ISSN 1693-9220 (Print) | 2987-8713 (Online), Volume 19, No. 3 (2025), pp. 241-250

International Journal of Enterprise Modelling

Published by: International Enterprise Integration Association

A Novel Adaptive Weighting Model for Multi-Criteria Decision-Making Under Uncertainty

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Abstract

This study proposes an adaptive weighting model for multi-criteria decision-making (MCDM) under uncertainty. The model addresses the limitations of conventional weighting methods by incorporating uncertainty measurement, adaptive weight adjustment, normalization, and convergence assessment into a unified framework. The proposed mechanism updates criterion weights according to predefined adjustment factors reflecting uncertainty, data reliability, and decision priorities. Comparisons with entropy and CRITIC weighting are intended to evaluate weight stability, ranking consistency, robustness, and computational efficiency. The principal methodological contribution is a structured approach to adaptive criterion weighting that distinguishes information uncertainty from substantive criterion importance. This distinction may help prevent uncertain information from automatically reducing the influence of strategically important criteria. The model may support organizational decision-making in resource allocation, supplier selection, risk assessment, and other applications involving incomplete or changing information. Nevertheless, the framework requires empirical validation across diverse datasets and uncertainty conditions. Future research should integrate fuzzy or probabilistic MCDM techniques, develop more interpretable adjustment functions, and evaluate performance in dynamic decision environments.

Article Info

Article history:

Received : Juli 17, 2025
Revised : Aug 10, 2025
Accepted : Sep 30, 2025

Keywords:

Adaptive Weighting Model;
Multi-Criteria Decision-Making (MCDM);
Robust Decision-Making.
Uncertainty Quantification;
Weight Stability.

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1. Introduction

Multi-criteria decision-making (MCDM) has become an essential approach for addressing complex problems that involve multiple evaluation criteria with different levels of importance and potentially conflicting objectives(Thakkar, 2021). MCDM provides a systematic framework for comparing alternatives and supporting decisions in various fields, including supplier selection, risk assessment, sustainable development, healthcare service prioritization, investment analysis, and technology and infrastructure evaluation. These weights determine the relative contribution of each criterion to the overall evaluation and can substantially influence the final ranking of alternatives.

Several weighting methods have been developed to address the problem of determining criterion importance. The Analytic Hierarchy Process (AHP) derives weights from pairwise

comparisons and provides a structured mechanism for incorporating expert preferences, although its outcomes may be affected by subjective judgments and inconsistencies. Entropy weighting determines criterion weights based on the distribution of available data, but data variability does not necessarily correspond to practical decision importance

Multi-criteria decision-making (MCDM) has developed considerably over the past decade, particularly in the determination of criterion weights, the integration of subjective and objective information, and the management of uncertainty. Zavadskas, Govindan, Antucheviciene, and Turskis (2016) reviewed hybrid MCDM methods applied to sustainability problems and demonstrated the importance of integrating different decision-making techniques to address complex evaluation requirements.

A further contribution was made by Keshavarz-Ghorabaee, Amiri, Zavadskas, Turskis, and Antucheviciene (2021), who introduced the removal effects of criteria (MEREC) method for determining objective weights. MEREC estimates criterion importance by examining how the overall performance of alternatives changes when an individual criterion is removed. This offers an alternative to weighting methods based solely on data dispersion or correlation.

Ponhan and Sureeyatanapas (2022) compared subjective and objective weighting approaches for industrial location selection. Their research is relevant because subjective methods capture decision-makers' preferences, whereas objective methods derive criterion importance from the available data. The comparison highlights why choosing a weighting method should depend on the decision context rather than assuming that one approach is universally superior.

Ferdous, Bensebaa, Milani, Hewage, Bhowmik, and Pelletier (2024) reviewed the integration of MCDM and multi-objective optimization under uncertainty for sustainability assessment. Their research is particularly relevant because it addresses the methodological choices involved in applying decision analysis when uncertainty affects sustainability-related evaluations.

Although existing MCDM methods provide valuable foundations for decision analysis, further investigation is needed into the integration of adaptive weight adjustment, uncertainty measurement, and robustness evaluation within a unified framework. In particular, uncertainty in observed data should be distinguished from the actual importance of a criterion, because highly uncertain information does not automatically imply that its associated criterion is less important. Without an explicit and transparent adaptation mechanism, decision-makers may find it difficult to determine whether changes in criterion weights reflect meaningful new information or fluctuations caused by uncertainty.

To address this gap, this study proposes a novel adaptive weighting model for multi-criteria decision-making under uncertainty. The proposed model is intended to integrate an initial weight estimation procedure with an uncertainty-sensitive adjustment mechanism that responds to changing information. Its methodological contribution will involve defining a mathematical weight-update rule, selecting appropriate uncertainty measures, and maintaining nonnegative normalized weights whose sum equals one(Levina et al., 2009). Where appropriate, the model may also integrate subjective expert preferences with objective data characteristics. The novelty of the approach will be established through mathematical formulation and comparative evaluation rather than through the combination of existing methods alone.

Accordingly, this study aims to develop the proposed model, formulate a systematic procedure for adjusting criterion weights, compare its performance with established weighting methods, and evaluate its stability, robustness, sensitivity, and computational efficiency under different uncertainty scenarios. The research addresses four questions: how criterion weights can be adaptively adjusted under uncertainty; whether the proposed model improves weight stability and decision consistency; how incomplete or changing information affects weights and alternative rankings; and under what conditions the model provides the greatest benefits.

2. Methods

2.1 Research Design

This study adopts a methodological and computational research design to develop and evaluate a novel adaptive weighting model for multi-criteria decision-making (MCDM) under uncertainty(Temur, 2016). The research focuses on formulating a mathematical weighting mechanism, implementing the proposed model, and assessing its performance through simulation experiments and comparative analysis. The research procedure consists of five interconnected stages. First, the decision problem is formulated by defining the alternatives, evaluation criteria, decision matrix, and sources of uncertainty. Second, the adaptive weighting model is developed by establishing an initial weight estimation procedure, an uncertainty measurement mechanism, and a mathematical rule for adjusting criterion weights. Third, the model is implemented computationally to calculate normalized weights under different decision conditions. Fourth, experimental evaluations are conducted by comparing the proposed model with established weighting methods across multiple uncertainty scenarios. Finally, validation and robustness analyses are performed to examine weight stability, ranking consistency, sensitivity to parameter changes, and computational efficiency.

2.2 Problem Formulation

The multi-criteria decision-making (MCDM) problem is formulated by defining a set of alternatives $A$and a set of evaluation criteria C. Let

$$A = \{A_1, A_2, \dots, A_m\}$$

denote the set of $m$decision alternatives, and let

$$C = \{C_1, C_2, \dots, C_n\}$$

represent the set of $n$evaluation criteria. The performance of each alternative with respect to each criterion is represented by the decision matrix X:

$$X = [x_{ij}]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

where x_{ij}denotes the performance value of alternative $A_i$under criterion C_j, $i = 1,2, \dots, m$, and $j = 1,2, \dots, n$. Each criterion is assigned a weight w_j, representing its relative importance in the decision-making process. The weight vector is defined as

$$W = (w_1, w_2, \dots, w_n)$$

subject to the following constraints:

$$w_j \geq 0,\ j = 1,2, \dots, n$$

$$\sum_{j=1}^{n} w_j = 1$$

These constraints ensure that all criterion weights are nonnegative and that their total equals one. Before calculating the weights, benefit-type criteria, for which higher values indicate better performance, and cost-type criteria, for which lower values are preferable, are identified.

2.3 Uncertainty Representation

Uncertainty is incorporated into the decision-making process to represent the limitations and variability of the available information(Kochenderfer, 2015). Depending on the experimental scenario, uncertainty may arise from incomplete observations, measurement noise, ambiguous expert assessments, or changes in the decision environment. For numerical data, uncertainty may be represented through controlled perturbations or probability distributions, whereas interval-valued observations can be used when the lower and upper bounds of measurements are known but their

precise values are unavailable. Fuzzy numbers may be employed when linguistic assessments, such as low, moderate, and high importance, need to be represented mathematically. Missing-data scenarios are introduced separately to evaluate the model's ability to operate when some criterion values are unavailable.

2.4 Proposed Adaptive Weighting Model

The proposed adaptive weighting model consists of five main stages: initial weight estimation, uncertainty measurement, adaptive weight adjustment, weight normalization, and convergence assessment. First, the initial weights of the evaluation criteria are determined using an appropriate subjective or objective weighting method(Bugallo et al., 2017). Objective methods, such as entropy weighting and the Criteria Importance Through Intercriteria Correlation (CRITIC) method, can be used to derive criterion weights from the available data. The selected initialization method is applied consistently across all experimental conditions to ensure a fair comparison between the proposed model and the baseline methods.

Second, uncertainty associated with each criterion is quantified using a measure appropriate to the underlying data representation. For example, normalized entropy can be used to quantify uncertainty in suitable probability distributions, whereas normalized interval width can be applied to bounded numerical observations. These measures represent uncertainty in the available information rather than the intrinsic importance of a criterion.

Third, the model updates criterion weights through an adaptive adjustment mechanism defined as

$$w_j^{(t+1)} = \frac{w_j^{(t)} g_j^{(t)}}{\sum_{k=1}^{n} w_k^{(t)} g_k^{(t)}}$$

where $w_j^{(t)}$denotes the weight of criterion $j$at iteration t, and $g_j^{(t)} > 0$represents an adjustment factor determined by a predefined function of uncertainty, criterion importance, data reliability, and other relevant decision information. The mathematical definition of $g_j^{(t)}$is a central component of the proposed model and must be explicitly specified and theoretically justified.

Fourth, the updated criterion weights are evaluated and normalized to ensure that they remain nonnegative and satisfy the constraint

$$w_j^{(t+1)} \geq 0, \sum_{j=1}^{n} w_j^{(t+1)} = 1.$$

If necessary, weight bounds or regularization constraints are introduced to prevent excessive fluctuations during the iterative updating process. These constraints should be defined before the experimental evaluation and applied consistently across relevant experimental conditions.

Finally, convergence is assessed by calculating the maximum absolute difference between successive weight vectors:

$$\Delta^{(t)} = \max_{1 \leq j \leq n} \left| w_j^{(t+1)} - w_j^{(t)} \right|.$$

The iterative procedure terminates when

$$\Delta^{(t)} \leq \varepsilon,$$

where $\varepsilon$is a predefined convergence threshold, or when the maximum number of iterations is reached.

2.5 Baseline Methods

The performance of the proposed model is evaluated against established weighting techniques, including entropy weighting, CRITIC, the Analytic Hierarchy Process (AHP), and an appropriate fuzzy or hybrid weighting method when the data support such comparisons. Entropy weighting is included because it derives criterion importance from the distribution of observed data, whereas CRITIC considers both contrast intensity and intercriterion correlation. AHP provides a subjective

benchmark based on pairwise expert comparisons, while a fuzzy or hybrid method offers a comparison with approaches designed to incorporate imprecise judgments or combine subjective and objective information(Chang et al., 2009).

2.6 Experimental Design and Data

The experimental evaluation uses synthetic data and, where available, an empirical dataset from a relevant decision-making application. Synthetic data provide controlled conditions for investigating how the model responds to known changes in criterion importance, measurement noise, and information completeness(Kiang, 2003). The data-generation procedure specifies the number of alternatives and criteria, the distributions used to generate criterion values, the proportions of missing observations, and the levels of uncertainty.

2.7 Evaluation Metrics

The proposed model is evaluated using complementary metrics that measure weighting behavior, decision consistency, robustness, and computational performance(Cai et al., 2018). Weight stability is assessed through the mean absolute change in criterion weights across successive observations or uncertainty scenarios. Ranking consistency is measured using Spearman's rank correlation coefficient or Kendall's tau to determine the agreement between alternative rankings produced under different conditions. Robustness is evaluated by measuring ranking reversals, top-(k) selection stability, and changes in the preferred alternative following controlled perturbations of the decision matrix. Finally, uncertainty response is examined by analyzing how criterion weights change across predefined uncertainty levels and whether those changes follow the intended adjustment mechanism.

2.8 Statistical Analysis and Reproducibility

The experimental results are summarized using appropriate descriptive statistics, including means, standard deviations, and confidence intervals across repeated trials. Comparative statistical tests are selected according to the distributional characteristics and dependence structure of the observed results. For paired experimental conditions, a paired-samples test may be applied when its assumptions are satisfied; otherwise, an appropriate nonparametric alternative, such as the Wilcoxon signed-rank test, may be used(Rietveld & van Hout, 2017). Statistical significance is evaluated using a predefined significance level, such as 0.05, alongside effect sizes and uncertainty intervals to assess the magnitude and practical importance of differences.

3. Results and discussion

3.1 Characteristics of the Dataset

The dataset characteristics are examined to establish the structure, quality, and uncertainty of the decision information used to evaluate the proposed adaptive weighting model. The analysis begins by identifying the number of alternatives and evaluation criteria included in the multi-criteria decision-making (MCDM) problem. Each alternative represents a potential decision option, while each criterion represents a specific attribute used to assess and compare the alternatives. The criteria are classified as benefit-type or cost-type variables to distinguish attributes for which higher values are preferred from those for which lower values are desirable.

The descriptive analysis summarizes the distribution of the criterion values using appropriate statistical measures, including the mean, standard deviation, median, minimum, maximum, and interquartile range. These statistics help identify differences in measurement scales, variability among alternatives, and potential extreme observation(Zuur et al., 2010)s. Where appropriate, the distribution of each criterion is also examined using histograms, box plots, or other visualizations to identify skewness, outliers, and heterogeneous data patterns.

Data completeness is assessed by examining the frequency and proportion of missing observations for each criterion. The analysis also identifies potentially inconsistent values,

measurement errors, and observations that fall outside predefined valid ranges. Missing values are handled using a predetermined procedure appropriate to the data characteristics, while the selected treatment is documented to ensure transparency and reproducibility. Where uncertainty is represented through probability distributions, intervals, or fuzzy values, the corresponding characteristics are described using suitable measures, such as distributional entropy, interval width, or fuzzy membership parameters.

The dataset is further examined to determine whether the criteria exhibit different levels of uncertainty, reliability, and interdependence(Das & Nazir, 2022). Correlations among criteria are analyzed to identify potentially redundant information, while differences in measurement scales are considered when selecting the normalization procedure. This assessment is particularly relevant because highly correlated criteria may contribute overlapping information, whereas uncertain or incomplete observations may affect the stability of the resulting criterion weights and alternative rankings. Consequently, the dataset is characterized not only by its size and numerical distributions but also by the quality and structure of the information available for decision-making.

3.2 Performance of the Proposed Adaptive Weighting Model

The performance of the proposed adaptive weighting model is evaluated by comparing its criterion weights with those generated by entropy weighting and the Criteria Importance Through Intercriteria Correlation (CRITIC) method. Three evaluation criteria, C_1, C_2, and C_3, are considered to illustrate differences in the resulting weight distributions. For this example, C_1represents decision performance, C_2represents operational cost, and C_3represents data reliability. The proposed model is assumed to incorporate initial objective weights and an explicitly defined adjustment mechanism that accounts for uncertainty, data reliability, and decision priorities.

Table 1. Comparison of Criterion Weights

Criterion	Entropy	CRITIC	Proposed Model
C_1: Decision performance	0.500	0.350	0.420
C_2: Operational cost	0.300	0.450	0.330
C_3: Data reliability	0.200	0.200	0.250
Total	1.000	1.000	1.000

The illustrative results show that the entropy method assigns the highest weight to C_1, with a weight of 0.500, indicating that this criterion receives the greatest relative importance according to the information distribution used by the method. In contrast, the CRITIC method assigns the highest weight to C_2, with a weight of 0.450, reflecting a different weighting outcome based on the variability and intercriteria correlation structure of the data(Wang et al., 2022). The proposed model assigns the highest weight to C_1, at 0.420, followed by C_2, at 0.330, and C_3, at 0.250.

Compared with entropy weighting, the proposed model reduces the weight of $C_1$by 0.080 and increases the weight of $C_3$by 0.050. Compared with CRITIC, it assigns a lower weight to C_2but a higher weight to $C_1$and C_3 (Žižović et al., 2020). These differences illustrate how an adaptive weighting mechanism could produce a more balanced distribution of criterion weights when uncertainty and data reliability are incorporated alongside the initial weights.

Changes in Weights Under Different Uncertainty Scenarios

To illustrate the model's adaptive behavior, three hypothetical scenarios are considered: low uncertainty, moderate uncertainty, and high uncertainty. The scenarios represent progressively greater uncertainty in the decision information, while the underlying criterion definitions and substantive decision priorities remain unchanged(Heazle & Pillar, 2012).

Table 2. Illustrative Adaptive Weights Under Different Uncertainty Scenarios

Criterion	Low Uncertainty	Moderate Uncertainty	High Uncertainty

C_1: Decision performance	0.440	0.420	0.400
C_2: Operational cost	0.320	0.330	0.340
C_3: Data reliability	0.240	0.250	0.260
Total	1.000	1.000	1.000

The simulated results illustrate a gradual change in the distribution of criterion weights as uncertainty increases(Blazkova & Beven, 2009). The weight assigned to C_1 decreases from 0.440 under low uncertainty to 0.400 under high uncertainty. Meanwhile, the weight of C_2 increases from 0.320 to 0.340, and the weight of C_3 increases from 0.240 to 0.260. The largest absolute change is observed for C_1, with a decrease of 0.040 across the scenarios.

These changes illustrate a possible adaptive response in which the model moderates the influence of decision-performance information as its uncertainty increases while placing relatively greater emphasis on operational cost and data reliability. Importantly, this behavior is an assumption of the example, not a universal consequence of uncertainty(Kocher et al., 2018). The direction of each adjustment must follow the mathematical definition of the adjustment factor $g_j^{(t)}$.

The changes shown in Table 2 are gradual rather than abrupt. Between consecutive scenarios, the weight of each criterion changes by only 0.010 or 0.020. This pattern illustrates the intended behavior of an adaptive weighting model that seeks to accommodate changing information conditions without producing excessive fluctuations in criterion importance.

The consistency of the proposed model should also be assessed by comparing the observed weight changes with the specified adjustment function. For the update rule

$$w_j^{(t+1)} = \frac{w_j^{(t)} g_j^{(t)}}{\sum_{k=1}^{n} w_k^{(t)} g_k^{(t)}},$$

the resulting weights depend on both the current weights and the relative adjustment factors. Consequently, a criterion's weight increases only when its adjustment factor is sufficiently favorable relative to those of the other criteria. The updated weights must remain nonnegative and sum to one after each iteration(He et al., 2017).

3.3 Comparative Analysis

The comparative analysis evaluates the performance of the proposed adaptive weighting model against two baseline methods: entropy weighting and the Criteria Importance Through Intercriteria Correlation (CRITIC) method. The comparison focuses on four principal dimensions: weight stability, ranking consistency, robustness under uncertainty, and computational efficiency. These dimensions are selected to determine whether the proposed model offers practical advantages over conventional weighting methods when the decision information is incomplete, variable, or uncertain.

Weight stability is assessed by examining changes in criterion weights across repeated experiments and different uncertainty levels(Shanian et al., 2008). A weighting method is considered more stable when small perturbations in the input data produce relatively small changes in the resulting weight vector. Entropy weighting and CRITIC provide reference points for determining whether the adaptive adjustment mechanism reduces unnecessary fluctuations or introduces additional sensitivity. Based on the illustrative results presented in Section 3.2, the proposed model exhibits gradual changes in criterion weights across the hypothetical uncertainty scenarios.

Ranking consistency is another important dimension of the comparative analysis(van Herk & van de Velden, 2007). Although weighting methods generate criterion weights, their practical significance lies in how those weights influence the ranking of decision alternatives. Ranking consistency can be evaluated using Spearman's rank correlation coefficient or Kendall's rank correlation coefficient to measure agreement between the rankings produced under different uncertainty conditions. If the proposed model maintains stronger ranking consistency than entropy

and CRITIC under comparable perturbations, this would suggest that its adaptive mechanism helps preserve decision outcomes when the input information changes.

Robustness is assessed by examining the ability of each weighting method to maintain reasonable and interpretable results when the decision matrix is affected by missing observations, measurement noise, outliers, or increasing uncertainty(Nardo et al., 2005). The experimental analysis should introduce predefined perturbations at several intensity levels and compare the resulting weights and alternative rankings with those obtained from the original dataset. Robustness can be quantified through normalized weight deviations, ranking correlations, rank-reversal rates, and changes in the selection of the highest-ranked alternative.

Computational efficiency is evaluated by measuring execution time, memory consumption, and the number of iterations required to achieve convergence, where applicable(Castaño-Díez et al., 2008). Entropy and CRITIC typically calculate criterion weights through direct procedures, whereas the proposed adaptive model may require repeated weight updates and convergence checks. This trade-off is particularly relevant when the number of alternatives and criteria increases or when the model must process frequently updated data.

3.4 Sensitivity Analysis

The sensitivity analysis examines how variations in the model's parameters and input conditions affect the performance of the proposed adaptive weighting model. First, the strength of the uncertainty adjustment is investigated to determine how strongly uncertainty influences the updating of criterion weights. A low adjustment strength is expected to produce weight distributions closer to the initial weights, whereas a high adjustment strength may lead to larger changes in criterion importance. The analysis should evaluate several predefined adjustment-strength values and measure their effects on weight stability, ranking consistency, convergence, and sensitivity to perturbations.

Second, the initial weight vector is varied to determine whether the proposed model depends excessively on its initialization. Alternative initial vectors can be generated using entropy weighting, CRITIC, expert assessments, or predefined perturbations of a reference weight vector(Gwet, 2014). The model is then executed under identical uncertainty conditions, and the resulting weights and rankings are compared.

Third, the proportion of missing data is varied to evaluate the model's resilience to incomplete observations. Experiments may consider increasing levels of missingness, such as 5%, 10%, 20%, and 30%, provided that these levels are appropriate for the intended application. For each level, missing observations should be introduced using clearly specified procedures, including random missingness and, where relevant, structured missingness affecting particular criteria or alternatives.

Fourth, measurement noise is introduced to examine how the model responds to inaccurate or fluctuating criterion values. Controlled perturbations can be applied at several predefined noise levels, with the magnitude of the perturbation adjusted according to each criterion's measurement scale. The resulting weights are compared with the reference weights, while ranking correlations and rank-reversal frequencies are used to assess decision stability.

Fifth, the effects of increasing the number of alternatives and evaluation criteria are examined to determine the model's scalability. Experiments should use decision matrices of different sizes, ranging from relatively small problems to larger configurations representative of the intended application. The analysis should record execution time, memory consumption, convergence iterations, weight stability, and ranking consistency(Chakrabarti, 2007). Increasing the number of alternatives may change the observed distributions used by objective weighting methods, while increasing the number of criteria may introduce greater interdependence, redundancy, and computational complexity.

3.5 Robustness Under Different Uncertainty Scenarios

The robustness evaluation investigates the ability of the proposed adaptive weighting model to generate meaningful criterion weights and maintain reliable alternative rankings under progressively more challenging uncertainty conditions. Three scenarios are considered: low uncertainty, moderate uncertainty, and high uncertainty. Under the low-uncertainty scenario, the decision matrix is assumed to contain relatively complete and reliable observations, with limited measurement noise and few missing values. This scenario provides a reference condition for evaluating the initial performance of the three weighting methods. The analysis examines whether the proposed model generates normalized, interpretable criterion weights and produces rankings that are broadly consistent with those obtained from the baseline methods.

Under the moderate-uncertainty scenario, the decision matrix is subjected to controlled levels of missing data, measurement noise, or variation in criterion values. Particular attention is given to the relationship between data reliability and criterion importance. A robust model should account for the reduced reliability of uncertain observations without automatically assigning lower weights to criteria that remain essential to the decision problem.

Under the high-uncertainty scenario, the decision matrix is exposed to more substantial data imperfections, including higher missing-data proportions, greater measurement noise, and larger changes in the observed criterion values. The robustness assessment also distinguishes between weight stability, ranking stability, and decision accuracy. Ranking stability concerns the consistency of alternative rankings across different uncertainty conditions. Decision accuracy, by contrast, concerns whether the resulting rankings agree with a defensible reference ranking or reflect the preferences of relevant decision-makers.

When ground-truth preferences are available, the proposed model should be evaluated against expert-derived rankings, established decision outcomes, or another justified reference standard. Measures such as rank correlation, top-(k) agreement, and ranking error can then be used to assess whether the model recovers the reference preferences under different uncertainty conditions. Expert assessments should be collected through a documented procedure, and disagreement among experts should be considered when defining the reference ranking(Gwet, 2014). If no ground-truth preferences are available, the evaluation should focus on stability, robustness, and sensitivity rather than claiming that the model produces more accurate decisions.

Conclusion

This study proposes an adaptive weighting model for multi-criteria decision-making (MCDM) under uncertainty. The model addresses the limitations of conventional weighting methods by incorporating uncertainty measurement, adaptive weight adjustment, normalization, and convergence assessment into a unified framework. The proposed mechanism updates criterion weights according to predefined adjustment factors reflecting uncertainty, data reliability, and decision priorities. Comparisons with entropy and CRITIC weighting are intended to evaluate weight stability, ranking consistency, robustness, and computational efficiency. However, because the numerical examples presented are illustrative and no actual experimental results are available, the model's superiority over baseline methods cannot yet be established. This distinction may help prevent uncertain information from automatically reducing the influence of strategically important criteria. The model may support organizational decision-making in resource allocation, supplier selection, risk assessment, and other applications involving incomplete or changing information. Future research should integrate fuzzy or probabilistic MCDM techniques, develop more interpretable adjustment functions, and evaluate performance in dynamic decision environments. Further investigation should also examine computational efficiency and scalability for large decision matrices.

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