criteria					
	Rental Cost	*Building Area*	*Accessibility*	*Consumer Traffic*	*Parking Availability*	*Infrastructure*
New Store Locations 1	45	120	8	550	10	9
New Store Locations 2	40	100	7	500	8	8
New Store Locations 3	55	150	9	600	12	9
New Store Locations 4	38	90	6	480	6	7
New Store Locations 5	60	160	8	620	15	10
New Store Locations 6	42	130	9	570	11	8
New Store Locations 7	36	110	7	510	9	7
New Store Locations 8	48	140	8	590	13	9

The data source obtained from Gunawan's research [17] serves as an important reference as it discusses the development of MCDM methods using distance-based weighting approaches to improve assessment accuracy. This study modifies the additive ratio assessment (ARAS) method by adding a weighting mechanism that accounts for the relative distance between criterion values, thereby reducing subjectivity and enhancing the representativeness of evaluation results. The study shows that the distance-based approach can produce a more proportional distribution of weights based on data variation and yield more stable alternative ranking results. Thus, this research provides a relevant theoretical basis for the application and comparison of various objective weighting methods within the SAW framework in this study.

The dataset of criteria used in this study includes six main criteria designed to represent key factors in multi-criteria alternative evaluation. Rental Cost (S1) is a cost criterion that reflects the financial expenditure required to use an alternative, so its value is expected to be as low as possible to improve budget efficiency. Building Size (S2) is a benefit criterion that reflects the physical capacity and flexibility of available space, with larger buildings generally offering better operational and business development opportunities. Accessibility (S3) represents the ease with which a location can be reached by consumers or suppliers, including proximity to main roads and transportation facilities, so the higher its value, the more it supports operational activities. Consumer Traffic (S4) reflects the potential level of visits or consumer flow around the location, which directly affects sales opportunities and business visibility. Parking Availability (S5) represents the adequacy and convenience of parking facilities for consumers, playing a key role in enhancing comfort and visit interest. Meanwhile, Infrastructure (S6) assesses the completeness and quality of supporting facilities, such as electricity, water, and communication networks, and the condition of the surrounding environment, which, overall, determine the smooth operation and sustainability of activities at the evaluated alternative.

3.2 Results

The analysis of the application of various objective weighting methods within the SAW framework indicates that variations in the criteria weights directly affect the aggregate values and the final ranking of the alternatives. The weight calculation process is carried out systematically based on the characteristics of the data obtained from the decision matrix, and these weights are then used to calculate the total scores for each alternative. The calculation results show differences in sensitivity levels across alternatives to changes in criterion weights, indicating that the composition of the weights plays an important role in determining the stability of the evaluation results. The final ranking from SAW reflects the alternatives' performance across all criteria in a measurable, objective manner.

3.2.1 Comparison Results of Criterion Weights

The results of the comparative analysis of the criteria weights obtained from various objective weighting methods are based on the same data. This process aims to identify the extent to which each method produces different weight distributions and how these differences reflect sensitivity to the characteristics of each criterion's data. The calculation results show that each criterion has varying levels of relative importance, depending on its information contribution to the decision matrix. The resulting weight values are then analyzed to observe patterns of criteria dominance, uniformity, and the balance among factors that influence alternative assessments. Through this comparison, the general characteristics of the weight distributions produced by each objective approach, along with their implications for evaluation processes based on the SAW method, can be understood.

This analysis was conducted using six objective weighting methods, namely Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, to observe how each method provides different weight distributions for each criterion based on data variation and the structure of relationships between parameters in the decision matrix. The calculation results indicate that although all methods employ different mathematical approaches, the resulting weight patterns remain consistent in highlighting criteria with significant levels of variation and data influence. Differences in weight values across methods also reflect the sensitivity of each approach in capturing data characteristics such as dispersion, correlation, and the impact of each criterion's contribution to the final result. Thus, this section serves as a basis for understanding how the weight variations produced by these six methods can affect evaluation outcomes and alternative rankings in the subsequent stage.

The Entropy Method is an objective approach used in determining the weights of criteria in the multi-criteria decision-making process. This approach is based on the principles of information theory, where the level of uncertainty or dispersion of data for each criterion serves as a basis for assessing its relative importance. The greater the variation in the values of a criterion among alternatives, the higher the information it contains and the greater the weight assigned. Thus, the Entropy Method allows for weight determination free of evaluators' subjectivity, as the weights are entirely based on the actual data distribution of the evaluated alternatives. This approach is often used in decision support systems due to its ability to produce objective, consistent, and representative weights for the analyzed data. Table 2 presents the results of the criteria weights, calculated using the entropy method and based on the data from the dataset in Table 1, employing equations (1) to (4).

Table 2 Results of the Entropy Method Calculation

Entropy Components	**Criteria**					
	Rental Cost	***Building Area***	***Accessibility***	***Consumer Traffic***	***Parking Availability***	***Infrastructure***
Entropy Value	0.9930	0.9918	0.9962	0.9982	0.9838	0.9966
Dispersion Value	0.0070	0.0082	0.0038	0.0018	0.0162	0.0034
Entropy Weight Result	0.1734	0.2019	0.0946	0.0450	0.4011	0.0840

The calculation results using the entropy method show that the entropy values for each criterion are as follows: the weight for criterion S1 is 0.9930, the weight for criterion S2 is 0.9918, the weight for criterion S3 is 0.9962, the weight for criterion S4 is 0.9982, the weight for criterion S5 is 0.9838, and the weight for criterion S6 is 0.9966. From these results, criterion S5 emerges as the most dominant factor in the evaluation process, as it has the highest weight. S2 and S1 follow this, while S4 has the lowest weight, so its influence on the final result is relatively small compared to the other criteria.

The MEREC method is an objective weighting approach that determines the relative importance of each criterion based on its influence on the overall evaluation results. The basic concept of this method is to assess the extent to which changes or the elimination of a criterion affect the total performance of all alternatives. Criteria that significantly impact changes in evaluation values are considered more important and assigned higher weights. Thus, the MEREC method can objectively reflect each criterion's actual contribution to the final result, without involving the decision maker's subjective preferences. This approach is widely used in decision support systems because it effectively produces weights that are consistent, rational, and sensitive to changes in the criteria.

Table 3 Results of the MEREC Method Calculation

MEREC Components	**Criteria**					
	Rental Cost	***Building Area***	***Accessibility***	***Consumer Traffic***	***Parking Availability***	***Infrastructure***
Effect Value of Criterion Removal	0.2604	0.2807	0.1658	0.1245	0.4221	0.1969
MEREC Weight Result	0.1795	0.1936	0.1143	0.0859	0.2910	0.1357

The results of the calculations using the MEREC method obtained the effect value of criterion removal for each criterion, namely the weight for criterion S1 is 0.2604, the weight for criterion S2 is 0.2807, the weight for criterion S3 is 0.1658, the weight for criterion S4 is 0.1245, the weight for criterion S5 is 0.4221, and the weight for criterion S6 is 0.1969. These values indicate the extent to which the overall performance changes if a criterion is removed from the analysis. From these results, criterion S5 has the most dominant influence on the decision results due to its highest weight, followed by S2 and S1. In contrast, S4 has the lowest weight, thus contributing the least to the evaluation process.

The RECA method is an objective weighting approach developed to assess the relative importance of each criterion based on evaluation data responses to changes in values among alternatives. The basic principle of this method is that criteria exhibiting high variation or sensitivity to differences in alternative performance are considered to play a more significant role in the decision-making process. Thus, RECA focuses on the dynamic relationship between criteria and alternatives, where the strength of data responses serves as the primary basis for determining weights. This approach provides weighting results that are more adaptive and representative of the actual data characteristics, thereby enhancing objectivity and accuracy in the multi-criteria evaluation process. Table 4 presents the results of the criterion weights, calculated using the RECA method and based on the data in Table 1, employing equations (10) to (15).

Table 4 Results of the RECA Method Calculation

RECA Components	**Criteria**					
	Rental Cost	***Building Area***	***Accessibility***	***Consumer Traffic***	***Parking Availability***	***Infrastructure***
Variability Value	0.1378	0.1641	0.0926	0.0477	0.2578	0.0788
Stability Measure Value	0.8622	0.8359	0.9074	0.9523	0.7422	0.9213
RECA Weight Result	0.1651	0.1601	0.1738	0.1824	0.1422	0.1764

The weighting results using the RECA method indicate that the weights for each criterion are as follows: the weight for criterion S1 is 0.1651, for S2 is 0.1601, for S3 is 0.1738, for S4 is 0.1824, for S5 is 0.1422, and for S6 is 0.1764. Based on these results, criterion S4 has the highest weight, indicating its most dominant role in the assessment process. S6 and S3 follow this, while S5 has the lowest weight, meaning its contribution to the final result is the smallest. These results show that S4 has the greatest influence on the evaluation process, followed by S6 and S3. In contrast, S5 has the lowest weight, indicating its relatively small contribution to the final decision.

The G2M method is an objective weighting approach that uses concepts from grey set theory and the geometric mean to determine the relative importance of each criterion. This method is designed to comprehensively capture the uncertainty and variation in the alternative assessment data. By combining the strengths of geometric analysis and the flexibility of grey theory, G2M can produce weights that reflect a balance among criteria based on the characteristics of uncertain data distribution. This approach offers advantages in generating more stable, accurate, and adaptive weighting results under complex data conditions, making it highly suitable for use in multi-criteria decision support systems. Table 5 presents the results of the criterion weights, calculated using the G2M method and based on the data in Table 1, employing equations (16) to (19).

Table 5 Results of the G2M Method Calculation

G2M Components	**Criteria**					
	Rental Cost	***Building Area***	***Accessibility***	***Consumer Traffic***	***Parking Availability***	***Infrastructure***
Grey Relational Value	1.0144	1.0175	1.0082	1.0038	1.0362	1.0072
G2M Weight Result	0.1666	0.1671	0.1656	0.1649	0.1702	0.1655

The calculations using the G2M method yielded weights for each criterion, indicating their relative importance in the decision-making process. The weight values for each criterion are as follows: criterion S1 is 0.1666, criterion S2 is 0.1671, criterion S3 is 0.1656, criterion S4 is 0.1649, criterion S5 is 0.1702, and criterion S6 is 0.1655. The differences in weight among the criteria appear relatively small, indicating that all criteria have a nearly equal level of influence on the evaluation results. Nevertheless, criterion S5 has the highest weight of 0.1702, indicating that it contributes most significantly to the decision-making process, followed by S2 and S1. Meanwhile, criterion S4 received the lowest weight of 0.1649, indicating that its influence on the overall result is the smallest among the criteria. This weighting result indicates that the G2M method can reveal subtle yet meaningful differences in the level of importance among criteria, thereby helping produce a more proportional and objective evaluation based on the relationships among the analyzed data.

The LOPCOW method is an objective weighting approach that determines the importance level of each criterion based on logarithmic changes in data values across alternatives. This approach focuses on data sensitivity to variations in alternative performance, using logarithmic percentage changes to assess the extent to which a criterion influences overall decision outcomes. By integrating the principles of relative change and logarithmic transformation, LOPCOW can produce weights that are more closely aligned with the actual data dynamics. The advantage of this method lies in its ability to reduce scale bias and provide stable, objective, and responsive weighting that accounts for value fluctuations among criteria in the multicriteria decision-making process. Table 6 presents the results of the criterion weights, calculated using the LOPCOW method and based on the data in Table 1, employing equations (20) to (22).

Table 6 Results of the LOPCOW Method Calculation

LOPCOW Components	**Criteria**					
	Rental Cost	***Building Area***	***Accessibility***	***Consumer Traffic***	***Parking Availability***	***Infrastructure***
Preference Value	0.0784	0.0260	0.5354	0.0049	0.4072	0.4895
LOPCOW Weight Result	0.0509	0.0168	0.3474	0.0032	0.2641	0.3176

The LOPCOW method calculates weights for each criterion, reflecting their relative importance in the evaluation process. The weight values for each criterion are: criterion S1 at 0.0509, criterion S2 at 0.0168, criterion S3 at 0.3474, criterion S4 at 0.0032, criterion S5 at 0.2641, and criterion S6 at 0.3176. These results show a significant variation between the criteria, with criterion S3 having the highest weight, indicating a dominant influence on the decision outcome. This is followed by S6 and S5, which also play important roles in the assessment process. Conversely, criterion S4 has the lowest weight, indicating the smallest contribution to the final result. The weight distribution from the LOPCOW method illustrates that most of the information and decision influence is concentrated on criteria with high rates of logarithmic preference change. This makes the method effective in highlighting the criteria most sensitive to data variations and relevant to the evaluation objectives.

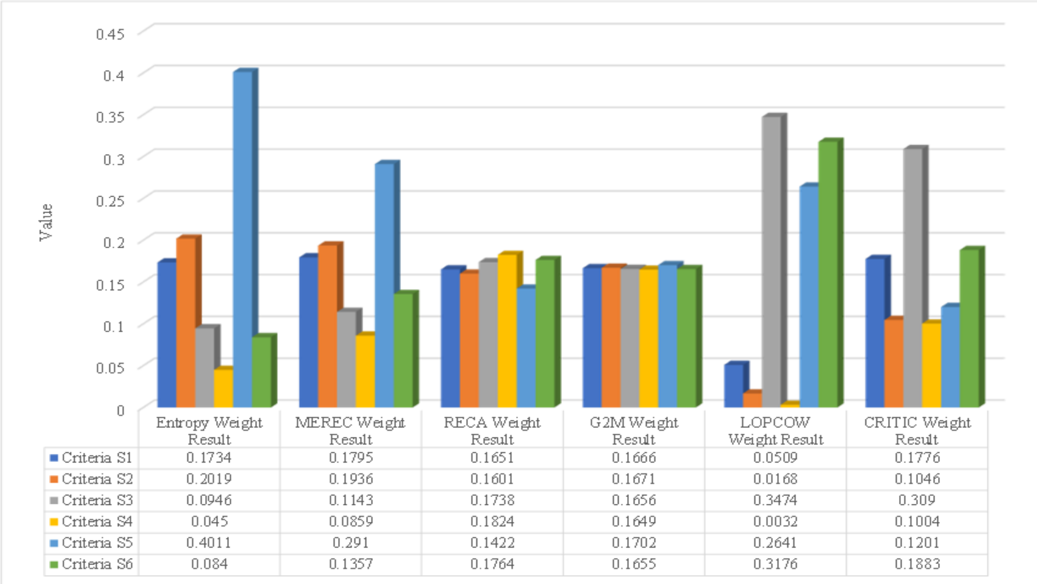
The CRITIC method is an objective weighting approach that determines the relative importance of each criterion based on two main aspects: the degree of data variability and the level of correlation among criteria. This method assumes that criteria with high data dispersion and low correlation with other criteria provide more information for decision-making. Thus, CRITIC allows for weighting that considers both the diversity of information and the independence among criteria, ensuring that the resulting weights are objective and proportionally reflect each criterion's contribution to the information. This approach is widely used in decision support systems because it produces weights that are rational, unbiased, and aligned with the characteristics of the analyzed data. Table 7 presents the results of the criterion weights, calculated using the CRITIC method and based on the data in Table 1, employing equations (23) to (27).

Table 7 Results of the CRITIC Method Calculation

CRITICS Components	**Criteria**					
	Rental Cost	***Building Area***	***Accessibility***	***Consumer Traffic***	***Parking Availability***	***Infrastructure***
Correlation Value	0.2711	0.1597	0.4717	0.1532	0.1833	0.2875
CRITIC Weight Result	0.1776	0.1046	0.3090	0.1004	0.1201	0.1883

The CRITIC method yielded weights that reflect the relative importance of each criterion, based on a combination of data variation and criterion correlations. The weights generated for each criterion are: criterion S1 at 0.1776, criterion S2 at 0.1046, criterion S3 at 0.3090, criterion S4 at 0.1004, criterion S5 at 0.1201, and criterion S6 at 0.1883. These results indicate that criterion S3 has the highest weight, suggesting that it contributes most to the decision-making process because it provides the most information and is the least dependent on other criteria. Criteria S6 and S1 rank next in terms of influence on the assessment results. In contrast, criterion S4 has the lowest weight, followed by S2, indicating that both have the least influence on the final results. Overall, the weighting results from the CRITIC method illustrate a balance between data variability and the interrelation among criteria, yielding objective weights that empirically reflect the significant role of each criterion in the evaluation process.

A comparison of the weighting results from six objective weighting methods: Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, was conducted to gain a comprehensive understanding of the characteristics, sensitivity, and consistency of each approach in determining the relative importance of criteria. Each method has a unique computational basis and highlights particular aspects in the weighting process: the Entropy method emphasizes the level of data dispersion to measure the information contained in each criterion; MEREC evaluates the impact of removing a criterion on the aggregation results; RECA assesses data responses to variations among alternatives; G2M integrates grey theory with geometric mean to handle data uncertainty; LOPCOW utilizes logarithmic changes in values to assess sensitivity among criteria; while CRITIC combines data variability and correlations among criteria to determine weights objectively. Through this comparison, it is possible to analyze how differences in these mathematical approaches affect the resulting weight distribution and the extent to which each method provides stable, proportional, and representative results, given the characteristics of the data used. This comparison aims to identify how differences in these mathematical approaches affect the weighting results and to examine the consistency of the resulting weight distributions. This analysis is an important step in understanding the characteristics of each method and assessing the stability and objectivity of the weighting results before they are used in the process of ranking alternatives. The results of the criteria weight comparison are shown in Figure 2.



	Entropy Weight Result	MEREC Weight Result	RECA Weight Result	G2M Weight Result	LOPCOW Weight Result	CRITIC Weight Result
Criteria S1	0.1734	0.1795	0.1651	0.1666	0.0509	0.1776
Criteria S2	0.2019	0.1936	0.1601	0.1671	0.0168	0.1046
Criteria S3	0.0946	0.1143	0.1738	0.1656	0.3474	0.309
Criteria S4	0.045	0.0859	0.1824	0.1649	0.0032	0.1004
Criteria S5	0.4011	0.291	0.1422	0.1702	0.2641	0.1201
Criteria S6	0.084	0.1357	0.1764	0.1655	0.3176	0.1883

Figure 2 Comparison Results of Criterion Weights

The results of the comparison of criterion weights obtained from six objective weighting methods, namely Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC. In general, each method provides a different weight distribution for the six criteria (S1 to S6), indicating variation in the sensitivity and approach of each method in assessing the importance level of the criteria. In the Entropy method, criterion S5 has the highest weight of 0.4011, followed by S2 and S1, while S4 has the lowest weight. A similar pattern is also observed in the MEREC method, where S5 again holds a dominant position with a weight of 0.2910. However, the RECA method yields different results, with the highest weight on S4 of 0.1824, followed by S6 and S3, indicating that it places greater emphasis on the stability of the criteria. Meanwhile, the G2M results show a relatively even distribution of weights among all criteria, with S5 slightly leading at 0.1702. In the LOPCOW method, a significant difference occurs, with S3 having the highest weight of 0.3474, indicating high sensitivity to changes in logarithmic preferences. Meanwhile, the CRITIC method ranks S3 as the most influential criterion (0.3090), followed by S6 and S1, with S4 having the lowest weight. Overall, these results show that criteria S5 and S3 tend to emerge as dominant factors across most methods, indicating that both make a significant and stable contribution to the evaluation process based on the objective approaches used. The most notable result from the weighting data shows a strong methodological character difference among the methods. The dominance of S5 in Entropy and MEREC occurs because these criteria have the highest level of variation and information uncertainty compared to other criteria, thereby increasing the weight in Entropy as a representation of the greatest information content, while in MEREC S5 shows the most significant impact on changes in evaluation results when the criteria are eliminated. In contrast, the G2M method produces nearly identical weights for all criteria because its approach emphasises balanced contributions and global proportion-based normalisation, which dampens the extreme influence of any particular criterion and results in a very uniform weight distribution. Different patterns are also apparent in LOPCOW and CRITIC, where S3, S5, and S6 become dominant due to a combination of wide value ranges, sensitivity to changes, and low correlation with other criteria, while RECA is in a middle position with a relatively balanced weight distribution, reflecting its ability to maintain stability and fairness among the criteria. Overall, these findings confirm that criteria that appear dominant are not merely due to subjective importance, but rather to the mathematical response of each method to the structure and characteristics of the data.

3.2.2 Comparison of Rankings Using the SAW Method

A comparison of rankings using the SAW method was conducted to analyze how differences in criterion weights from various objective approaches can affect the outcome in the multi-criteria decision-making process. The SAW method was chosen for its simplicity in aggregating the performance values of alternatives against the criterion weights, making it easier to clearly see even small changes in weighting reflected in the resulting ranking. In this context, the preference value of each alternative is calculated based on a linear combination of the normalized criterion values and the assigned weights, producing a final score that reflects the relative feasibility or performance among alternatives. Through this approach, each weighting method, such as Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, can be tested for its effectiveness in providing consistent and logical results in the evaluation process. This comparative analysis also provides an understanding of the extent to which different weighting methods can maintain the stability of ranking results when applied to the same dataset.

In addition, comparing rankings using the SAW method helps identify the potential sensitivity of results to variations in weights generated by each weighting method. Different ranking results reflect that each approach has specific characteristics in interpreting the relative contribution of each criterion to the overall value of alternatives. Thus, this analysis not only highlights differences in final results but also provides insights into the reliability, objectivity, and degree of influence of each weighting method on the decision-making process. This understanding is crucial for decision support system developers to determine the most appropriate weighting method based on data characteristics and analysis objectives, and to ensure that the ranking results truly reflect empirically relevant conditions and preferences. Table 8 shows the final scores of each alternative from the SAW method combined with the criteria weights.

Table 8 Final Score Results of Each Alternative

Alternative	**SAW Final Score**					
	Entropy	***MEREC***	***RECA***	***G2M***	***LOPCOW***	***CRITIC***
New Store Locations 1	0.7572	0.7827	0.8220	0.8145	0.8269	0.8338
New Store Locations 2	0.6732	0.7045	0.7479	0.7393	0.7240	0.7612
New Store Locations 3	0.8374	0.8513	0.8810	0.8760	0.8967	0.8860
New Store Locations 4	0.5950	0.6330	0.6839	0.6738	0.6197	0.6907
New Store Locations 5	0.9201	0.9155	0.9146	0.9149	0.9410	0.8946
New Store Locations 6	0.8100	0.8264	0.8585	0.8530	0.8554	0.8772
New Store Locations 7	0.7223	0.7417	0.7692	0.7639	0.7161	0.7763
New Store Locations 8	0.8568	0.8617	0.8740	0.8717	0.8794	0.8685

Ranking using the SAW method is one of the most basic and popular approaches in multi-criteria decision support systems due to its simplicity and transparency in processing alternative evaluation data. In this method, each alternative is evaluated based on several criteria, each weighted according to its level of importance. The values of each criterion are normalized to ensure scale equivalence across attributes, then multiplied by their respective weights to obtain an aggregate score. The final value reflects each alternative's preference level, with the alternative with the highest value considered to have the best performance. This process allows for easily understandable analysis while providing intuitive results for decision-making. Thus, the SAW method can provide a comprehensive overview of the relative performance of alternatives by combining criterion values with applied weights.

Meanwhile, applying weighting methods to the final SAW scores deepens the analysis of each criterion's relative influence on the overall ranking results. This approach not only focuses on obtaining the final score but also evaluates the contribution and sensitivity of the weights to changes in the ranking results. By relating the final SAW scores to objective weighting methods such as Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, it is possible to determine the extent to which differences in weighting strategies affect the ranking positions of alternatives. This analysis is important for testing the consistency and stability of decision results and assessing whether specific weighting methods produce a weight distribution that better represents the actual data. In other words, the combination of SAW and objective weighting methods provides a comprehensive analytical framework for producing decisions that are accurate, rational, and scientifically accountable. Figure 3 shows the results of the comparison of alternative rankings.

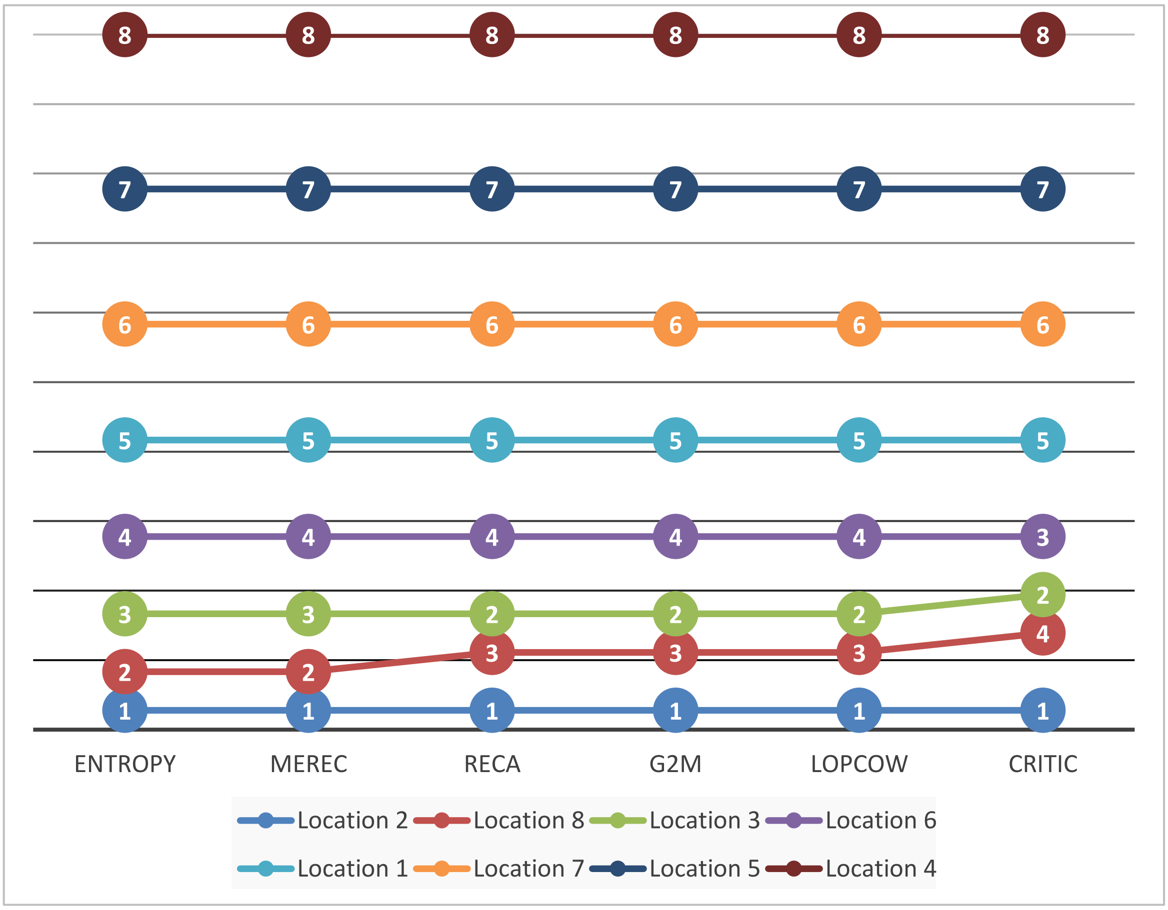


Figure 3 Comparison Results of Alternative Rankings

The comparison results of the final rankings of alternatives show high consistency among all objective weighting methods, namely Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC. New Store Location 5 consistently occupies the top position (rank 1) across all methods, indicating that this location is the most optimal alternative. New Store Location 3 and New Store Location 8 occupy the following positions with slight variations, particularly in the RECA and CRITIC methods, where Location 8's position declines slightly. Meanwhile, New Store Locations 6, 1, 7, and 2 show ranking stability, ranging from fourth to seventh across all methods, reflecting consistent relative performance among the alternatives. The New Store 4 location consistently ranked last (rank 8), indicating the lowest level of feasibility. Overall, this line graph shows a similar pattern of results across all objective methods, indicating that each method produces a similar decision tendency in determining the best store location.

3.3 Sensitivity Analysis

Sensitivity analysis in the ranking of alternatives is an evaluation process that assesses the extent to which changes in parameters, particularly the weights of criteria, can affect the final ranking results in a multi-criteria decision-making system. This approach is important because, in practice, weight values are often obtained through estimation, objective calculation, or subjective consideration, which are inherently subject to uncertainty and variation. By conducting sensitivity analysis, it is possible to determine how stable and reliable the ranking outcomes are against minor changes in weights or the evaluation values of alternatives. If the ranking results remain consistent despite changes in criteria weights, the decision-making system is considered to have a high level of stability and reliability. Conversely, if changes in weights cause significant shifts in the positions of alternatives, it indicates that the decision outcomes are highly sensitive to the weighting assumptions used.

In addition to testing the stability of decision outcomes, sensitivity analysis also serves as a validation tool for the weighting methods and decision-making models applied. By comparing the responses to rank changes across weighting methods such as Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, it is possible to identify which method produces the most stable and representative results relative to the actual data. This analysis helps decision-makers understand which criteria have the most significant influence on the outcome. It also allows strategic adjustments to the weights or models, ensuring more accurate, rational decisions. In the context of modern decision support systems, sensitivity analysis is crucial to ensure that decisions are not based solely on mathematical calculations but are also evaluated for the model's robustness and reliability under various possible changes in data and conditions.

Sensitivity analysis using Spearman's correlation is an approach for assessing the stability of alternative rankings under changes in weights or weighting methods in a multi-criteria decision-making system. Spearman correlation, which is based on the monotonic relationship between two sets of rankings, allows measurement of the extent to which the order of alternatives produced by one method is consistent with the order produced by another method. The correlation coefficient values range from -1 to 1. A value close to 1 indicates a high degree of similarity or consistency between the two ranking results. In contrast, a value close to -1 indicates significant differences or ranking inversions. Through this approach, sensitivity analysis not only highlights changes in numerical values but also evaluates the stability of alternative ranking structures under varying weightings. The use of Spearman correlation in sensitivity analysis provides a clear quantitative picture of the reliability and robustness of the decision-making model and helps determine which weighting method produces the most consistent and rational results when comparing alternative rankings. The comparison of correlation values for each weighting method is presented in Figure 4.

The comparison of correlation values using the Spearman correlation test shows a very high level of agreement among the objective weighting methods in producing the final ranking of alternatives. The correlation values for the RECA, G2M, and LOPCOW methods reach a perfect score of 1, indicating complete alignment between the ranking results of these three methods and the comparison method. Meanwhile, the Entropy, MEREC, and CRITIC methods show a correlation value of 0.9879, reflecting a powerful and nearly identical relationship with the other methods. Overall, these results confirm that all applied objective methods have a high level of consistency in determining the priority of alternatives, with minimal variation among methods. This consistency leads to the conclusion that the approach used provides stable and reliable results in the context of multi-criteria decision making.

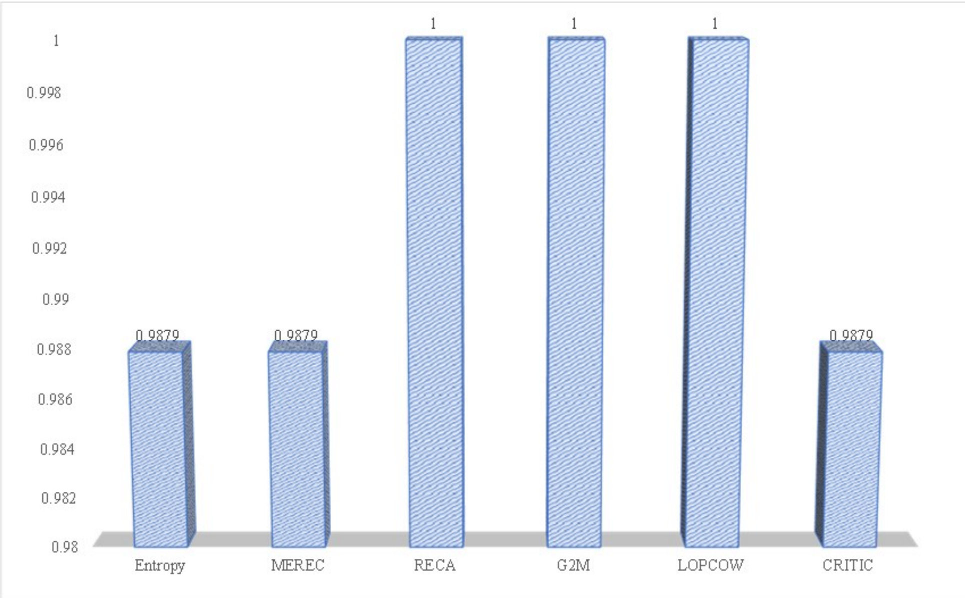


Figure 4 Comparison Results of Correlation Values

The correlation values indicate that the RECA, G2M, and LOPCOW methods exhibit the most consistent performance, achieving a perfect correlation score of 1, reflecting a complete alignment between the generated criteria weights and the variation patterns of the analysed data. These results suggest that these three methods are highly stable in representing the objective information in the data and can optimally capture differences in performance across criteria. In contrast, the Entropy, MEREC, and CRITIC methods yielded identical correlation values of 0.9879, which, although slightly lower than the maximum value, still indicate a very high level of correspondence. The similarity of correlation values across these three methods indicates that calculation mechanisms based on variation and criterion conflicts produce almost equivalent weighting patterns in the context of the data used. Overall, these results confirm that all methods have strong reliability, yet RECA, G2M, and LOPCOW show marginal advantages in maintaining consistency and sensitivity to data structure, making them more suitable for decision-making that demands high accuracy and stability of criterion weights.

3.4 Discussion

The results of the criteria weighting analysis show a variation in weight distribution that reflects the differences in each method's sensitivity to the data characteristics. The Entropy method gives the highest weight to criterion S5 at 0.4011, indicating that the information variability in this criterion is the most significant in influencing decisions. Similar results are observed with the MEREC method, where S5 also receives a dominant weight of 0.2910, indicating that removing this criterion would have the greatest impact on changes in the aggregate alternative values. Conversely, methods such as LOPCOW and CRITIC show a more balanced weighting pattern, yet still maintain the dominance of criteria S5 and S3. This indicates that most objective methods confirm the importance of these criteria as key factors in the alternative evaluation process, although the mathematical approaches used to determine the weights differ.

The consistency of the ranking results across the six objective weighting methods reinforces the validity of the evaluation model used in this study. Based on the final results using the SAW method, New Store Location 5 consistently ranks first across all weighting methods, followed by New Store Location 3 and New Store Location 8 in second and third place, respectively. This consistency indicates that differences do not significantly influence the best alternative in the weighting determination algorithms; rather, the quality of the attributes possessed by the alternative does. Furthermore, New Store Location 4, which consistently ranks last, indicates that this option performs poorly across almost all criteria, making the decision not to choose it justifiable on quantitative grounds. Thus, these results demonstrate that the objective weighting method provides consistent guidance for decision-making and can serve as a reliable basis for strategic recommendations.

Spearman's correlation analysis reinforces this conclusion by showing a strong relationship among the rankings obtained from each weighting method. The correlation value of 1 achieved by the RECA, G2M, and LOPCOW methods confirms that all three produce identical rankings, despite their differing weight calculation mechanisms. Meanwhile, the correlation value of 0.9879 for the Entropy, MEREC, and CRITIC methods also indicates an almost perfect relationship, meaning that the differences in results between the methods are only minor and do not change the main order of alternative rankings. These findings indicate that the six objective methods exhibit high convergence, leading to the conclusion that the objective weighting approach remains stable and consistent across changes in the mathematical model. Empirically, this reinforces the reliability of the objective approach as a basis for decision-making with minimal subjective bias.

Overall, this study's results confirm that using multiple objective methods in the criteria weighting process not only provides a comprehensive perspective but also increases confidence in the final results. With a very high level of correlation between methods, the process of determining new store locations is based on strong decision-making, both mathematically and empirically. Although each method has a different formulation, such as information entropy in Entropy, the effect of criteria elimination in MEREC, and the relationship between criteria in CRITIC, the final results still show a consistent decision pattern. These findings reinforce the view that a data-driven, systematic approach to weighting criteria is more effective than a subjective one, as it can yield consistent, measurable, and replicable results. Thus, the application of objective weighting methods, as used in this study, contributes to improving the quality of multi-criteria decision-making in business location planning and other strategic evaluation contexts.

The practical implication of the study, Comparison of Objective Weighting Methods in SAW and Their Effect on Alternative Ranking Results, is that decision-makers in the real world can make more conscious and informed choices when selecting objective weighting methods that suit the characteristics of the data and decision objectives. The study's results confirm that differences in weighting methods can lead to dominance patterns in criteria and significant changes in alternative rankings, even when the same ranking framework, namely SAW, is used. Therefore, DSS practitioners in areas such as supplier selection, employee performance evaluation, business partner selection, or project prioritisation are advised not to use default weighting, but rather to consider whether the decision requires emphasis on information variation (Entropy, MEREC), balance of contribution

(G2M, RECA), or criteria discriminative power (LOPCOW, CRITIC). With SAW's transparent, easily interpretable nature, these findings help decision-makers understand the direct impact of weights on final results, thereby enhancing trust, accountability, and decision quality in the implementation of decision support systems in real operational environments.

4 Conclusion

The results of the comparative analysis of the six objective weighting methods: Entropy, MEREC, RECA, G2M, LOPCOW, and CRITIC, provide consistent and mutually supportive outcomes in determining the criteria weights and alternative rankings. Overall, criterion S5 has the highest weight in most methods, indicating that it has the greatest influence on the decision-making process. Meanwhile, the ranking results using the SAW method show that New Store Location 5 consistently ranks first across all weighting approaches, followed by Location 3 and Location 8. The Spearman correlation test results show very high correlations: the RECA, G2M, and LOPCOW methods achieve a perfect correlation of 1, while Entropy, MEREC, and CRITIC show a correlation of 0.9879. This indicates that all methods produce almost identical ranking patterns, suggesting that the objective weighting approach is highly stable and reliable. This study demonstrates that applying objective weighting methods can reduce subjectivity and improve accuracy in the multi-criteria decision-making process. The comparative use of several methods also provides stronger validation of the results obtained. Thus, this approach can serve as a reference for research and decision-making practices across various fields, particularly for selecting strategic locations or evaluating alternatives involving multiple criteria in a quantitative, objective manner.

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