Equal Criteria Influence Approach (ECIA): Balancing Criteria Impact in Multi-Criteria Decision Analysis

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Abstract

In multi-criteria decision-making, determining the importance of individual criteria remains a crucial problem. Traditional approaches to weighting criteria often result in insufficient consideration of the varying influence of criteria on decision outcomes. This paper introduces a novel iterative method called the Equal Criteria Influence Approach (ECIA) to tackle this problem. ECIA aims to equalize the influence of criteria by iteratively adjusting their weights. Unlike conventional methods, ECIA emphasizes the impact of criteria on the preference of alternatives. This approach is comprehensively analyzed through a small simulation study and analysis of the decision problem of assessing crisis management systems. Studies show that ECIA offers a unique solution to dealing with variability in the impact of criteria, leading to a more balanced and stable decision-making model.

Keywords: ECIA, Criteria Influence, criteria weights, Decision-making, MCDA

1. Introduction

The decision-making process is crucial today and relevant in many fields, such as medicine [12], logistics [9], energy management [7], and engineering [13]. Consequently, tools are being developed to support this process. However, one of the critical tools used to solve multi-criteria problems is Multiple Criteria Decision Analysis (MCDA).

MCDA is an approach that considers multiple factors and criteria when deciding effectively. It allows the selection of an appropriate decision option and the determination of the relevance of individual criteria [8]. With MCDA, it is possible to compare a set of alternatives, taking into account various aspects and preferences of the decision maker.

Determining the relevance of criteria in multi-criteria decision analysis can take various forms, the two main ones being the subjective approach and the objective approach [10]. The subjective approach involves using the opinions or preferences of the decision-makers themselves to determine the relevance of individual criteria. In this case, the decision-maker assesses the relative importance of each criterion and assigns them corresponding weights based on their perceived significance.

Conversely, the objective approach relies on using measures of information and analytical data to determine the significance of criteria. Mathematical and statistical tools are used in this case, such as determining weights using entropy, standard deviation, variance, or Pearson's correlation measure [11].

However, there are some challenges associated with these approaches. In the subjective approach, the relevance of the criteria is based on the subjective judgments of the decision-maker, which can lead to potential errors or a lack of consideration of the objective impact of the criteria on the decision-making process [19]. On the other hand, the objective approach based on mathematical measures and data analysis often needs to consider the context of the decision to allow for a complete consideration of the impact of individual criteria on the outcome of the decision. In addition, a characteristic feature of this approach is the lack of consideration of the specific preferences of the decision-maker.

Moreover, a vital issue in both methodologies is the variability in the impact of criteria on decision outcomes depending on their scope or value. In particular, changes in one criterion may disproportionately impact the final solution compared to modifications in others. This aspect warrants analysis and highlights a critical research gap in multi-criteria decision analysis.

Therefore, in this study, we introduce a novel iteration-based approach aimed at accommodating the variability in criteria impact on the final preferences of alternatives. This approach is based on MCDA sensitivity analysis, wherein individual criteria are systematically excluded from the decision matrix. Consequently, this enables the assessment of each criterion's impact based on the deviation of preferences relative to the baseline preferences. The devised model facilitates the derivation of a weight vector predicated on the identified criterion influence, thereby fostering the development of a more robust decision-making framework, a critical aspect of multi-criteria decision analysis. This allows for a more flexible and balanced approach to addressing the decision problem, effectively accounting for the variability in criteria influence on the ultimate decision outcomes.

The subsequent sections of the paper are structured as follows: Section 2 delineates the techniques and methodologies employed in multi-criteria decision-making within this study. Section 3 introduces a novel decision-making approach, the Equal Criteria Importance Approach (ECIA), providing a detailed description. Section 4 presents the characteristics of the proposed approach, with an analysis of the decision problem of assessing crisis management systems solved using ECIA, a brief simulation study, and an exploration of the limitations of the proposed approach. Finally, Section 5 draws conclusions from the research and outlines directions for future research.

2. Methodology

This section aims to provide a comprehensive overview of the methodologies employed in this study to ensure the replicability of results. It delineates the rationale behind selecting each multi-criteria decision analysis solution and includes citations for a more thorough understanding of the methods used.

2.1. Methods and approaches used

In this study, several different methods from the field of multi-criteria decision-making were used. Specifically, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was employed as the primary MCDM method. Recognized for its widespread acceptance and familiarity within the field, TOPSIS is one of the most prominent approaches in multi-criteria decision-making [2]. This method was initially introduced by Ching-Lai Hwang and Yoon in [4].

Furthermore, objective weighting methodologies were employed, a common practice in decision-making literature, to assign significance values to the impact of criteria. These methodologies are often compared based on the nature of their weighting outcomes, as exemplified in the study by Paradowski et al. [11]. This study contrasts the proposed approach with the two simplest yet frequently utilized methods: equal weights, prevalent across many studies [5, 1], and weights derived from criteria entropy, a prominent objective weighting technique [18, 6].

Within the realm of multi-criteria decision-making (MCDM) methods, the culmination typically results in a ranking. The comparative analysis of rankings derived from different approaches serves as a mechanism for assessing the extent of divergence among methodologies, as exemplified by previous studies such as [14]. The adoption of the weighted Spearman's correlation coefficient in this study stems from its widespread usage and prominence in existing literature [17, 3, 16].

3. Equal Criteria Influence Approach (ECIA)

The main aim of the Equal Criteria Influence Approach was to provide an easy procedure for reaching a solution that would provide an alternative to the frequently used naive weighting method, which equally distributes weight across all criteria. The procedure for the proposed approach is shown in the flowchart in Figure 1. Where eps is the desired precision, the lower the eps, the more criteria influence is equalized.

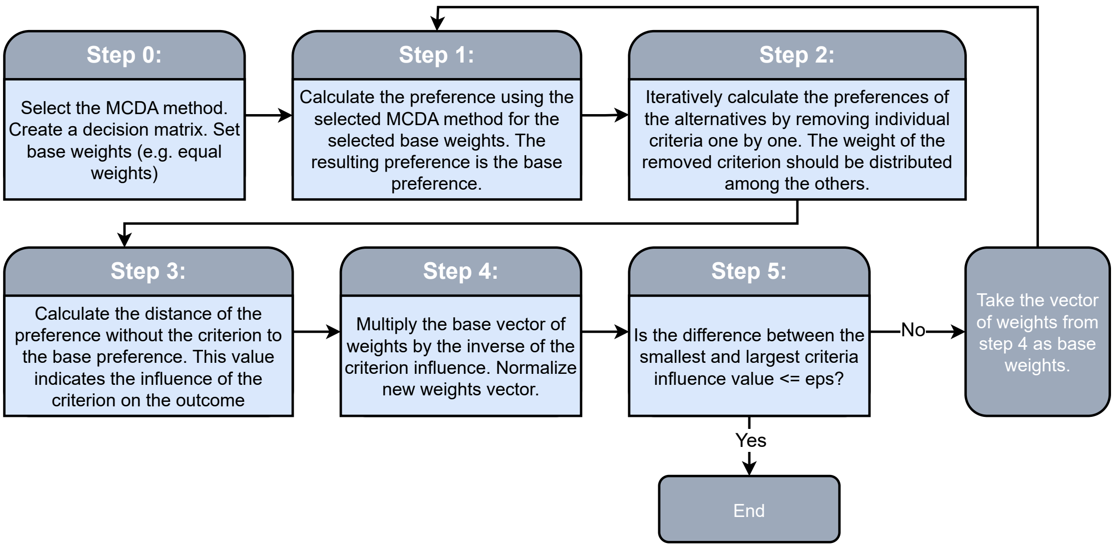


Fig. 1. Equal Criteria Influence Approach flowchart.

The outlined procedure exhibits flexibility for modification by incorporating different distance measures or altering its objective. For instance, it can transition from equalizing the impact of criteria on the preference values of alternatives to equalizing their influence on the final ranking. However, this study focused on the former approach, specifically examining the influence of criteria on preference values. The Euclidean distance metric was adopted to compute the distance between the acquired preference values, as depicted in Equation (1), wherein variables have been suitably adjusted. The impact of a specific criterion is calculated by calculating the preferences without that criterion and its distance from base preferences.

$$influence_i = \sqrt{\sum_{j=1}^{n} (p_j - p\prime_j)^2} \tag{1}$$

where i – criterion number, j – alternative number, $influence_i$ – the influence of i-th criterion, p – base preference, $p\prime$ – preference without a specific criterion, n – number of alternatives

Step 4 involves aggregating the influence of each criterion, necessitating an equation that promotes closer similarity in influence among all criteria in each iteration. The equation employed in this study is delineated in Equation (2). This approach aggregated weights utilized in the current step with the computed influence, yielding a new vector of weights for the subsequent iteration. Influence represents the degree of impact a specific criterion exerts on the outcome. To equalize influence values, the weights are adjusted by dividing them by the influence or multiplying them by the inverse of the influence. Subsequently, the lowest influence value is subtracted to enhance stability and minimize variability in weight adjustments. The additional increment is included to ensure that the weight of the criterion with the highest influence remains unchanged.

$$new\_weights_i = weights_i * \left(\frac{1}{influence_i} - min\left(\frac{1}{influence}\right) + 1\right) \tag{2}$$

where i – criterion number, $new\_weights_i$ – newly calculated weight for the i-th criterion in the current iteration and will be used as $weights_i$ in the next iteration

The multi-criteria decision-making methods require that the vector of weights sums up to one, which must be taken into account. Equation (3) illustrates that following each iteration, the weight vector is normalized by its sum to ensure compliance with this requirement.

$$new\_weights_i = \frac{new\_weights_i}{\sum_{i=1}^{m} new\_weights_i} \tag{3}$$

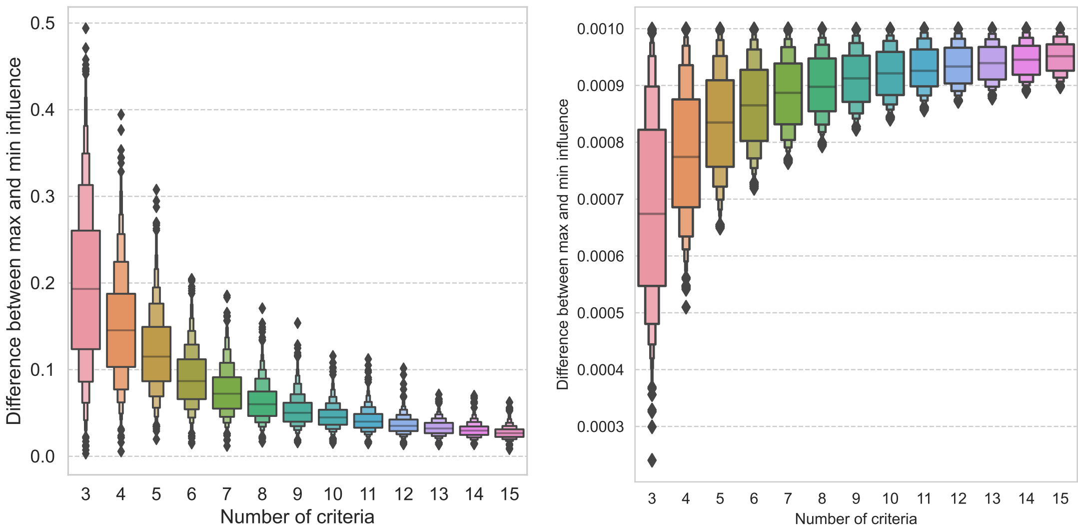
4. Results and discussion

This section is dedicated to describing the results obtained using the proposed approach and comparing it to other classical methodologies. First, the characteristics of ECIA will be highlighted, indicating what a decision-maker can expect using this approach. Subsequently, an illustrative case study will be expounded upon, followed by a comparative analysis vis-à-vis the entropy-based weighting technique and equal weights. Furthermore, a concise simulation study will be outlined to delineate disparities between the proposed approach and the utilization of equal weights or entropy. Lastly, potential limitations inherent to ECIA and strategies for mitigation will be explicated.

4.1. Analysis of proposed approach

The most important part of this approach is the influence of a criterion on the resulting ranking. Therefore, we should first examine how the influence changes depending on the number of criteria in the decision-making problem. For each size of the decision matrix (a variable number of criteria ranging from 3 to 15 and ten alternatives), a thousand random decision problems were generated from a normal distribution with values between 0 and 1. The eps was set to 0.001. Figure 2 with its sub-figures presents influence between the first and last iteration separately with a scale corresponding to the data. Figure 2a depicts how initial influence changes depending on the size of the considered problem. The presented values highlight the differences of influence across problems with different number of criteria. As the number of criteria is lower, the variability is higher, averaging the difference between the lowest and the highest value of influence around 0.1969. However, a higher number of criteria forces the influence to spread more evenly and moves the average to around 0.0273. In Figure 2b, we can see that for all problems, the difference between influence values resulted in a lower or equal to eps value. It is worth noting that the variability is still present, the highest being in the problems with the lowest number of criteria. Such behavior might indicate that the step of iterations is lower in problems with a higher number of criteria.

One of the most critical factors of the proposed approach is iterations, as they are the basis of this proposed procedure. The variation in the number of required iterations to reach a solution where all criteria have a similar influence on the resulting ranking is presented in Fig. 3a across different sizes of multi-criteria decision-making problems. The number of iterations was

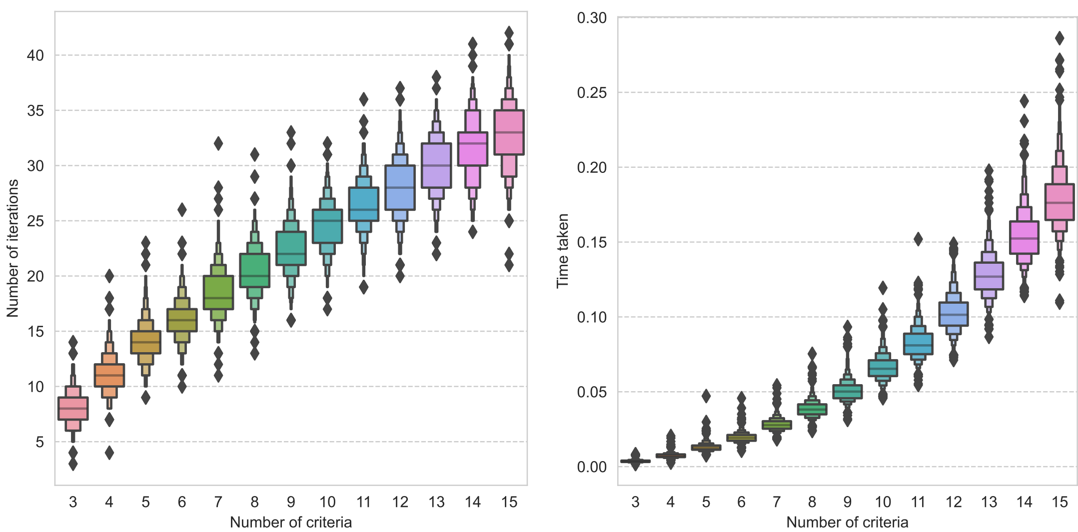


(a) First iteration.

(b) Last iteration.

Fig. 2. Difference between the highest and the lowest influence value.

counted for the same thousand problems with eps set to 0.001 as previously. As can be seen, the number of iterations highly depends on the number of considered criteria. This is expected as a higher number of criteria brings higher variability in the value of weights and makes influence more devised between criteria. Considering a small problem with three criteria, the number of required iterations oscillates from 5 to 12, with the mean around 8. However, a large problem, e.g., one where fifteen criteria would be present in the decision matrix, would require 33 iterations on average to finish the procedure. Similarly, it is crucial to observe the variation in execution time as a function of the number of iterations. The computational cost of the employed MCDA method predominantly influences the execution time. However, as illustrated in Figure 3b, the required time increases at a rate faster than the number of iterations. The execution times were measured using a Ryzen 5 3600 processor.



(a) Number of iterations.

(b) Execution time.

Fig. 3. Resources necessary to reach $eps = 0.001$.

4.2. Example decision-making problem

This section illustrates the application of the Equal Criteria Influence Approach (ECIA) in evaluating crisis management systems within the petrochemical industry. The problem, initially introduced by Salehi et al. [15], aims to propose an effective strategy for crisis managers to protect personnel and property in such environments. The decision scenario encompasses the assessment of five alternatives - distinct petrochemical plants across three critical criteria: C_1 – technical aspect, C_2 – human aspect, and C_3 – organisational aspect. Table 1 provides a decision matrix featuring all relevant data. Notably, all criteria within this decision problem are classified as profit type.

Table 1. Decision matrix for the problem of assessing crisis management systems in petrochemical industries.

	C_1 – technical aspect	C_2 – human aspect	C_3 – organisational aspect
A_1	3.364	3.656	3.88
A_2	3.525	3.300	3.316
A_3	3.439	2.983	2.897
A_4	3.286	3.557	3.714
A_5	3.494	3.543	3.846

In cases where no expert is available, objective weighting methods are necessary. Equal weights, where each criterion holds identical significance (e.g., 0.(3) weight for each of the three criteria), are commonly employed to address this. However, conducting sensitivity analyses, such as individual criterion removal, unveils varying impacts among criteria within the decision problem. As depicted in Figure 4, removing criterion C_1 induces the most significant fluctuations in the preference values of alternatives, with an average difference of 0.2168 observed. Conversely, removing C_2 and C_3 yields comparatively smaller average differences of 0.0624 and 0.0650, respectively. Notably, criterion C_1 introduces the most significant changes despite the equal weighting applied, indicating its dominant influence.

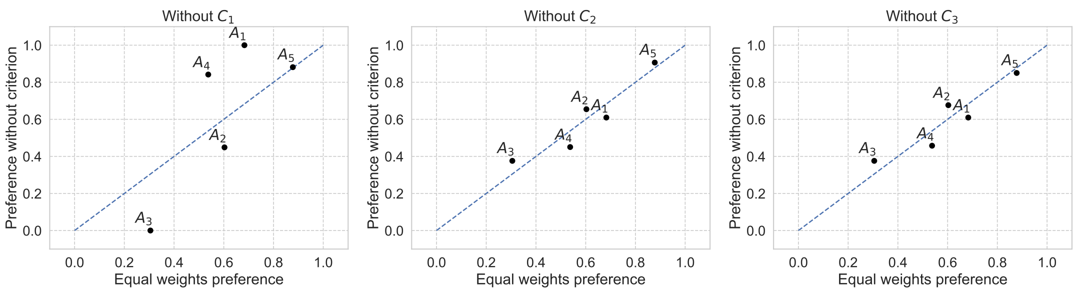


Fig. 4. Comparison of preferences without specific criteria before ECIA.

Following the execution of the ECIA procedure with $eps = 0.001$, a similar analysis is conducted on the resultant outcomes. These are depicted in Figure 5, revealing notably diminished changes upon the removal of criterion C_1. Post-ECIA, the criterion weights are determined as $w_1 = 0.1635$, $w_2 = 0.4202$, and $w_3 = 0.4162$. Regarding the average difference in preference values, removal of C_1 yields 0.0926, while for C_2 and C_3, the values are 0.1043 and 0.1051, respectively. These results indicate a more equitable impact distribution than the case with equal weights.

Utilizing specific weights or employing ECIA inevitably induces alterations in ranking, warranting further analysis. Salehi et al. adopted objective weights derived from entropy, defined as $w_1 = 0.07$, $w_2 = 0.48$, $w_3 = 0.45$. Notably, the weights yielded by ECIA exhibit sim-

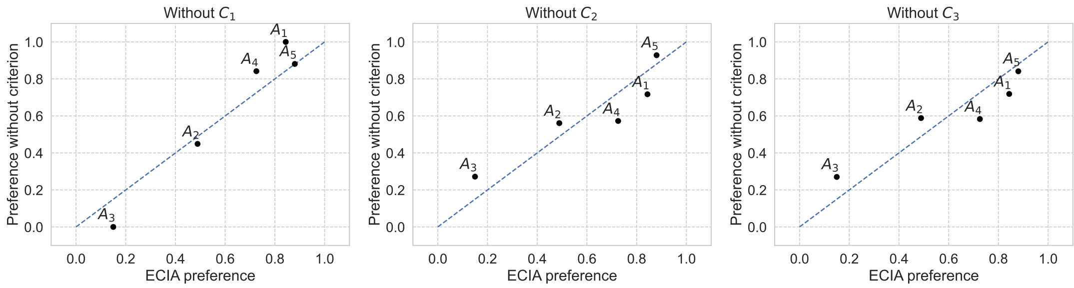


Fig. 5. Comparison of preferences without specific criteria after ECIA.

ilarity, with criterion two garnering the highest weight and criterion one the lowest. The resultant rankings are presented in Table 2. A comparison reveals that the ranking post-ECIA closely resembles that derived from entropy-based weights, albeit with a mere interchange in the positions of alternatives A_1 and A_2. This seemingly subtle alteration may carry substantial implications in decision-making, particularly given these alternatives' prominence in the ranking hierarchy. In contrast, the ranking obtained using equal weights diverges significantly, with only alternative A_5 securing the same top position as with ECIA. Evaluating the disparities via Spearman's weighted correlation coefficient, the correlation between the ECIA ranking and the equal weights ranking stands at 0.7, whereas with the entropy-based ranking, it climbs to 0.85, underscoring the closer resemblance to the entropy-derived solution.

Table 2. Ranking of the alternatives in the problem of assessing crisis management systems in petrochemical industries.

	Equal weights ranking	**Entropy weights ranking**	**ECIA ranking**
$\boldsymbol{A_1}$	3	1	2
$\boldsymbol{A_2}$	2	4	4
$\boldsymbol{A_3}$	5	5	5
$\boldsymbol{A_4}$	4	3	3
$\boldsymbol{A_5}$	1	2	1

4.3. Simulation study

The decision problem analysis reveals a resemblance between ECIA and solutions derived from entropy-based criterion weighting, prompting further investigation into potential convergences. Additionally, given the semantic proximity of equal weights to ECIA, an inquiry into the prevalence of disparities in outcomes is warranted. To this end, a brief simulation study was conducted, mirroring the methodology outlined in Section 4.1, across one thousand randomly generated decision problems. Given the paramount importance of rankings in decision-making contexts, our focus lies predominantly on these metrics. Spearman's weighted correlation values between rankings obtained via ECIA and equal weights are depicted in Figure 6. Notably, rankings exhibited minor deviations across most cases, seldom aligning perfectly. For instances involving three criteria, correlation values ranged from a minimum of approximately 0.6386 to a maximum of 1.0. In larger-scale problems featuring fifteen criteria, slight discrepancies were observed, with correlation values ranging from 0.6760 to 1.0. This phenomenon can be attributed to the dispersion of influence across a greater number of criteria, underscoring the improbability of achieving similar criterion influence on preference values using equal weights. These findings emphasize the distinctiveness of solutions obtained through ECIA, reaffirming its methodological specificity.

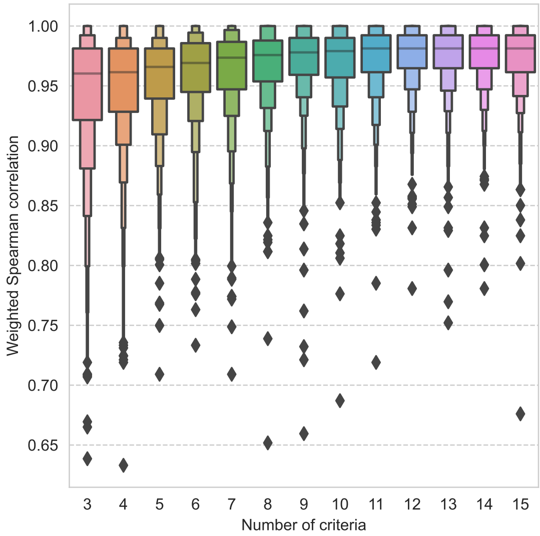


Fig. 6. Weighted Spearman's similarity coefficient between ranking obtained with ECIA and the one resulting from equal weights.

A similar summary of results is shown in Figure 7 for comparing results between those obtained using ECIA and entropy-based weights. In this case, the same rankings are rarely obtained using the two approaches but are often close. It is worth noting that, in contrast to equal weights when using entropy, the similarity between the obtained rankings decreases as the size of the decision problem increases. For smaller-scale problems featuring three criteria, the average correlation approaches 0.85; conversely, in larger problems comprising fifteen criteria, this average reduces to approximately 0.75. Moreover, the discrepancy between solutions is more pronounced with entropy-based weights, manifesting in correlations approaching zero or even negative values more frequently than with equal weights. These observations underscore that solutions generated through ECIA lean closer to those yielded by equal weights than entropy, offering a distinctive alternative.

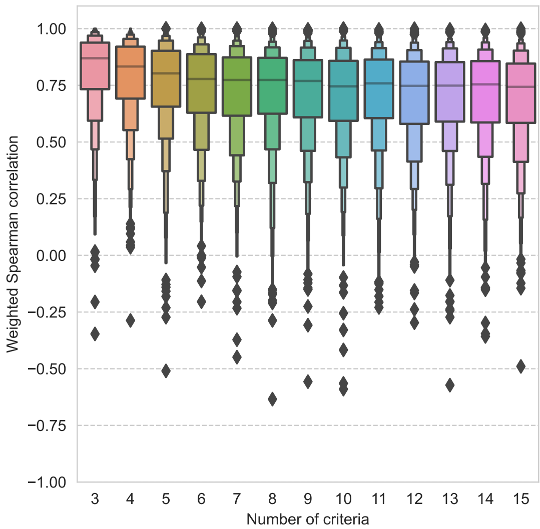


Fig. 7. Weighted Spearman's similarity coefficient between ranking obtained with ECIA and the one resulting from entropy weights.

4.4. Limitations

When introducing new methodologies, it is essential to assess their limitations. In the case of ECIA, its iterative structure significantly increases the computational complexity compared to conventional methods, representing a fundamental limitation. In addition, other potential limitations need to be explored and mitigated. Therefore, this section systematically analyses the limitations caused by setting initial weighting values and the impact of eps value on the number of iterations required and the resulting variability in results.

Changing precision

In the context of the proposed approach, it is pertinent to emphasize its iterative nature, wherein the primary determinant of computational complexity is the chosen multi-criteria decision-making (MCDM) method. Moreover, as demonstrated earlier, outcomes may exhibit slight variations contingent upon the initial weights selected, reflecting the procedure's sensitivity to such inputs. For this analysis, the parameter eps was adjusted to 0.01. Results were collected using the same set of random problems as detailed in Sections 4.1 and 4.3. As depicted in Figure 8, elevating the eps value correlates with a reduction in the requisite number of iterations. Notably, smaller problems featuring three criteria necessitated an average of five iterations, while larger problems with fifteen criteria required approximately eleven iterations on average. Additionally, it is noteworthy that the number of iterations plateaued once the criteria count exceeded nine.

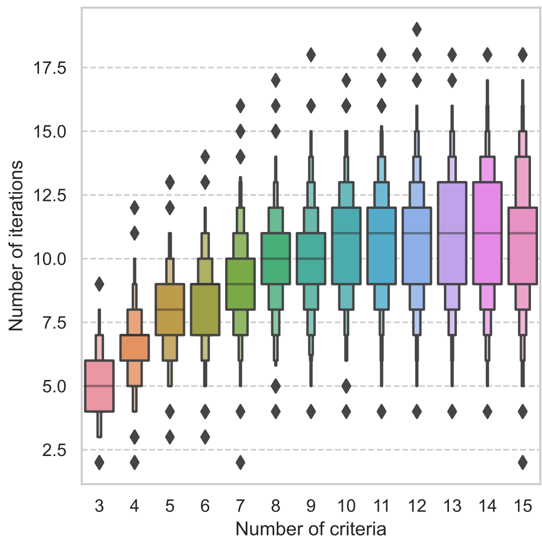


Fig. 8. Number of iterations necessary to reach $eps = 0.01$.

Nevertheless, it is essential to acknowledge that this adjustment is correlated with an augmented disparity in the outcomes, as illustrated in Figure 9, presenting a comparison of rankings attained for eps values set at 0.001 and 0.01. With a greater number of criteria, a notably expanded discrepancy is evident, attributable to the phenomenon wherein minor alterations in individual criterion weights manifest as substantial shifts in ranking.

Different initial weights

This approach to solving multi-criteria problems raises the question of whether there are more configurations of criteria weights for which individual criteria achieve a similar value of influence on the outcome of the multi-criteria decision-making method. For this purpose, a random decision problem with values from normal distribution and range 0, 1, and initial weights with

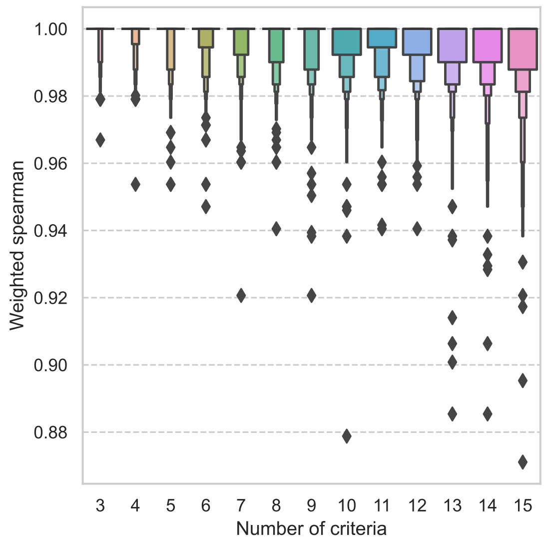


Fig. 9. Weighted Spearman's correlation coefficient between rankings calculated using ECIA where $eps = 0.01$ and $eps = 0.001$

a step of 0.05 were generated, which resulted in 171 different weight vectors. Weight vectors containing values of 0 were excluded due to their inability to be further modified. Subsequently, ECIA was conducted for all weight vectors, and the resulting vectors were compared. As depicted in Table 3, the summary reveals nearly identical values for each criterion, characterized by minimal standard deviations ranging from 0.000655 to 0.000371. This variability stems from the procedure's step size, contingent upon the distance obtained, which, in turn, is influenced by the weights vector. Consequently, alterations in the initial weights yield these observed differences.

Table 3. Summary of values of weights obtained using ECIA, starting from different initial weights vectors.

	Criterion 1	Criterion 2	Criterion 3
Min	0.276704	0.378180	0.341833
Mean	0.278110	0.379041	0.342849
Max	0.279071	0.379948	0.343874
Standard deviation	0.000655	0.000371	0.000528

5. Conclusions and future directions

There are many challenges in multi-criteria decision-making, which arise from factors such as the selection of the multi-criteria decision-making method itself, followed by the selection of the weights of the individual criteria, which often comes down to the choice of an objective or subjective weighting method. Regarding objective weighting methods, each is based on specific mathematical characteristics that most often are calculated based on the values in the decision matrix. However, no method considers that the criteria can influence the result obtained to varying degrees and that weighting alone does not reflect this influence.

This study introduced an Equal Criteria Influence Approach (ECIA), offering an extensive examination of its characteristics via a case study and a concise simulation analysis. The study underscores the significance of criteria influence on the final ranking. ECIA ensures a uniform impact of criteria, presenting a compelling alternative to the prevalent practice of uniform weight distribution among criteria.

In future studies, it would be essential to test other distance measures and see how they affect the impact of the criteria on the outcome. Furthermore, it would be worth modifying the procedure to minimize the necessary iterations to reach specified precision and include different objective functions, e.g., minimizing the influence of criteria on resulting ranking. In addition, it would be worthwhile to test the approach using other multi-criteria decision-making methods to present an application to a real-world problem with an additional comparison of the results with an approach using equal weights.

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