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SIWEC-R: A rank-sensitive improvement to SIWEC methodology

Do Duc Trung[1], Mehmet Özçalıcı[2], Nazlı Ersoy[3*], Duong Van Duc[1], Nguyen Chi Bao[1] and Nguyen Hoai Son[1]

[1] School of Mechanical and Automotive Engineering, Hanoi University of Industry, **Vietnam**
[2] Kilis 7 Aralik Üniversitesi, **Türkiye**
[3] Osmaniye Korkut Ata University, **Türkiye**

* Corresponding Author: nazliersoy@osmaniye.edu.tr

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Abstract: Determining the weights of criteria is a critical step in ranking alternatives characterized by multiple, often conflicting criteria which is a core challenge in Multi-Criteria Decision Making (MCDM). This study introduces the SIWEC-R method, a novel two-stage approach that integrates the SIWEC and R methodology to achieve more accurate and reliable weighting of criteria. Alongside the SIWEC-R method, a new performance metric, the UTAC score, was introduced to capture ranking consistency and strength across various MCDM methods. To ensure a comprehensive evaluation, sensitivity analysis was extended to cover all possible subsets of alternatives, offering an unprecedented level of scrutiny. Comparative assessments across three diverse case studies demonstrated that SIWEC-R consistently outperforms the original SIWEC method, achieving higher Spearman rank correlation coefficients and demonstrating superior robustness under sensitivity analysis. These compelling results firmly establish SIWEC-R as a significant advancement in the field of criteria weighting, delivering enhanced decision-making reliability for complex and uncertain environments.

Keywords: MCDM; SIWEC method; R method; SIWEC-R; UTAC

1. Introduction

Assigning weights to criteria is an indispensable task when employing MCDM methodologies for ranking alternatives [1][2][3]. The selection of a specific method for determining criteria weights exerts a substantial and direct influence on the resulting rank order of the alternatives under consideration [4][5][6][7]. When opting for a particular criteria weighting approach, decision-makers must consider various factors, including the nature of the decision problem, data type, measurement scale, and interrelationships among the criteria [8]. While no specific statistical data on the total number of criteria weighting methods has been published, they are generally categorized into three groups: objective weighting methods, subjective weighting methods, and integrated weighting methods that incorporate both subjective and objective elements [9][10][11].

Objective weighting methods, such as Entropy [12], MEREC [13], LOPCOW [14] CRITIC [15], SPC [16] and others, determine criteria weights solely based on the data values of the criteria across alternatives, disregarding expert opinions. This can lead to a detachment from the practicalities of needing to rank alternatives according to specific expected outcomes [17][18]. Furthermore, while some reports suggest the suitability of a particular method for a specific application, this is not universally accepted. For instance, the Entropy method is considered appropriate for weighting criteria in machining operations [19], however, other reports indicate that when using this method, a criterion exhibiting significant variance across alternatives tends to receive a high weight [20]. This is clearly unsuitable in many scenarios, particularly when considering a mechanical machine process with multiple alternatives, where surface roughness will invariably exhibit substantial differences across the options. If the Entropy method is used for weighting, the surface roughness criterion will consistently receive a high weight. Similarly, a study reported that the MEREC method is perceived as more practical and accurate than the Entropy method [21] which, however, demonstrates superior stability in the ranking of alternatives [22]. Thus, the limitations inherent in employing purely objective weighting methods are evident.

Conversely, subjective weighting methods, which determine criteria weights exclusively based on input from decision-makers, stand in contrast to objective methods that rely solely on numerical data. Examples include direct weight assignment, the RS method [23], the RR method [23], the ROC method [23], SWARA [24], SMART [25], and the PIPRECIA method [26], among others. Clearly, this reliance on individual judgment and perspectives can significantly influence the ranking of alternatives [27]. The use of subjective weighting methods also faces challenges in ensuring consensus among experts regarding the relative importance of criteria. Another limitation lies in the challenge of ensuring the validity of criterion weights, especially in the presence of many criteria [28]. Also, when the decision-maker has insufficient specialized knowledge regarding the topic being evaluated or is subject to psychological biases, it may result in making the wrong decision [29]. Lastly, subjective weighting approaches tend to be susceptible to biases [30]. This raises the inherent limits that arise where only subjective weighting techniques are employed.

The weighting of criteria in MCDM models is a fundamental step with respect to the accuracy and reliability of the achieved decisions. In recent years, numerous methods for criterion weighting have been developed, such as WENSLO [31], RANCOM [32], OWCM [33], and LBWA [34]. For instance, however, in this field, the weight according to one methodology may not always be consistent with the decision maker's expectations. Thus, more balanced and integrated outcomes can be obtained by integrating various criterion weighting techniques.

To address the identified gap in existing weighting techniques, this study proposes a novel hybrid method, termed SIWEC-R, which integrates the expert-based subjective evaluations of the SIWEC method with the rank-oriented objective analysis of the R method. The proposed approach aims to overcome the limitations of current hybrid methods by enhancing the reliability, consistency, and robustness of the weighting process. Unlike traditional approaches that overlook rank sensitivity, SIWEC-R explicitly considers the relative rankings of alternatives, thereby improving decision robustness, particularly under uncertainty or when alternatives exhibit close performance levels. Furthermore, a new performance indicator, the Upper Triangular Average Correlation (UTAC) score, is introduced to assess ranking consistency, while an extensive sensitivity analysis across all possible subsets of alternatives is conducted to verify the method's robustness. Overall, the SIWEC-R method provides a balanced and comprehensive weighting mechanism that combines subjective expertise with data-driven objectivity, representing a significant methodological advancement for multi-criteria decision-making applications in engineering domains.

2. Literature review

2.1 A literature review on the integration of MCDM weighting methods

To overcome the limitations inherent in both subjective and objective weighting methods, as discussed above, the development of integrated weighting approaches that incorporate both subjective and objective considerations is essential [35]. The Analytic Hierarchy Process (AHP) was employed to determine the subjective weights of the criteria, followed by the application of the Entropy method to decide on their objective weights [36]. Similarly, the subjective AHP weighting approach, the objective Entropy weighting approach, and game theory concepts were integrated to develop a hybrid model, which was used to compute the weights of the criteria [37]. The Entropy method was employed to calculate subjective weights, the CRITIC method was utilized to calculate objective weights, and game theory was applied to compute the integrated criteria weights [38].

The AHP, Entropy, and VCM methods were applied to compute the initial weights of the criteria, with the t-distribution employed at different confidence levels to determine the intervals of the weights. The LPOA was then applied to derive the final weights of the criteria [39]. Rough set theory was employed to calculate the subjective weights of the criteria, and the AHP method was subsequently used to derive the final weights [40]. Conversely, the AHP method was used to calculate the subjective weights of the criteria, while the CV method was applied to calculate the objective weights. The combined criteria weights were derived using the minimum information principle of entropy [41] It can be observed that numerous studies have proposed combined weighting methods by integrating the subjective AHP weight method with one or more other techniques to derive the weights of the criteria. However, some reports have quoted that the usage of the AHP method depends heavily on the subjectivity and consistency of the decision-maker, which can thus reduce the accuracy of the integrated weighting method [41].

Previous studies have addressed the combination of the AHP technique with other techniques with the aim of developing hybrid weighting techniques. Most other studies have also pursued other ways of developing integrated weighting techniques. The Delphi technique was used to exclude insignificant criteria, and then the ANP and Entropy techniques were combined to acquire the weights of the integrated criteria [42]. Furthermore, the NWBM operator was employed to aggregate the outputs of experts, compute the criteria weights using the DIBR and DIBR II methods, and derive the weight values of the criteria for final use by using the BM method [43]. A fuzzy subjective weighting method was integrated with the CRITIC method, and the 2-tuple linguistic representation of Z-numbers was subsequently employed to determine the criteria weights [30]. However, it should be noted that these approaches cannot fully guarantee decision stability, as the ranking relationships among alternatives are not taken into account. Building on this line of research, an integrated weighting method called OSWMI was developed, which combines techniques such as CRITIC, LINMAP, BWM methods, and nonlinear programming [18]. More complex hybridizations have also been proposed, including DEMATEL-BWM [44] and MEREC-MAUT [45] which incorporate causal relationships and utility-based normalization, respectively. However, even these methods still lack rank sensitivity. This deficiency limits the stability of the evaluation results, especially if the relative performance of the alternatives is not included in the weight derivation process. This is where the SIWEC-R approach comes in; it produces more robust results under uncertainty by integrating the relative rankings of the alternatives into the weight derivation process.

2.2 A review of the application of SIWEC and R methods

The SIWEC method subjectively determines the importance of criteria based on expert evaluations. Its distinction from other subjective weighting methods lies in the fact that experts are required only to assess the relative importance of the criteria, without the need for pairwise comparisons[46]. Although this method is relatively new, it has rapidly attracted the attention of researchers for its application in criteria weighting across various domains. The SIWEC and Fuzzy SIWEC methods were applied to identify the criteria exerting the greatest influence on food losses in agricultural-food companies [47]. In a related context, the SIWEC method was adopted to rank factors considered essential for sustainable development in agritourism in Serbia [48]. Furthermore, the SIWEC -CORASO model was implemented to determine the most suitable spraying drone for the Semberija Agricultural Products Company [49], while the Fuzzy-Rough SIWEC method was employed to select the most appropriate tractor for small farms in the same region [50]. In addition, the SIWEC-MACONT model was utilized to evaluate the risks associated with the costs of municipal water supply and drainage projects [51]. Similarly, the SIWEC-CoCoSo model was introduced to identify the most efficient renewable energy system for the BD Green Energy investor operating in the Brčko District of Bosnia and Herzegovina [52]. Moreover, the Fuzzy SIWEC-RAWEC model was used to determine the most suitable sustainable solid waste disposal technology

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for the planned Çivril Solid Waste Disposal Facility in Denizli Province [53]. It is worth noting that the SIWEC method was initially developed to assess the importance of criteria related to agricultural product sales needs in the Semberija region [46].

Building upon the use of SIWEC-based approaches for criteria evaluation and alternative ranking, the R method was proposed as an MCDM technique that simultaneously performs criteria weighting and alternative ranking[54]. This method has subsequently been applied in multiple domains to rank alternatives across a variety of decision contexts. Specifically, it was introduced to address decision problems such as vendor selection, industrial robot selection, material selection, and flexible manufacturing system selection [54]. Furthermore, the R approach was employed to consider the selection problem for five types of material handling equipment, namely conveyors, automated guided vehicles (AGVs), stackers, wheel loaders, and excavators [55].

Drawing on earlier research, the R method comprises both subjective and objective elements in the determination of criterion weights. In the present study, a combination of the R and SIWEC methods is proposed; however, the subjective component of the R method was not utilized. Instead, the evaluation criteria were assessed using the subjective judgments derived from the SIWEC method, followed by the application of the objective component of the R method to calculate the criteria weights. This integration of the subjective insights of SIWEC with the objective data processing of the R method represents a novel contribution to the research field. The resulting hybrid approach has been designated as SIWEC-R, emphasizing its combined methodology and distinctive advantage over existing weighting techniques.

3. Methods

In this section, the original SIWEC technique is briefly outlined, and the modifications introduced in the proposed SIWEC-R version are described. The Upper Triangular Average Correlation (UTAC) metric, which was employed as the primary performance evaluation measure, is introduced. Furthermore, the sensitivity analysis procedure developed in this study is presented, where an exhaustive evaluation across all possible alternative subsets was conducted to ensure a robust and unbiased assessment of stability and effectiveness.

3.1 Proposed method

To develop the SIWEC-R method, it is essential to begin by outlining the procedural steps of its component methods, the SIWEC and R methods. Consequently, this section will provide the mathematical formulations underlying these methods. The process of calculating criteria weights using the SIWEC method follows a systematic sequence [46]:

Step 1: Expert opinions are solicited to assess the relative importance of the criteria. In this context, e denotes the number of experts involved in the evaluation. This step culminates in the formation of a matrix, where n criteria are associated with each alternative, and e_{kj} represents the importance of criterion j as evaluated by the expert k. The matrix is formally represented by Equation (1).

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \cdots & \cdots & e_{kj} & \cdots \\ e_{k1} & e_{k2} & \cdots & e_{kn} \end{bmatrix} \tag{1}$$

Step 2: Normalize matrix E using Equation (2). The denominator in Equation (2) represents the maximum importance value across all criteria and experts.

$$n_{kj} = \frac{e_{kj}}{\max(e_{kj})} \tag{2}$$

Step 3: Calculate the standard deviation of the importance ratings for each criterion across the experts.

Step 4: Multiply the normalized values by their corresponding standard deviations according to Equation (3).

$$v_{ij} = n_{kj} \times st.dev_j \tag{3}$$

Step 5: Calculate the aggregate weight of a specific criterion using Equation (4).

$$s_{ej} = \sum_{k=1}^{e} v_e \tag{4}$$

Step 6: Calculate the weight of criterion j using Equation (5).

$$w_j = \frac{s_{kj}}{\sum_{j=1}^{n} s_{kj}} \tag{5}$$

As previously mentioned, R is a method that performs both criteria weighting and alternative ranking; however, in this study, this method is used for criteria weighting. The steps for calculating criteria weights using the R method are as follows [54]:

Step 1: Rank the criteria in descending order of their perceived importance.

Step 2: Calculate the weights for the ranks of the criteria using Equation (6), where r_j is the rank value of the j-th ranked criterion.

$$w^{(j)} = \frac{1}{1 + \frac{1}{2} + \cdots + \frac{1}{r_j}}, j = 1 \div n \tag{6}$$

Step 3: Calculate the weights for the criteria using Equation (7).

$$w_j = \frac{w^{(j)}}{\sum_{j=1}^{n} w^{(j)}}, j = 1 \div n \tag{7}$$

The SIWEC-R method represents a seamless integration of all steps of the SIWEC approach and the weighting stage of the R method. In more detail, after the initial criterion weights are calculated using SIWEC, these weights are used directly as inputs for Step 1 of the R method. The subsequent application of Equations (6) and (7) in sequence yields the final criterion weights in the second stage. Unlike the traditional R method, which begins with a subjective ranking of criteria, SIWEC-R replaces this subjective component with an objective one, with the data-driven ordering derived from the SIWEC-generated weights. Specifically, the normalized weights obtained from SIWEC are sorted in descending order and treated as ordinal ranks for the R-based calculation. This transformation enables the R procedure to operate on consistent, scale-independent information rather than expert-based judgments. Although this conversion from continuous to ordinal form may imply minor information abstraction, it enhances the robustness of the weighting process by reducing scale sensitivity and mitigating dominance bias among heterogeneous criteria. The computational flow of the SIWEC-R method is illustrated in Figure 1.

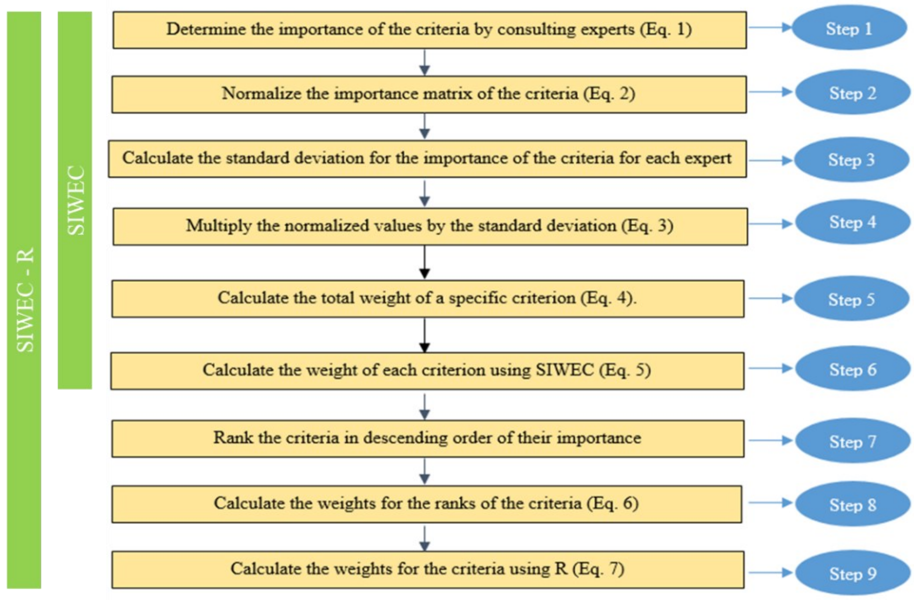


Figure 1. Block diagram of the steps of the SIWEC-R method

Although the R method is mathematically applied as a post-processing step (Steps 7–9), the input ranks originate entirely from the subjective SIWEC weights. Therefore, SIWEC-R remains a subjective, rank-sensitive weighting approach rather than a hybrid subjective–objective framework.

3.2 Performance measurement metric: Upper Triangular Average Correlation (UTAC)

In this study, we introduce the UTAC as a novel evaluation metric to objectively and quantitatively demonstrate the superiority of the modified SIWEC-R model over the baseline SIWEC model. The UTAC metric is employed to measure the overall consistency between the weightings produced by the SIWEC and SIWEC-R techniques and the outcomes of several well-established MCDM methods, including SAW, TOPSIS, MOORA, COPRAS, PIV, ROV, and RAM. The benchmark set of seven MCDM methods (SAW, TOPSIS, MOORA, COPRAS, PIV, ROV, and RAM) was selected to represent diverse conceptual families-additive, distance-based, ratio-based, and reference-dependent, enabling UTAC to capture consensus across heterogeneous decision-making paradigms. By focusing on the average strength of correlation across all pairwise comparisons (excluding redundant and trivial elements), UTAC provides a concise and powerful summary of alignment between methods.

There is a strong need for such a metric because it enables the performance evaluation of the proposed SIWEC-R method in a numerical, transparent, and unbiased manner, independent of subjective interpretation. A higher UTAC value indicates a stronger agreement between the weighting method and the rankings generated by established MCDM techniques, thus serving as evidence of greater reliability and generalizability. Consequently, a consistently higher UTAC score for SIWEC-R compared to SIWEC would confirm that the modifications introduced are not only theoretically justified but also empirically superior.
UTAC is a metric that summarizes the overall degree of association among variables in a correlation matrix. Specifically, UTAC is calculated as the arithmetic mean of the correlation coefficients

located in the upper triangular portion of the matrix (excluding the main diagonal). Because correlation matrices are symmetric and the diagonal elements are trivially equal to one, only the upper (or equivalent, the lower) triangular part carries the unique information regarding pairwise relationships. UTAC captures the average strength and direction of these inter-variable associations, providing a concise, single-value summary of overall correlation patterns. UTAC is calculated with Equation 8.

$$UTAC = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \rho_{ij} \tag{8}$$

where, ρ_{ij} is the correlation coefficient between variables i and j, and n is the number of variables. This coefficient is calculated according to Equation (9), where D_i is the difference in the rank of alternative i when ranked by different MCDM methods [56][57].

$$\rho_{ij} = 1 - \frac{6\sum_{t=1}^{m} D_t^2}{m(m^2-1)} \tag{9}$$

The proposed UTAC performance metric presents a notable drawback: its score is sensitive to the choice of MCDM techniques used in computing the correlation matrix. Consequently, altering the MCDM method can lead to variations in the UTAC score. To ensure robust and objective outcomes, it is therefore essential to employ multiple MCDM techniques in the evaluation process. The UTAC score reflects the degree of convergence between various MCDM techniques when applied using the same set of weights. A high UTAC value indicates that the rankings generated by the different methods exhibit strong agreement and demonstrate the internal consistency and robustness of the decision structure. Therefore, UTAC should be interpreted as a stability-focused diagnostic criterion rather than a strict validation criterion.

3.3 Sensitivity analysis

To empirically validate the higher performance of the new SIWEC-R approach over the conventional SIWEC approach, an extensive sensitivity analysis is undertaken. As proposed in earlier works, sensitivity analysis is typically conducted by sequentially eliminating alternatives from the decision matrix and then re-executing the evaluation protocols [56][57]. This process aims to investigate the robustness of decision-making models in relation to slight modifications in the set of alternatives. Yet, the sequential nature of the alternative elimination generates a fundamental methodological problem. That is, the order of alternative elimination can have a profound influence on the ultimate outcomes, thus adding another layer of bias and variability. Given that the original construction of alternatives in the decision matrix necessarily influences the sensitivity results, this type of sequential elimination does not yield a purely objective or reproducible assessment.

To overcome these limitations, we propose a more systematic and objective sensitivity analysis framework. In our approach, instead of removing alternatives sequentially, we generate all possible non-empty subsets of the original set of alternatives, that is, $2^m - 1 - m$ distinct combinations, where m is the total number of alternatives. In a set containing m elements, the total number of possible subsets is calculated as 2^m. However, since the empty set and single-element subsets are not meaningful for MCDM applications, they are excluded from the analysis. For each subset, the analysis is re-executed independently, and the corresponding results are recorded. This enhanced method offers three major advantages:

a. Exhaustive Coverage: By considering every possible subset, we ensure a significantly larger number of trials compared to the traditional sequential removal method, leading to a more thorough assessment of the method's stability.
b. Order Independence: Since all subsets are systematically evaluated, the initial ordering of alternatives in the decision matrix has no influence on the sensitivity outcomes, thus eliminating a major source of bias.
c. Statistical Tests: As the proposed sensitivity analysis approach generates many outcomes, it enables the application of statistical analyses on the results, thereby allowing for a more rigorous and comprehensive evaluation of method performance.

Through this rigorous and objective sensitivity analysis procedure, we can reliably determine the robustness of both SIWEC and SIWEC-R methods and quantitatively demonstrate the superior stability and performance of the proposed SIWEC-R model. Workflow of the sensitivity analysis is presented in Figure 2.

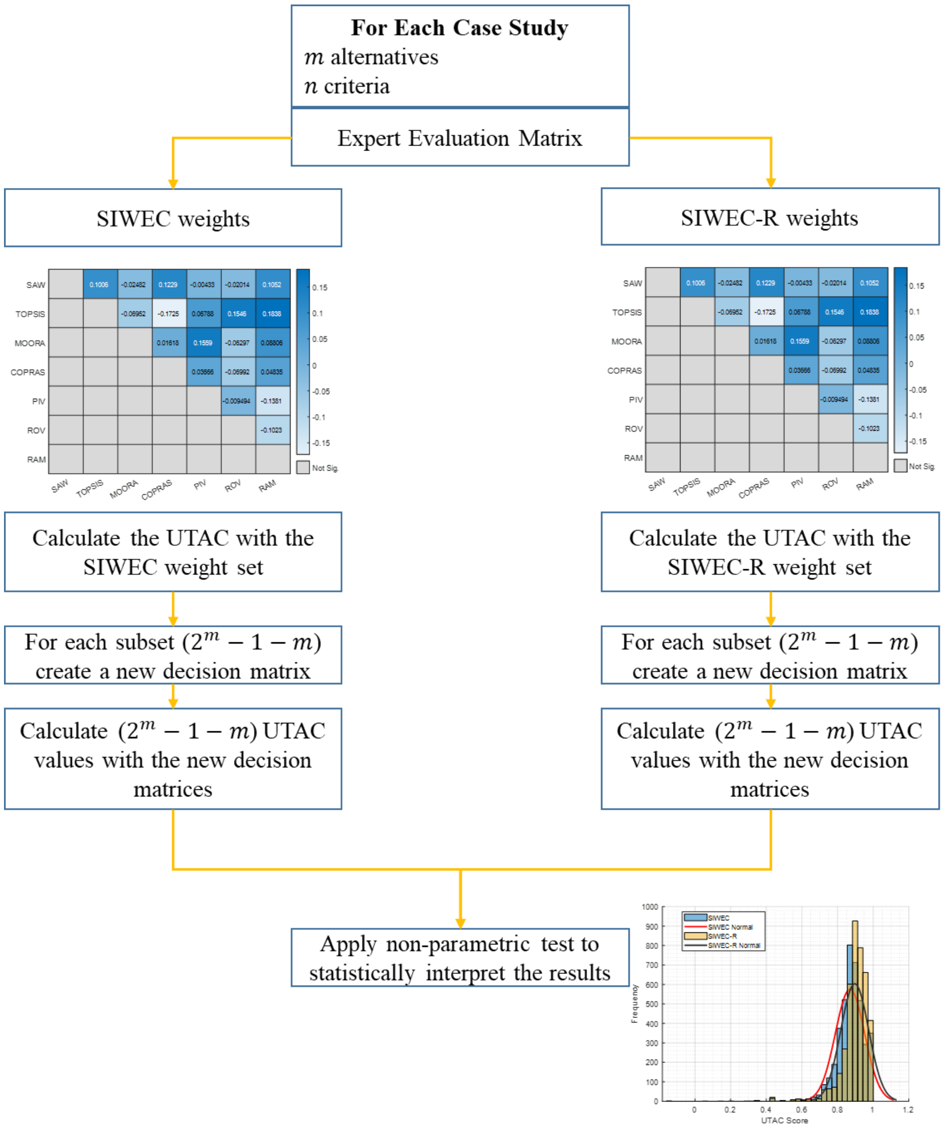


Figure 2. Workflow of the sensitivity analysis

4. Results and discussion

To evaluate the effectiveness of the SIWEC-R method, this section will compare SIWEC-R and SIWEC. For this comparison, three numerical case studies were conducted. These case studies were intentionally designed with variations in the number of alternatives, the number and type of criteria, and the hypothetical number of experts consulted in each case. This approach attempts to allow a more objective comparison of the effectiveness of SIWEC-R compared to SIWEC. In every case, both SIWEC-R and SIWEC were used to determine the criteria weights, and subsequently, seven different MCDM methods: SAW, TOPSIS, MOORA, COPRAS, PIV, ROV, and RAM, were used to rank the alternatives. The brief reasoning for the selection of these seven MCDM methods is as follows: SAW is a method with very easy application steps [58]. TOPSIS, MOORA, COPRAS, and ROV were chosen because of their wide application and successful history in various fields [12][59]. The application of PIV is justifiable because of its efficiency in handling rank reversal issues [60]. RAM was chosen as a simple and relatively new technique (released in September 2023) which can handle both positive and negative criteria equally well [61]. The criterion for comparing SIWEC-R and SIWEC is the average Spearman rank correlation coefficient among the MCDM methods.

4.1 Case-based validation: Case study 1

In this scenario, it is assumed that 12 alternatives, labeled A1 to A12, need to be ranked, each described by 6 criteria, labeled C1 to C6, as shown in Table 1. The first three criteria are benefit-type criteria (Type B), and the remaining three are cost-type criteria (Type C).

Table 1. Numerical example for case 1

Alt.	C1	C2	C3	C4	C5	C6
A1	54	1.82	11.4	0.76	46.4	0.12
A2	36	2.33	12.6	0.56	54.2	0.43
A3	49	2.12	13.2	0.98	37.4	0.42
A4	55	2.55	9.5	1.12	39.2	0.09
A5	58	1.99	18.2	0.98	44	0.17
A6	35	1.72	17.3	1.33	49.6	0.49
A7	49	1.79	14.5	0.99	32.7	1.02
A8	37	2.18	13.9	1.12	39	0.59
A9	48	2.33	18.1	0.85	42.6	0.49
A10	52	2.82	10.6	1.06	44.6	0.82
A11	65	2.46	9.6	0.84	39.6	0.69
A12	47	1.97	9.8	0.96	43.2	0.42

The calculation of criteria weights was performed in the following sequence:

Assume that 7 experts were consulted to evaluate the criteria, and their opinions are presented in Table 2.

Table 2. Expert opinions on criteria in case 1

Exp.	C1	C2	C3	C4	C5	C6
E1	7	6	3	2	4	6
E2	7	5	3	2	4	4
E3	6	5	4	1	4	5
E4	5	6	3	1	5	5
E5	7	6	4	1	4	4
E6	7	6	3	1	5	4
E7	7	7	3	2	5	6

Applying Equations (2) to (5) yielded the criteria weights shown in the second row of Table 3. From these weights, the importance ranking of the criteria is as follows: C1 > C2 > C6 > C5 > C3 > C4. Using this ranking, Equations (6) and (7) were applied to calculate the criteria weights using the R method, as shown in the third row of this table. Since the criteria weights calculated by the R method are based on the criteria ranking determined by the SIWEC method, these R-derived weights represent the SIWEC-R weights proposed in this study.

Table 3. Criteria weights in case 1

Weight method	C1	C2	C3	C4	C5	C6
SIWEC	0.249	0.223	0.124	0.054	0.168	0.183
SIWEC-R	0.283	0.188	0.124	0.115	0.136	0.154
Max/min	1.14	1.19	1.00	2.13	1.24	1.19

It is observed that although the weights calculated by SIWEC-R are derived from the SIWEC results, the weights have changed significantly. Notably, the weight of criterion C4 changed by a factor of 2.13. Applying the SAW, TOPSIS, MOORA, COPRAS, PIV, ROV, and RAM methods resulted in the ranking of alternatives for the two different sets of weights calculated by SIWEC and SIWEC-R, as presented in Tables 4 and 5, respectively.

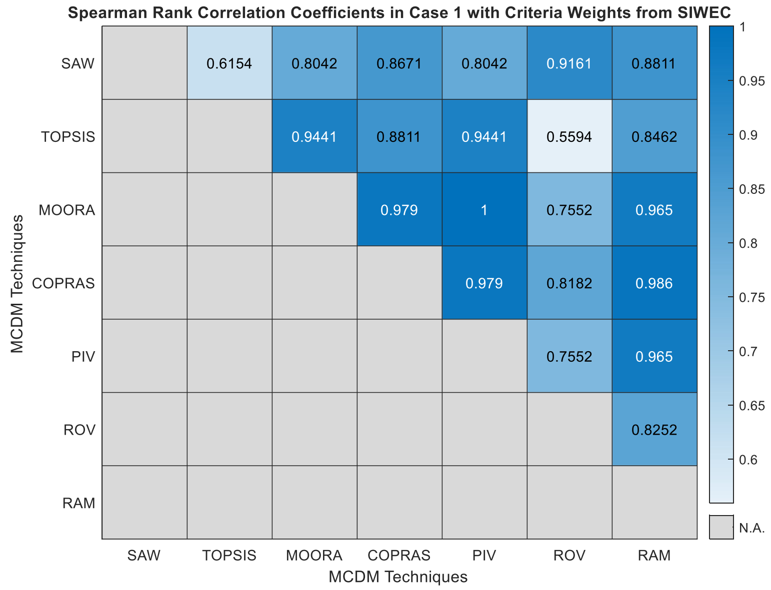
Table 4. Alternative rankings in case 1 with criteria weights from SIWEC

Alt.	SAW	TOPSIS	MOORA	COPRAS	PIV	ROV	RAM
A1	3	3	3	3	3	7	3
A2	10	7	8	9	8	11	8
A3	7	4	5	5	5	5	6
A4	1	1	1	1	1	1	2
A5	2	2	2	2	2	2	1
A6	12	9	11	11	11	12	12
A7	8	12	12	12	12	8	11
A8	9	10	10	10	10	9	10
A9	5	5	4	4	4	4	4
A10	6	11	9	7	9	6	7
A11	4	8	6	6	6	3	5
A12	11	6	7	8	7	10	9

Table 5. Alternative rankings in case 1 with criteria weights from SIWEC-R

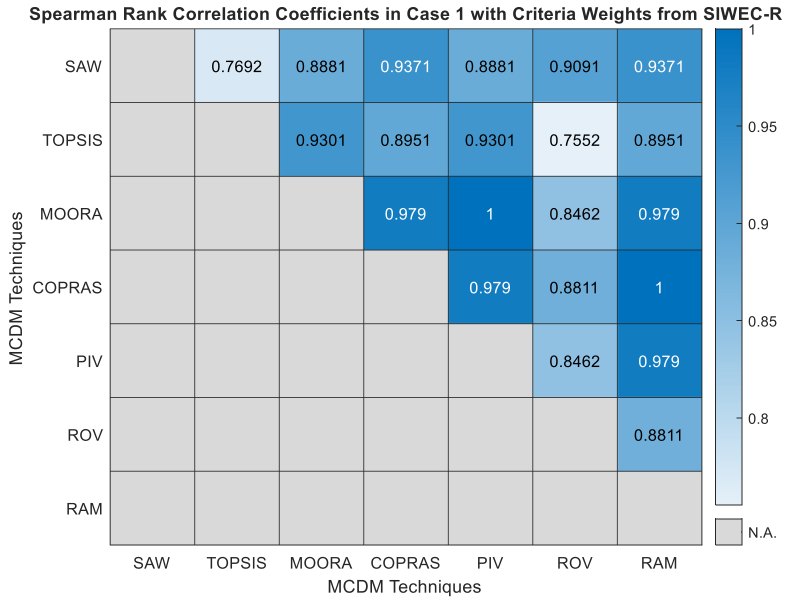
Alt.	SAW	TOPSIS	MOORA	COPRAS	PIV	ROV	RAM
A1	3	3	3	3	3	6	3
A2	9	8	7	8	7	10	8
A3	7	4	6	6	6	5	6
A4	1	2	2	2	2	3	2
A5	2	1	1	1	1	1	1
A6	12	9	12	12	12	12	12
A7	8	12	11	11	11	8	11
A8	11	11	10	10	10	11	10
A9	5	5	4	4	4	4	4
A10	6	10	9	7	9	7	7
A11	4	6	5	5	5	2	5
A12	10	7	8	9	8	9	9

Figure 3 summarizes the Spearman rank correlation coefficient values for the two scenarios using the two different weighting methods.



$$\text{UTAC Score with SWEC} = \frac{0.6154+0.8042+\cdots+0.7552+0.965+0.8252}{21} = 0.8615$$

(a)



$$\text{UTAC Score with SIWEC-R} = \frac{0.7692+0.8881+\cdots+0.8462+0.979+0.8811}{21} = 0.9098$$

(b)

Figure 3. Spearman rank correlation coefficients in case 1. (a) with criteria weights from SIWEC (b) with SIWEC-R

It is observed that UTAC score (0.9098) with the SIWEC-R method for criteria weighting is higher than that obtained from using the SIWEC method (0.8615). Furthermore, a detailed examination reveals that when SIWEC-R is used for weighting, the lowest Spearman coefficient value is 0.7552 (between ROV and TOPSIS), whereas with SIWEC weighting, the lowest value is 0.5594 (also between SAW and TOPSIS). This result partially indicates that SIWEC-R achieves higher performance than SIWEC in this case. However, to further substantiate this observation, a comparison of these two methods in additional cases is necessary.

4.2 Case-based validation: Case study 2

In this scenario, it is assumed that 8 alternatives, labeled A1 to A8, need to be ranked, each described by 7 criteria, labeled C1 to C7, as shown in Table 6. The first four criteria are benefit-type criteria (Type B), and the remaining three are cost-type criteria (Type C).

Table 6. Numerical example for case 2

Alt.	C1	C2	C3	C4	C5	C6	C7
A1	12	62	46.4	4.6	119.4	37.6	21.4
A2	13	74	38.9	6.3	108.5	40.2	20.6
A3	12.6	72	49.2	5.7	112.3	39.4	22.6
A4	13.1	80	48.2	7.2	107.5	41.2	18.6
A5	11.4	60	37.8	6.7	104.2	40.9	19.5
A6	14	85	45.6	6.5	123.6	39.6	18.9
A7	13.2	65	44.2	5.9	121.3	40.2	20.8
A8	12.6	47	66.3	5.2	107.6	41.2	19.5

In this case, it is also assumed that 7 experts were consulted to evaluate the criteria, and their opinions are presented in Table 7.

Table 7. Expert opinions on criteria in case 2

Exp.	C1	C2	C3	C4	C5	C6	C7
E1	1	2	7	3	10	7	8
E2	2	1	7	3	10	8	8
E3	2	2	6	3	9	8	10
E4	1	2	7	3	10	8	7
E5	2	2	7	4	9	10	9
E6	1	2	7	3	10	7	8
E7	1	2	7	3	10	7	9

The calculation of criteria weights using both SIWEC and SIWEC-R was performed similarly to Case 1, and the results are summarized in Table 8. It is observed that in this case, the criteria weights also exhibit significant changes when calculated by SIWEC and SIWEC-R, with the weight of C1, for example, changing by a factor of 2.72.

Table 8. Criteria weights in case 2

Weight method	C1	C2	C3	C4	C5	C6	C7
SIWEC	0.036	0.047	0.175	0.080	0.247	0.200	0.215
SIWEC-R	0.098	0.104	0.122	0.112	0.255	0.139	0.170
max/min	2.72	2.21	1.43	1.40	1.03	1.44	1.26

Tables 9 and 10 summarize the rankings of the alternatives when ranked by SAW, TOPSIS, MOORA, COPRAS, PIV, ROV, and RAM, with weights determined by SIWEC and SIWEC-R, respectively. The average Spearman rank correlation coefficient among the MCDM methods was calculated from the data in these two tables and is presented in the last row of each table.

Table 9. Alternative rankings in case 2 with criteria weights from SIWEC

Alt.	SAW	TOPSIS	MOORA	COPRAS	PIV	ROV	RAM
A1	8	7	8	8	8	6	8
A2	5	6	5	5	6	5	5
A3	6	4	6	6	5	7	4
A4	1	2	2	2	2	1	2
A5	4	5	4	4	4	3	6
A6	3	3	3	3	3	4	3
A7	7	8	7	7	7	8	7
A8	2	1	1	1	1	2	1
UTAC score: 0.9070							

Table 10. Alternative rankings in case 2 with criteria weights from SIWEC-R

Alt.	SAW	TOPSIS	MOORA	COPRAS	PIV	ROV	RAM
A1	7	8	8	8	8	8	8
A2	6	5	4	4	4	4	4
A3	8	4	6	6	6	6	5
A4	1	1	1	1	1	1	1
A5	3	6	5	5	5	5	6
A6	4	3	2	2	2	2	2
A7	5	7	7	7	7	7	7
A8	2	2	3	3	3	3	3
UTAC Score: 0.9694							

In this case as well, the UTAC score among the MCDM methods when using SIWEC-R for criteria weighting is higher than when using SIWEC. Thus, this case also supports the conclusion that the performance of SIWEC-R is superior to that of SIWEC. The two cases conducted so far both indicate that SIWEC-R achieves higher performance than SIWEC. A subsequent example will be conducted to verify the complete accuracy of this observation.

4.3 Case-based validation: Case study 3

In this scenario, it is assumed that 10 alternatives, labeled A1 to A10, need to be ranked, each described by 8 criteria, labeled C1 to C8, as shown in Table 11. The first two criteria are cost-type criteria (Type C), and the remaining six are benefit-type criteria (Type B).

Table 11. Numerical example for case 3

Alt.	C1	C2	C3	C4	C5	C6	C7	C8
A1	21.4	4.6	0.45	17.2	127	4.37	72	452
A2	22.7	4.3	0.54	18	126	4.12	71	396
A3	20.6	5.1	0.57	18.5	126	5.17	69	434
A4	23.5	3.9	0.55	18.2	118	5.06	78	440
A5	24.1	4.9	0.67	17.5	131	5.26	69	398
A6	25	4.2	0.62	16.4	136	5.45	69	420
A7	24.2	4.1	0.54	17.2	124	5.02	72	406
A8	20.8	5.2	0.46	16.1	109	6.02	73	408
A9	22.8	5.4	0.52	16.6	125	6.08	64	400
A10	25	4.7	0.58	17.8	120	4.17	72	392

In this case, it is assumed that only 6 experts were consulted to evaluate the criteria, and their opinions are presented in Table 12.

Table 12. Expert opinions on criteria in case 3

	C1	C2	C3	C4	C5	C6	C7	C8
DM1	4	3	8	5	7	7	4	4
DM2	4	3	8	5	7	7	4	4
DM3	3	2	8	5	6	6	3	4
DM4	3	2	8	5	7	6	5	3
DM5	3	3	8	5	7	6	5	4
DM6	4	3	7	6	6	7	4	3

The calculation of criteria weights using both SIWEC and SIWEC-R was performed similarly to Case 1, and the results are summarized in Table 13. In this case, the changes in criteria weights between SIWEC and SIWEC-R are not as substantial as in the previous two cases, with the largest change in weight value occurring for criterion C2, by a factor of 1.3.

Table 13. Criteria weights in case 3

Weight method	C1	C2	C3	C4	C5	C6	C7	C8
SIWEC	0.087	0.066	0.196	0.128	0.166	0.162	0.104	0.091
SIWEC-R	0.090	0.086	0.233	0.112	0.155	0.127	0.102	0.095
max/min	1.03	1.30	1.19	1.14	1.07	1.28	1.02	1.04

Tables 14 and 15 summarize the rankings of the alternatives when ranked by SAW, TOPSIS, MOORA, COPRAS, PIV, ROV, and RAM, with weights determined by SIWEC and SIWEC-R, respectively. The average Spearman rank correlation coefficient among the MCDM methods was calculated from the data in these two tables and is presented in the last row of each table. Once again, the average Spearman rank correlation coefficient among the MCDM methods when using SIWEC-R for criteria weighting is higher than when using SIWEC. In other words, SIWEC-R also demonstrates better effectiveness than SIWEC in this case.

Table 14. Alternative rankings in case 3 with criteria weights from SIWEC

Alt.	SAW	TOPSIS	MOORA	COPRAS	PIV	ROV	RAM
A1	10	10	7	7	10	6	10
A2	7	9	6	6	7	7	7
A3	3	3	3	3	3	1	3
A4	4	5	2	1	4	2	4
A5	1	1	4	4	1	3	1
A6	2	2	1	2	2	4	2
A7	5	6	5	5	5	5	6
A8	8	7	9	9	8	10	8
A9	6	4	8	8	6	8	5
A10	9	8	10	10	9	9	9
UTAC Score: 0.8274							

Table 15. Alternative rankings in case 3 with criteria weights from SIWEC-R

Alt.	SAW	TOPSIS	MOORA	COPRAS	PIV	ROV	RAM
A1	9	10	7	7	9	7	10
A2	6	8	6	6	7	6	7
A3	4	3	4	4	4	1	3
A4	3	4	1	1	3	2	4
A5	1	1	3	3	1	3	1
A6	2	2	2	2	2	4	2
A7	5	6	5	5	5	5	5
A8	10	9	10	10	10	10	9
A9	7	7	9	9	6	9	6
A10	8	5	8	8	8	8	8
UTAC Score: 0.8696							

In summary, the three conducted cases are as follows: Case 1 involved ranking 12 alternatives with 3 benefit-type and 3 cost-type criteria. Case 2 involved ranking 8 alternatives with 4 benefit-type and 3 cost-type criteria. Case 3 involved ranking 10 alternatives with 6 benefit-type and 2 cost-type criteria. Regarding the hypothetical number of experts consulted, 7 experts were considered in the first two cases, and 6 experts in the third case. This indicates significant diversity across the three cases in terms of the number of alternatives to be ranked, the number of benefit-type criteria, the number of cost-type criteria, and the number of experts consulted. Despite these substantial differences, all three cases consistently showed that the UTAC score among the MCDM methods when using the SIWEC-R method for criteria weighting was higher than when using the SIWEC method. All these findings provide a robust conclusion that the SIWEC-R method achieves higher effectiveness than the SIWEC method.

4.4 Validation of the results

In all three cases conducted in Section 5, it was consistently observed that the average Spearman rank correlation coefficient among the MCDM methods was higher when using the SIWEC-R method for criteria weighting compared to using the SIWEC method. Furthermore, Section 5 suggested that a robust conclusion could be drawn regarding the superior effectiveness of SIWEC-R over SIWEC. To further reinforce this conclusion, the sensitivity analysis framework described earlier will be implemented across all three sample datasets.

Since $m = 12$ in the first example dataset, a total of $2^{12} - 1 - 12 = 4083$ trials were conducted, and the alternative scores were calculated accordingly. Table 16 presents the descriptive profile of the UTAC values. The reporting has been organized separately based on the number of elements k in each subset.

For all subset sizes, the SIWEC-R method consistently demonstrates higher mean UTAC values compared to the original SIWEC method. This suggests that SIWEC-R achieves a stronger overall alignment with the MCDM techniques across different alternative groupings. Moreover, the minimum UTAC values observed for SIWEC-R subsets are generally higher than those of SIWEC, indicating enhanced robustness even under less favorable configurations.

The distributional characteristics, as reflected by skewness and kurtosis values, reveal that UTAC scores for SIWEC-R are more symmetrically distributed and exhibit less variability at higher subset sizes (e.g., $k \geq 7$). In addition, the lower standard deviations associated with SIWEC-R outcomes further suggest that the proposed method yields more stable and consistent performance across various scenarios. Overall, the descriptive profile strongly supports the superiority of the SIWEC-R model over the original SIWEC technique in terms of both average performance and robustness across different subset configurations.

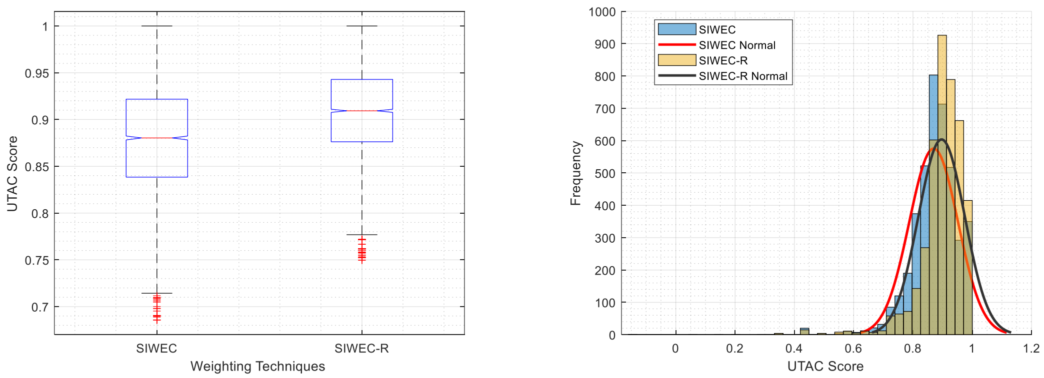
Table 16. Descriptive statistical profile of the UTAC scores in sample dataset 1

k	Weighting Technique	Number of Cases	Minimum	Maximum	Mean	%25	Median (%50)	%75	Standard Deviation	Skewness	Kurtosis
2	SIWEC	66	-0.1429	1.0000	0.8182	0.4286	1.0000	1.0000	0.2863	-1.1459	3.1176
	SIWEC-R	66	-0.1429	1.0000	0.8470	1.0000	1.0000	1.0000	0.2839	-1.5765	4.3868
3	SIWEC	220	0.2143	1.0000	0.8683	0.8571	0.8571	1.0000	0.1508	-1.5682	6.1327
	SIWEC-R	220	0.1429	1.0000	0.8722	0.7619	0.8571	1.0000	0.1595	-1.6853	6.4990
4	SIWEC	495	0.3143	1.0000	0.8738	0.8286	0.8857	0.9429	0.1021	-1.0379	4.6152
	SIWEC-R	495	0.4476	1.0000	0.8858	0.8476	0.9048	0.9429	0.1016	-1.3628	5.0007
5	SIWEC	792	0.5429	1.0000	0.8718	0.8238	0.8857	0.9238	0.0784	-0.8194	4.0207
	SIWEC-R	792	0.5810	1.0000	0.8943	0.8571	0.9143	0.9429	0.0717	-1.2061	5.0054
6	SIWEC	924	0.6435	1.0000	0.8713	0.8313	0.8830	0.9184	0.0629	-0.6165	3.3464
	SIWEC-R	924	0.6435	0.9837	0.8996	0.8694	0.9061	0.9401	0.0528	-0.9560	4.4369
7	SIWEC	792	0.6599	1.0000	0.8702	0.8384	0.8741	0.9082	0.0514	-0.5234	3.4242
	SIWEC-R	792	0.7534	0.9796	0.9032	0.8776	0.9065	0.9337	0.0405	-0.6468	3.5182
8	SIWEC	495	0.7234	0.9853	0.8682	0.8401	0.8696	0.8999	0.0429	-0.3388	3.0873
	SIWEC-R	495	0.8095	0.9796	0.9055	0.8866	0.9082	0.9274	0.0318	-0.4182	2.9536
9	SIWEC	220	0.7667	0.9571	0.8676	0.8456	0.8694	0.8897	0.0347	-0.2709	3.0005
	SIWEC-R	220	0.8429	0.9706	0.9065	0.8873	0.9075	0.9262	0.0246	-0.0756	2.4076
10	SIWEC	66	0.8003	0.9180	0.8651	0.8418	0.8678	0.8874	0.0282	-0.2998	2.4051
	SIWEC-R	66	0.8713	0.9481	0.9064	0.8915	0.9030	0.9232	0.0187	0.4851	2.3336
11	SIWEC	12	0.8333	0.8926	0.8640	0.8481	0.8641	0.8814	0.0199	-0.0694	1.5484
	SIWEC-R	12	0.8935	0.9403	0.9076	0.9000	0.9056	0.9119	0.0124	1.4943	5.1152
12	SIWEC	1	0.8615	0.8615	0.8615	0.8615	0.8615	0.8615	NA	NA	NA
	SIWEC-R	1	0.9098	0.9098	0.9098	0.9098	0.9098	0.9098	NA	NA	NA
	Total	**4083**									

To further confirm the superiority of the SIWEC-R method, a non-parametric Rank-Sum test (also known as the Mann–Whitney U test) was performed. This test is widely used in literature for comparing two independent samples without assuming normality [62].

$$H_0: Median_{SIWEC-R} \leq Median_{SIWEC}$$
$$H_1: Median_{SIWEC-R} > Median_{SIWEC}$$

The test yielded a p-value of 1.29×10^{-255}, with a z-value of 34.1307 and a signed rank statistic of 5,067,183. These results provide overwhelming evidence against the null hypothesis, strongly indicating that the SIWEC-R method significantly outperforms the original SIWEC in terms of UTAC score distribution. Furthermore, the effect size, as reflected by the test statistics, suggests a substantial and consistent improvement across the dataset. This statistical evidence is further supported by histogram plots (Figure 4) that visually depict a clear rightward shift in the UTAC score distribution under SIWEC-R, reinforcing the effectiveness of the proposed refinements.



(a) (b)

Figure 4. (a) Box plot and (b) histogram of the UTAC scores in sample dataset 1

To comprehensively evaluate the effectiveness of the proposed SIWEC-R weighting scheme, we extended our analysis to the second case study, which involves 8 alternatives. This setting allows for $2^8 - 1 - 8 = 247$ unique subset configurations for UTAC score computation. For each subset, UTAC scores were calculated using both the original SIWEC and the refined SIWEC-R weighting methods. The descriptive statistics of these scores, segmented by subset cardinality (from 2 to 8 alternatives), are presented in Table 17.

Across all subset sizes, SIWEC-R consistently demonstrates superior performance relative to SIWEC. Most notably, the mean, median, and upper quartile (75th percentile) values of the UTAC scores are systematically higher under SIWEC-R, indicating a robust uplift in utility estimation. For example, in the case of 3-alternative subsets, the mean UTAC score increases from 0.8176 (SIWEC) to 0.8912 (SIWEC-R), while the median rises from 0.8571 to 1, suggesting that SIWEC-R not only improves average performance but also pushes a significant proportion of scores toward the upper bound of the utility scale.

Furthermore, the standard deviation under SIWEC-R tends to be slightly lower or comparable, implying that the enhanced method achieves improved central tendency without increasing variability. The observed negative skewness and relatively platykurtic distributions in both methods suggest that scores are generally left-tailed and moderately concentrated around the upper end; however, SIWEC-R often exhibits stronger left skew (e.g., skewness of -1.9882 vs. -1.5071 in 4-alternative subsets), highlighting a more pronounced accumulation of high-utility configurations.

Table 17. Descriptive statistical profile of the UTAC scores in sample dataset 2

k	Weighting Technique	Number of Cases	Minimum	Maximum	Mean	%25	Median (%50)	%75	Standard Deviation	Skewness	Kurtosis
2	SIWEC	28	-0.1429	1.0000	0.7347	0.4286	1.0000	1.0000	0.3641	-1.0095	2.9476
	SIWEC-R	28	-0.1429	1.0000	0.7619	0.4286	1.0000	1.0000	0.3463	-1.0520	2.9028
3	SIWEC	56	0.0476	1.0000	0.8176	0.7143	0.8571	1.0000	0.1830	-1.6525	7.3380
	SIWEC-R	56	0.3333	1.0000	0.8912	0.8571	1.0000	1.0000	0.1552	-1.4975	4.9194
4	SIWEC	70	0.5619	1.0000	0.8690	0.8476	0.8952	0.9048	0.1000	-1.5071	5.0022
	SIWEC-R	70	0.4857	1.0000	0.9239	0.8857	0.9429	1.0000	0.0911	-1.9882	9.2092
5	SIWEC	56	0.7095	0.9714	0.8916	0.8762	0.9048	0.9429	0.0614	-1.2192	4.0373
	SIWEC-R	56	0.7619	1.0000	0.9349	0.9095	0.9429	0.9714	0.0627	-1.1930	3.9493
6	SIWEC	28	0.8395	0.9510	0.9094	0.8735	0.9143	0.9388	0.0318	-0.4087	1.9673
	SIWEC-R	28	0.8639	1.0000	0.9423	0.9265	0.9537	0.9701	0.0412	-0.7725	2.4419
7	SIWEC	8	0.8861	0.9439	0.9150	0.9039	0.9158	0.9252	0.0177	0.0276	2.4700
	SIWEC-R	8	0.915	0.9796	0.9534	0.9337	0.9617	0.9711	0.0254	-0.7490	1.9972
8	SIWEC	1	0.9070	0.9070	0.9070	0.9070	0.9070	0.9070	NA	NA	NA
	SIWEC-R	1	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	NA	NA	NA
	Total	**247**									

To statistically validate the performance improvement observed with the SIWEC-R method in the second case study, we conducted a one-sided Wilcoxon signed-rank test comparing the UTAC scores obtained using SIWEC versus those using SIWEC-R across all 247 non-trivial subsets. The test was designed to assess whether the median UTAC score under SIWEC-R exceeds that under SIWEC as in the first case.

The test yielded a p-value of 2.16×10^{-13}, a z-statistic of 7.2451, and a signed rank statistic of 14,570, all of which provide strong statistical evidence in favor of the alternative hypothesis. This indicates that the improvement in UTAC scores achieved through the SIWEC-R weighting scheme is not only systematic but also statistically significant at an extremely stringent level ($p < 0.0001$). The magnitude of the z-value further reinforces the robustness of this result, suggesting a substantial effect size. Taken together with the previously reported descriptive statistics, particularly the consistent elevation in mean and median scores under SIWEC-R, these results validate the superiority of the refined weighting mechanism across a wide range of decision contexts.

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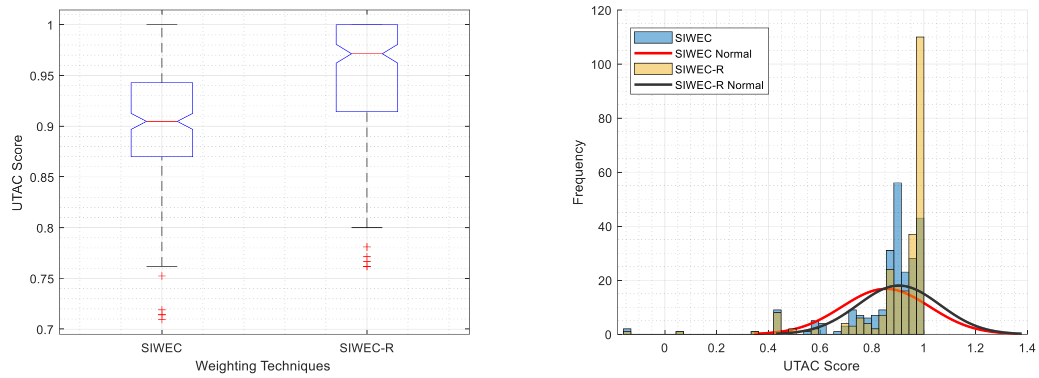


(a) (b)

Figure 5. (a) Box plot and (b) histogram of the UTAC scores in sample dataset 2

In the third case study, which involves 10 alternatives, we leveraged the full combinatorial space to compute a total of 1,013 unique UTAC scores using both the baseline SIWEC and the enhanced SIWEC-R weighting schemes. The descriptive statistics of these scores, segmented by subset size, are summarized in Table 18.

Table 18. Descriptive statistical profile of the UTAC scores in sample dataset 3

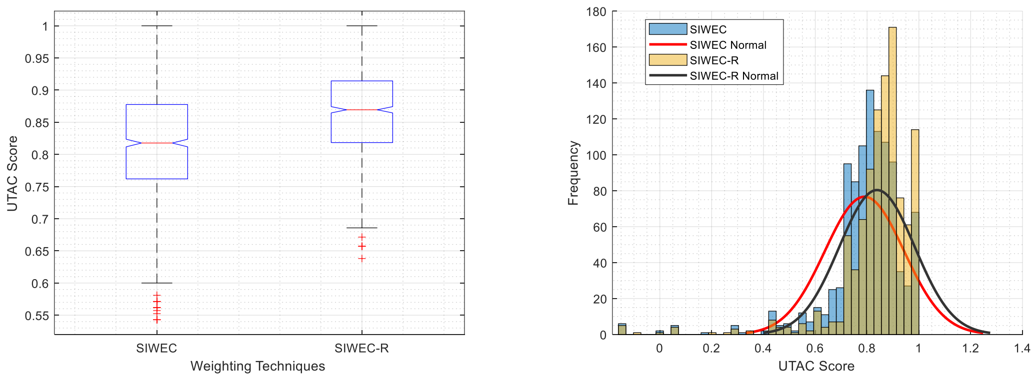
k	Weighting Technique	Number of Cases	Minimum	Maximum	Mean	%25	Median (%50)	%75	Standard Deviation	Skewness	Kurtosis
2	SIWEC	45	-0.1429	1.0000	0.6741	0.4286	1.0000	1.0000	0.4348	-0.8132	2.0689
	SIWEC-R	45	-0.1429	1.0000	0.6995	0.4286	1.0000	1.0000	0.4364	-0.9535	2.2514
3	SIWEC	120	-0.1429	1.0000	0.7548	0.7143	0.7619	0.8571	0.2317	-1.5375	5.8063
	SIWEC-R	120	-0.0952	1.0000	0.8129	0.7143	0.8571	1.0000	0.2160	-1.6653	6.4769
4	SIWEC	210	0.1619	1.0000	0.7828	0.7143	0.8000	0.8857	0.1396	-1.0404	4.6035
	SIWEC-R	210	0.2571	1.0000	0.8339	0.7905	0.8810	0.9048	0.1277	-1.3611	5.6562
5	SIWEC	252	0.4143	1.0000	0.7975	0.7429	0.8000	0.8667	0.0982	-0.8182	4.1105
	SIWEC-R	252	0.4857	1.0000	0.8481	0.8000	0.8571	0.9143	0.0866	-1.0620	4.7017
6	SIWEC	210	0.6027	0.9510	0.8092	0.7660	0.8109	0.8585	0.0700	-0.4345	2.8136
	SIWEC-R	210	0.6082	0.9728	0.8555	0.8150	0.8653	0.9020	0.0624	-0.7105	3.5836
7	SIWEC	120	0.7160	0.9337	0.8153	0.7738	0.8155	0.8520	0.0491	0.0148	2.1819
	SIWEC-R	120	0.7313	0.9371	0.8610	0.8308	0.8639	0.8963	0.0441	-0.4066	2.5861
8	SIWEC	45	0.7630	0.8968	0.8237	0.7985	0.8197	0.8495	0.0344	0.1035	2.2571
	SIWEC-R	45	0.7982	0.9172	0.8646	0.8407	0.8673	0.8872	0.0294	-0.3003	2.4195
9	SIWEC	10	0.7841	0.8556	0.8287	0.8198	0.8254	0.8484	0.0216	-0.5199	2.9193
	SIWEC-R	10	0.8365	0.8873	0.8684	0.8603	0.8706	0.8810	0.0163	-0.7330	2.4584
10	SIWEC	1	0.8274	0.8274	0.8274	0.8274	0.8274	0.8274	NA	NA	NA
	SIWEC-R	1	0.8696	0.8696	0.8696	0.8696	0.8696	0.8696	NA	NA	NA
	Total	**1013**									

A consistent and notable advantage of SIWEC-R over SIWEC is observed across all subset cardinalities. Specifically, SIWEC-R yields higher mean and median UTAC scores for every subset size, reflecting a systematic improvement in utility estimation. For example, in subsets of size 4, the mean score increases from 0.7828 (SIWEC) to 0.8339 (SIWEC-R), and the median increases from 0.8000 to 0.8810. This pattern holds even for the smallest and largest configurations, where SIWEC-R again outperforms SIWEC (e.g., in the full set of 10 alternatives, UTAC increases from 0.8274 to 0.8696).

In addition to central tendency, distributional characteristics also favor SIWEC-R. The standard deviation values are generally lower for SIWEC-R, particularly for mid-sized subsets (e.g., for subsets of size 5, SD drops from 0.0982 to 0.0866), indicating reduced variability and more stable scoring. Furthermore, skewness values under SIWEC-R are consistently more negative or closer to zero, indicating a stronger or more balanced concentration toward higher utility scores. The kurtosis values also suggest a more peaked distribution under SIWEC-R, reinforcing the presence of sharper central tendencies. Taken together, these statistical profiles demonstrate that SIWEC-R not only improves overall utility scoring but also promotes greater consistency, reduced dispersion, and more favorable score distributions. This comprehensive enhancement across descriptive metrics highlights the robustness of SIWEC-R, making it a more effective and reliable method for multi-alternative decision-making under uncertainty.

To statistically substantiate the performance advantage of the SIWEC-R weighting approach observed in the third case study, we conducted a one-sided Wilcoxon signed-rank test across all 1,013 UTAC score comparisons between SIWEC and SIWEC-R. The hypotheses tested in this third case study are identical to those formulated in the first case study. The test yielded an extremely small p-value of 3.59×10^{-79}, a z-statistic of 18.8026, and a signed rank statistic of 315,457, providing overwhelming statistical evidence against the null hypothesis. This result confirms that the median UTAC scores obtained using the SIWEC-R method are significantly greater than those from the original SIWEC model.

The magnitude of the test statistics, particularly the near-zero p-value and exceptionally high z-value, reflects a large effect size and a highly consistent trend in favor of SIWEC-R across the full range of subset combinations. This finding aligns closely with the descriptive statistics previously reported, further validating that SIWEC-R offers not only marginal improvements but a systematic and statistically robust enhancement in utility-based decision performance.



(a) (b)

Figure 6. (a) Box plot and (b) histogram of the UTAC scores in sample dataset 3

Across all three case studies, the SIWEC-R method consistently outperforms the original SIWEC weighting scheme in terms of utility estimation. Whether evaluated through descriptive statistics or rigorous hypothesis testing, the results uniformly favor SIWEC-R, demonstrating statistically significant improvements in median, mean, and upper-quartile UTAC scores. Moreover, the method exhibits favorable distributional characteristics, such as reduced variance and increased concentration toward high-utility outcomes, further underscoring its robustness. These findings collectively establish SIWEC-R as a demonstrably superior alternative, offering enhanced accuracy and consistency in multi-alternative decision-making contexts under uncertainty.

While the proposed subset-based sensitivity analysis offers comprehensive robustness assessment, its computational cost grows exponentially with the number of alternatives (O(2^m)). For m > 15–20, full enumeration becomes infeasible. In such cases, a sampling-based approach can be used, selecting a small representative fraction (e.g., 1–3%) of all subsets randomly or stratifiedly. Preliminary results show that this method produces UTAC scores closely matching those from full enumeration while reducing computation time by several orders of magnitude, ensuring scalability and applicability to real-world problems with many alternatives.

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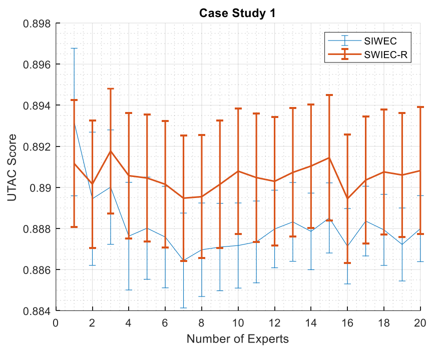
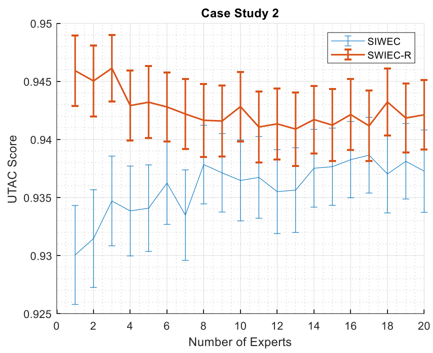
4.5 Simulation

Although the preceding sections have provided compelling evidence, both statistical and practical, that the SIWEC-R technique consistently outperforms the original SIWEC method in terms of higher UTAC scores, it was considered essential to further strengthen the analysis by introducing a simulation-based evaluation. In both techniques, expert assessments play a central role; however, to test the robustness of the observed performance gap, this simulation assumes that expert evaluations are not deterministic but rather assigned at random. Specifically, the simulation framework generates integer scores from 1 to 10 uniformly at random, thereby mimicking a stochastic evaluation environment. This methodological extension serves two critical purposes: first, it enables an exploration of how each technique performs under uncertainty and variability in expert judgment; second, it provides a more stress-tested validation of the SIWEC-R technique's advantage. By incorporating randomness into the evaluative process, we aim to assess not only the efficacy but also the resilience of the proposed method across a broader spectrum of potential application scenarios.

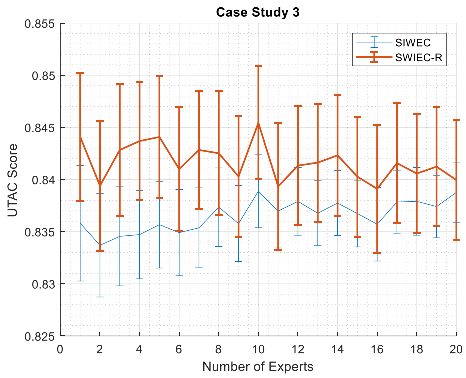
To operationalize this simulation, the number of experts varied systematically from 2 to 21, and for each expert count, 1,000 independent trials were conducted, resulting in a total of 20,000 simulations for each case study. In each trial, both SIWEC and SIWEC-R techniques were evaluated based on randomly generated expert scores, as described previously. The aggregated results of these simulations provide a comprehensive view of how each technique performs under varying levels of expert participation and randomness. The UTAC scores for each scenario are presented graphically (Figure 7), enabling a direct comparison between the two techniques across the full range of simulated conditions.



(a)



(b)



(c)

Figure 7. Simulation results

The simulation outcomes, visualized in the accompanying Figure 7, reinforce the consistent and notable performance advantage of the SIWEC-R technique over the original SIWEC method across all three case studies. Regardless of the number of experts involved, from as few as 2 to as many as 21, SIWEC-R systematically yields higher UTAC scores, reflecting its superior robustness and reliability in diverse evaluation scenarios. This advantage is not marginal; particularly in Case Study 2, the performance gap between SIWEC-R and SIWEC is pronounced, with SIWEC-R maintaining significantly higher UTAC values across all expert group sizes. Even in more conservative settings like Case Study 3, where baseline SIWEC scores are relatively lower, SIWEC-R demonstrates a steady and meaningful uplift in evaluation outcomes. These findings suggest that SIWEC-R is not only effective under ideal conditions but remains resilient and performance-consistent even when subjected to randomized, less controlled expert assessments, further attesting to its robustness as a decision-support technique.

5. Conclusion

In this study, a novel methodology for determining criteria weights, termed SIWEC-R, has been proposed. The SIWEC-R method evolved through the integration of the positive features of the SIWEC and R techniques, facilitated by the two-stage weighting scheme. The method's efficacy was assessed by comparative analyses implemented in three different case studies, which differed with respect to the number of alternatives, the nature of the criteria employed, and the number of experts involved. In addition, a new performance measure, called the UTAC score, was proposed to enable a more detailed assessment of ranking consistency among MCDM methods. Sensitivity analysis was extended by systematically investigating all possible subsets of alternatives, thus providing a complete analysis of robustness.

Throughout all analyses, it was consistently observed that SIWEC-R outperformed the original SIWEC method, yielding higher average Spearman rank correlation coefficients, superior utility distributions, and improved stability under sensitivity analysis. The statistical significance of these improvements was confirmed through hypothesis testing. Consequently, SIWEC-R is considered a valuable and reliable advancement in criteria weighting methodologies, offering enhanced performance for complex decision-making problems under uncertainty.

The SIWEC-R method integrates the complementary strengths of two weighting paradigms: SIWEC's expert-based normalized scoring and the R method's rank-based refinement. SIWEC generates objective, normalized weights reflecting aggregated expert judgments while addressing inter-expert variability, yet its continuous scores may be sensitive to scale heterogeneity and extreme values. The R method, relying on ordinal data, offers a robust rank-sensitive re-weighting that emphasizes relative order over magnitude. By transforming SIWEC's normalized weights into ordinal inputs for R, SIWEC-R removes the subjectivity of R's initial step while gaining robustness against scale effects and dominance bias. This hybridization enables (i) preservation of expert knowledge, (ii) reduced scale sensitivity, and (iii) rank-consistent refinement under uncertainty. Empirical results confirm higher Spearman correlations, improved UTAC scores, and enhanced stability in sensitivity analyses.

The recent applications of the SIWEC framework, such as in solar energy project evaluation [63] and sustainable waste management [64], highlight its increasing adoption across decision domains. Building on this evolving research line, SIWEC-R provides an advanced extension that introduces rank-sensitivity and a comprehensive robustness validation process. Therefore, the proposed approach not only enhances the methodological foundation of SIWEC but also aligns with current developments in hybrid and fuzzy decision-making frameworks.

While statistical analyses confirm that SIWEC-R yields significantly higher scores than the original SIWEC, the practical implications are equally important. Higher UTAC and correlation values demonstrate that SIWEC-R produces more stable and consensus-oriented rankings across MCDM settings, leading to greater reliability under uncertainty or expert inconsistency. Beyond statistical superiority, SIWEC-R enhances the robustness and interpretability of results, giving decision-makers greater confidence and reducing ranking reversals during sensitivity analysis.

While SIWEC-R shows clear improvements over SIWEC in rank-sensitivity and robustness, several limitations exist. The exhaustive subset-based sensitivity analysis can be computationally intensive for large problems ($m > 20$). Empirical evaluation only compares SIWEC-R with SIWEC, lacking broader benchmarking against other hybrid weighting methods. The method has mainly been tested on deterministic datasets, with uncertain or fuzzy data largely unexplored. Finally, although three case studies offer insights, more diverse applications are needed to fully validate generalizability. For future research, it is suggested that SIWEC-R and the UTAC framework be applied to more dynamic, real-world decision-making environments, including multi-stage or time-dependent problems. The UTAC metric could also be tested using additional techniques such as RAFSI, MAIRCA, ELECTRE, and PROMETHEE, which employ distinct computational principles. Moreover, the integration of UTAC with machine learning models or optimization algorithms could be explored to further enhance its scalability and applicability in advanced decision support systems.

Author's declaration

Author contribution

Do Duc Trung: Conceptualization, validation, formal analysis, investigation, visualization, Writing-original draft, Writing -review & editing. **Mehmet Özçalıcı**: Conceptualization, validation, formal analysis, investigation, visualization, Writing-original draft, Writing -review & editing. **Nazlı Ersoy**: Supervision, funding acquisition, writing -review & editing. **Duong Van Duc**: Supervision, funding acquisition, writing -review & editing. **Nguyen Chi Bao**: Supervision, funding acquisition, writing -review & editing. **Nguyen Hoai Son:** Investigation.

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Data Availability

The raw data of this study is available. If anyone wishes to use it as a basis for further research, please contact the corresponding author.

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Competing interest

The authors declare that they are NOT affiliated with or involved in any organization or entity that has a financial interest.

Ethical clearance

This study did not involve human subjects. All expert opinions used in the analysis were hypothetical, and no real survey, personal data, or identifiable information was collected. Therefore, ethical committee approval was not required. The study was conducted in accordance with relevant ethical standards.

AI statement

The grammatical structure of this article was initially improved by using ChatGPT by the authors. However, this paper was comprehensively proofread by an English language expert to ensure the proper language use and none of the AI-generated sentences included in this article.

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Nomenclature

MCDM	Multi-Criteria Decision-Making
SIWEC	Simple Weight Calculation
UTAC	Upper Triangular Average Correlation
MEREC	Method Based on the Removal Effects of Criteria
LOPCOW	LOgarithmic Percentage Change-driven Objective Weighting
CRITIC	CRiteria Importance Through Inter-criteria Correlation
SPC	Symmetry Point of Criterion
RS	rank sum
RR	rank reciprocal
ROC	Rank Order Centroid
SWARA	step-wise weight assessment ratio analysis

SMART	Simple Multi-Attribute Rating Technique
PIPRECIA	Pivot Pair-wise Relative Criteria Importance Assessment
WENSLO	Weights by envelope and slope
RANCOM	RANking COMparison
OWCM	Opinion Weight Criteria Method
LBWA	Level Based Weight Assessment
AHP	Analytic Hierarchy Process
(VCM)	Variance Component Model
(LPOA)	Linear Programming Optimization Algorithm
DIBR	Defining Interrelationships Between Ranked criteria
OSWMI	Objective-Subjective Weighted method for Minimizing Inconsistency
LINMAP	Linear programming technique for multidimensional analysis of preference
BWM	Best worst method
CORASO	COmpromise Ranking from Alternative SOlutions
MACONT	mixed aggregation by comprehensive normalization technique
CoCoSo	A combined compromise solution
RAWEC	Ranking of Alternatives with Weights of Criterion
AGVs	automated guided vehicles
UTAC	The Upper Triangular Average Correlation
SAW	simple additive weighting
TOPSIS	Techniques for Order Preference by Similarity to an Ideal Solution
MOORA	Multi-Objective Optimization by Ratio Analysis
COPRAS	Complex Proportional Assessment
PIV	Preference Index Value
ROV	Range of Value
RAM	Root Assessment Method