SCIENTIFIC OASIS

Spectrum of Decision Making and Applications

Journal homepage: http://www.dmap-journal.org/
eISSN: 1804-9796

Sensitivity Analysis and Validation in MCDM Methods: A Comprehensive Review with Advancements, Applications, and Future Directions

Arkyadeep Sarkar[1], Shankha Shubhra Goswami[1,*], Krishna Kumar Gupta[1]

[1] Department of Mechanical Engineering, Abacus Institute of Engineering and Management, India

ARTICLE INFO

Article history:
Received 11 December 2025
Received in revised form 27 January 2025
Accepted 13 March 2026
Available online 18 March 2026

Keywords:
Multi-criteria decision-making; Weighting methods; Hybrid data-driven weights; Machine learning–based weighting; Uncertainty modelling; Fuzzy and entropy techniques; MCDM

ABSTRACT

The accelerated development of multi-criteria decision-making (MCDM) tools in engineering, management, environmental planning, and financial analytics has increased the demand for more precise and responsive weighting methods. Stereotypical subjective and objective weighting methods tend to be biased, inflexible, or fail to react to dynamic decision settings. The review summarizes a series of newly developed novel weighting approaches, such as hybrid, data-driven, machine-learning-assisted, and uncertainty-adaptive approaches, to address these limitations. Drawing from a broad scope of published literature, this paper assesses the methodological developments, including fuzzy-enhanced weighting, the use of entropy-based extensions, CRITIC variants, Bayesian and probabilistic schemes, combined Delphi-ANP-DEMATEL approaches, best-worst method (BWM) refinements, and new deep-learning-based weight estimators. The review points out the ability of such modern approaches to boost robustness, decrease subjectivity, and increase transparency in decision-making in a variety of MCDM models. It also establishes the gaps in methodology, current trends, and future research directions and sets new weighting strategies as a key tool in managing complex, uncertain, and high-dimensional decision problems. This combination helps them gain a better theoretical insight as well as provide some practical advice to researchers and practitioners wishing to apply advanced weighting methods in MCDM.

1. Introduction

Multi-Criteria Decision-Making (MCDM) has come out as a significant analysis instrument to be applied in order to resolve complex decisions in fields of engineering, management, environmental studies, finance, urban planning, and other data-related subject areas. Since contemporary decision-making situations are becoming more and more associated with conflicting goals, heterogeneous information, experience, and uncertainty, MCDM methods provide systematic solutions to the process of assessing alternatives and establishing rational preference listings. In the last decades,

* *Corresponding author.*
E-mail address: ssg.mech.official@gmail.com

https://doi.org/10.31181/sdmap41202769

AHP, ANP, TOPSIS, VIKOR, DEMATEL, MOORA, COPRAS, ARAS, and many of the hybrid extensions were developed and became commonly used to support the strategic decision-making process [1,2].

The increased acceptance of these methods in both scholarly studies and practice has added an urgency to study not merely the ways these methods can provide results, but also the extent to which these results can be reliable and robust. This increased focus on reliability has placed sensitivity analysis and validation as an important part of the MCDM procedure. Sensitivity analysis enables the scientists to assess the extent to which variations in the input parameters will influence the resulting ranking of the choices including criteria weights, decision matrices or methodological assumptions [3]. Validation in its turn explores the credibility, stability, and consistency of the results by means of reliability test, expert test, cross-method test, and statistical test. The two components taken together are the basis of the trustworthy decision support, but they have been typically considered as the additional steps instead of the parts of the methodological design.

Even though many studies make use of MCDM models in different fields, there is a lack of systematic review of sensitivity analysis and validation methods design, implementation and interpretation. Numerous published studies use simple tests of variation of weight or general tests of consistency, yet there are only a few studies of complete frameworks that deal with robustness and methodological soundness [4,5]. Also, we find that because of the varied contexts of the studies, variability in validation across studies, and absence of uniform protocols, it is hard to compare the findings across methods or domains. All these gaps demonstrate the necessity of an organized synthesis that would encompass the current methods, reveal gaps in methodology, and present the new developments in terms of uncertainty assessment in MCDM. Table 1 has presented the classification of major MCDM methods and approaches of weighting them.

This review is aimed at resolving such gaps by providing a synthesized analysis on sensitivity analysis and validation methods applied in current MCDM studies [6]. This paper summarizes dispersed inputs in a wide range of fields of application, outlines the progress in hybrid and data-driven models, and analyzes the usefulness of current robustness strategies. The review also comments on the methodological issues and suggests future research directions that will move towards more reliable, transparent and the standard practices of MCDM [7]. By means of this synthesis, the research will contribute to the enhancement of the theoretical basis of MCDM and allow researchers to create more credible decision-making models.

Table 1
Classification of major MCDM methods and their weighting approaches

MCDM Method	Decision-Rule Logic	Typical Weighting Approaches Used
AHP	Pairwise comparison of criteria and alternatives; hierarchical structuring; priority vector generation.	Subjective: Expert judgments (Saaty scale). Hybrid: Fuzzy AHP, consistency-based adjustments.
ANP	Network-based interdependency modeling; supermatrix formulation; feedback and dependence among criteria.	Subjective: Pairwise comparisons. Hybrid: Fuzzy ANP, BOCR-based weighting.
TOPSIS	Ranking based on distances from ideal and anti-ideal solutions.	Objective: Entropy, CRITIC. Hybrid: AHP-TOPSIS, ANP-TOPSIS, fuzzy weighting.
VIKOR	Compromise ranking approach minimizing group utility and individual regret.	Objective: Entropy, standard deviation. Hybrid: AHP-VIKOR, fuzzy VIKOR.
COPRAS	Proportional evaluation based on maximizing beneficial attributes and minimizing cost attributes.	Objective: Entropy, CRITIC. Hybrid: AHP-COPRAS, fuzzy weighting.

Table 1
Continued

MCDM Method	Decision-Rule Logic	Typical Weighting Approaches Used
MOORA	Ratio-based assessment combining normalization and aggregation rules.	Objective: Entropy, CRITIC. Hybrid: AHP-MOORA, fuzzy MOORA.
ARAS	Utility-based evaluation where alternatives are compared with a reference ideal.	Objective: Entropy, CRITIC. Hybrid: AHP-ARAS, fuzzy ARAS.
DEMATEL	Causal relationship analysis to derive influence weights through direct–indirect impact matrices.	Subjective: Expert evaluations. Hybrid: Fuzzy DEMATEL, rough DEMATEL, DEMATEL–ANP (DANP).
WASPAS	Weighted aggregation of additive and multiplicative models for ranking.	Objective: Entropy, CRITIC. Hybrid: AHP-WASPAS, fuzzy WASPAS.

2. Overview of MCDM Methods

MCDM is a wide category of methods assisting in the organized assessment of the situation when multiple, and frequently mutually exclusive, criteria are involved. The general categories of these methods include pairwise comparison-based methods, distance-based methods, outranking procedures and integrated or hybrid frameworks [5, 6]. The classical models of pairwise comparison such as the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP) are based on the use of expert judgments to compute the weights of the criteria as well as get preference scores. AHP determines the decision in form of a hierarchical structure and ANP takes into account the feedback and dependence of criteria hence it is suitable when the number of relationships is great in a network. The distance-based methods, including TOPSIS, WASPAS, contrast the performance of the alternatives to the ideal and anti-ideal solutions to give explicit and interpretable ranking mechanisms [3,5]. Outranking approaches such as VIKOR which enables making of balanced decisions under opposing objectives are emphasized to compromise solutions. Other models such as MOORA, COPRAS and ARAS provide less sophisticated forms of computations and provide fast analysis but they, in turn, process a large number of data formats [8]. The methods like the DEMATEL are not only restricted to ranking, hence, it can be applied to quantify the cause and effect relationships among variables, however, it also finds application in understanding the structural interactions of decision systems. The new techniques of weighting in the new literature have been sampled in Table 2.

Even though processes of MCDM vary in terms of methodology, all of them share the similarity that they demand the quality of input information, expert judgments, methodological assumptions, and weighting schemes. A small variation in these factors may cause quite disparate rankings that demonstrate the sensitivity of this kind of models [6,7]. The sensitivity analysis is therefore necessary in testing the effect of the changes in criteria weights, the normalization procedures or performance scores to final decisions. It ensures that the model results are not the results of arbitrary choices but it is consistent to reasonable perturbations. In the same vein, validation is crucial in all the MCDM techniques to determine the reliability and credibility of the results [2,4,6]. Regardless of consistency measures of AHP, cross-method comparison of distance-based techniques, causal verification of DEMATEL, or benchmarks evaluations of hybrid models, validation can give confidence that the decision structure, assumptions and rankings are valid to the context of the problem. Sensitivity and validation in combination are the key to methodological strength, making it easier to trust the results of MCDM, despite the method employed.

Table 2
Overview of Emerging Weighting Methods

Weighting Method	Advantages	Drawbacks	Common Application Domains
Entropy Weighting	Reflects objective data variability; reduces human bias; straightforward implementation.	Highly dependent on data quality; does not incorporate expert judgment.	Energy systems, supplier selection, environmental analysis.
CRITIC	Accounts for both variability and inter-criteria correlation; effective for interdependent datasets.	Relatively complex computations; may undervalue weakly correlated criteria.	Industrial optimization, material selection, risk evaluation.
IVIF Weighting	Effectively captures uncertainty, hesitation, and ambiguity in expert opinions.	Mathematically intensive; results may vary based on expert interpretation.	Medical decision-making, sustainability studies, social research.
Rough Set-Based Weighting	Handles vague and incomplete data without predefined membership functions; data-oriented.	Strongly influenced by discretization methods; may reduce data precision.	Urban planning, environmental systems, classification tasks.
BWM	Requires fewer pairwise comparisons; generates consistent weights; lowers cognitive effort.	Dependent on identifying best and worst criteria; potential expert bias.	Logistics, supply chain optimization, investment decisions.
LBWA	Enhances BWM with logarithmic scaling for improved stability and consistency.	Still influenced by subjective inputs; mainly applicable in expert-based scenarios.	Financial analysis, system evaluation, infrastructure planning.
SWARA	Supports stepwise expert evaluation; adaptable for group decision processes.	Sensitive to the sequence of criteria; subjectivity may influence results.	Project management, policy analysis, technology evaluation.
FUCOM	Achieves high consistency with minimal comparisons; avoids redundancy.	Limited capability to model uncertainty; depends on clearly defined priorities.	Renewable energy planning, logistics, multi-criteria assessments.
Bayesian Weighting	Incorporates prior knowledge; handles uncertainty probabilistically; allows dynamic updates.	Requires strong statistical expertise; sensitive to prior assumptions.	Risk management, system reliability, adaptive decision-making.

3. Sensitivity Analysis in MCDM

Sensitivity analysis is a more basic part of MCDM and it evaluates the effect of changes of the input parameters on the ultimate ranking or selection of alternatives [9]. Since MCDM methods rely on expert decisions to a great extent, the weighting plans, the process of normalization and performance evaluation, any slightest change in these parameters may change the final decision. Sensitivity analysis is a systematized approach to assessing the strength of the decision-making model based on the degree of stability or instability of the results to controlled perturbations [9,10]. It is mainly meant to find out the extent to which the adopted solution can be truly reliable or are very reliant on certain presumptions that are not often true to the real-world scenario.

Sensitivity analysis in MCDM studies can be of main three types. Weight based sensitivity analysis examines the impact of variations in criteria weights on the ranking of alternatives [4,5]. As the issue of weighting is a direct indicator of the priorities held by decision-makers, this kind of analysis is paramount to the interpretation of the impact of subjective preferences on the final decision. The level of criteria-based sensitivity analysis concentrates on the alteration of the performance values of the individual criteria to establish whether variations in the data input would result in varying outcomes. The method is especially relevant in cases when the data are uncertain, measured with errors or incomplete information [8]. Alternative-level sensitivity analysis is the study that observes the effects that the variation in the attributes of the choices has on the ranking structure to assist the investigators in determining the alternatives that are robust and those that are very sensitive to slight modifications.

In literature on MCDM several different frameworks of sensitivity analysis have been suggested with varying degrees of complexity, computing needs, and levels of interpretation [10,11]. Simple structures modify variations of weights or measures of performance in an incremental form to observe reversal in ranks giving simple but informative data concerning the stability of the models. More sophisticated methods entail scenario-based analysis where various hypothetical conditions are modeled to test the behavior of rankings under a set of different decision settings [12]. Others use probabilistic or fuzzy-based sensitivity models, in which the underlying uncertainty in judgments is modeled by the representation of inputs as probability distribution or fuzzy numbers, instead of as constant numbers. Hybrid frameworks involve sensitivity analysis and further analysis with techniques like Monte Carlo simulation, bootstrapping or statistical analysis of variance, allowing exploring more deeply the propagation of uncertainty within the decision model [9,10]. Table 3 has compared different sensitivity analysis frameworks of MCDM studies.

Simpler frameworks have the advantage of being easy to use and understand, but can be unproductive in complex interactions in high-dimensional decision problems [13]. By comparison, probabilistic and hybrid models are more informative, but more complex to compute and more sophisticated. All the frameworks, however, have in common the idea of making the results of MCDM more reliable with the identification of the stable decisions, the possibility of identifiable reversal of the ranks, and the disclosures of the important parameters that affect the decision [14]. With the development of MCDM applications in the field where there are increased uncertainty and dynamism, sensitivity analysis has remained pivotal in helping to make decisions that are not only defendable but also robust.

Table 3
Comparison of sensitivity analysis frameworks in MCDM studies

Sensitivity Analysis Framework	Key Features	Advantages	Limitations	Typical MCDM Applications
Deterministic Weight-Variation Analysis	Adjusts criteria weights gradually (±5%, ±10%, etc.) to observe rank changes	Simple, transparent, easy to implement	Limited ability to capture complex uncertainty patterns	AHP, ANP, TOPSIS, COPRAS
Criteria-Level Performance Perturbation	Varies performance scores to test robustness under data fluctuations	Useful when data have measurement errors or uncertainty	May become computationally intensive with many criteria	MOORA, WASPAS, ARAS
Alternative-Level Sensitivity Testing	Alters attributes of specific alternatives to evaluate ranking stability	Identifies robust vs. fragile alternatives clearly	Does not assess global model uncertainty	VIKOR, TOPSIS, AHP
Scenario-Based Sensitivity Analysis	Compares rankings under multiple hypothetical or realistic decision scenarios	Captures multi-dimensional uncertainty; flexible	Requires expert input for scenario design	Hybrid MCDM, energy planning, supply chain studies
Probabilistic Sensitivity Analysis	Uses probability distributions for weights/performance values	Reflects real-world uncertainty; statistically sound	Requires statistical modeling expertise	Fuzzy MCDM, stochastic MCDM

Table 3
Continued

Sensitivity Analysis Framework	Key Features	Advantages	Limitations	Typical MCDM Applications
Fuzzy-Based Sensitivity Analysis	Incorporates uncertainty using fuzzy numbers or intervals	Effective for subjective judgments; handles vagueness	Interpretation may be complex	Fuzzy AHP, Fuzzy DEMATEL, Fuzzy TOPSIS
Monte Carlo Simulation Frameworks	Runs large numbers of random simulations to observe ranking stability	Highly robust; ideal for high-uncertainty problems	Computationally heavy; requires specialized software	Hybrid MCDM, risk assessment
Bootstrapping and Resampling-Based Methods	Generates multiple resampled datasets to evaluate ranking variability	Provides strong statistical validation	More suitable for large datasets; requires automation	Data-driven MCDM, machine learning–assisted models
Hybrid Sensitivity–Validation Frameworks	Combines deterministic, probabilistic, and statistical tools	Offers comprehensive robustness assessment	Complex implementation; needs multi-method expertise	Complex network decisions, DEMATEL–ANP–TOPSIS hybrids

4. Validation Techniques in MCDM

Validation as MCDM is an important process through which the quality of the results generated by a decision model can be evaluated as both credible and consistent as well as being reflective of the underlying problem structure [14,15]. Since MCDM techniques are based on subjective decisions, data quality, and a set of assumptions of the methodology, validation makes sure that all these factors together result in reliable conclusions not arbitrary or method-related artifacts. Techniques of validation applied in literature may be classified as internal and external techniques, and each has focused on the various aspects of methodological soundness.

Internal validation concentrates on testing the level of consistency and stability of decision model on its own structure [16). Consistency checks and especially in the pair-wise comparison tools like AHP and ANP, consist of checking the judgment of the experts according to their logical pattern and that they do not have contradictory preferences. Another internal strategy is the robustness testing, which studies how changes in weights, performance scores, or model parameters, which are considered minor, affect the rankings of models [17]. Such a validation contributes to the discovery of implicit biases or structural flaws, which can affect the outcome of the decision. Other studies also examine redundancy and convergence checks, to check whether repeating the evaluation or doing iterative weighting to test the results, but this internal confidence enhances internal trusts on the model.

External validation is used to analyze the consistency of MCDM results using external sources of truth, expert knowledge or other decision-support systems [18,19]. One of the most popular types is expert validation; in this case, the domain specialists are consulted to determine whether the ranking generated by the model is within realistic expectations or industry standards. Another significant external technique is benchmark comparison where MCDM outcome is compared to the preset reference techniques or empirical data or known optimal solutions [20]. External credibility is also strengthened by statistical validation methods like correlation analysis, variance testing or hypothesis testing, which measure the extent of congruence between MCDM rankings and independent datasets. Cross-method triangulation, which is being embraced in recent research, is the analysis of the same decision and more than one MCDM technique under investigation to see whether similar ranking patterns can be observed [21,22]. Consistency among the various models implies good external validity, whereas inconsistency reveals the aspects that need to be refined in the methodology or be better understood. Table 4 reflects the various validation methods in MCDM and their major features.

The internal and external validation approaches are joined together to create a unified system that amplifies the credibility of MCDM models in different fields [18,21]. Using logical consistency, evaluation on the basis of experts, strong statistical indicators and comparison by means of several methods, the researchers can not only ensure that the results of the decision-making are completely justified, but also ensure that they can be studied. As the MCDM solutions are currently being expanded to complex and unpredictable conditions, the validation is needed to ensure the transparency of the methodology and that the inferences drawn with the help of the tools in question are relevant in the real world.

Table 4
Validation techniques in MCDM and their key characteristics

Validation Technique	Key Characteristics	Typical Purpose in MCDM
Internal Validation (CR – Consistency Ratio)	Evaluates logical consistency of pairwise comparisons in hierarchical and network methods.	Ensures reliability of subjective judgments in AHP/ANP.
Internal Validation (Cronbach's α)	Measures internal coherence among criteria assessments; suitable for expert-based surveys.	Tests reliability of expert inputs and questionnaire stability.
External Validation (Benchmark Comparison)	Compares results with established models, known rankings, or prior studies.	Confirms alignment with proven decision outcomes and industry standards.
Robustness Checks	Examines stability of rankings under small changes in weights, criteria importance, or preference parameters.	Determines whether the MCDM model is resilient to input perturbations.
Monte Carlo Simulation	Generates random variations in weights or performance scores; produces probabilistic ranking distributions.	Quantifies uncertainty and assesses probabilistic robustness of decisions.
Expert Validation	Involves domain specialists reviewing criteria, weights, and final rankings.	Adds credibility and domain relevance to the final decision outcomes.
Statistical Validation Techniques	Includes correlation analysis, rank similarity indices, ANOVA, and significance tests.	Measures agreement between methods and detects significant differences in results.
Cross-Method Triangulation	Compares rankings from multiple MCDM methods to evaluate convergence and consistency.	Increases confidence in results by confirming stability across methods.

5. Integrated Review of Sensitivity Analysis and Validation Approaches

The current literature demonstrates an increasing literature on sensitivity analysis explicitly integrated with a validation procedure to provide more robust results of MCDM, extensive reviews and state-of-the-art surveys report not only the wide range of sensitivity methods (deterministic, probabilistic, fuzzy, simulation-based) but also the range of validation mechanisms (consistency checks, cross-method comparison, expert and statistical validation) that are employed to verify the results [18,20,22]. Numerous applied works use hybrid workflows e.g. combining DEMATEL to provide causal structure, ANP to provide interdependent weighting, and Delphi to provide consensus-building and then test the resulting rankings by weight-variation tests, Monte Carlo and bootstrapping to quantify ranking stability; such hybrid pipelines have been found to be useful in revealing which criteria or alternatives drive sensitivity and why.

Those developments methodologically are the increased application of probabilistic sensitivity (expressing weights or scores as distributions), fuzzy-interval analogies of linguistic or imprecise judgments, and large-scale simulation (Monte Carlo) to estimate the likelihood of rank reversal-all come at the cost of more complex computational and modelling. In the reviewed literature a number of typical strengths have been identified: (1) integrated sensitivity-validation workflows are more transparent (providing a mapping between assumptions and outcomes), (2) cross-method triangulation (running multiple MCDM methods on the same data) is a pragmatic external validation where ground truth is not available, and (3) quantitative resampling or simulation provides statistical estimates (confidence intervals, rank-probabilities) instead of the binary labels stable/unstable.

Nevertheless, common weaknesses and shortcomings are apparent: most papers continue to use ad-hoc perturbation ranges with little explanation, expert validation processes are often described insufficiently (inhibiting reproducibility), most papers do not report standardized effect sizes or uncertainty measures, and hybrid models, although potentially promising, are sometimes unclear on how uncertainty in their input propagates to their outputs (e.g., what implications fuzziness of Delphi inputs has on the causal strengths of DEMATEL and the ANP weights generated by them). Table 5 illustrates some of the combined sensitivity-validation methods in literature.

Table 5
Integration of Sensitivity Analysis and Validation Approaches

Key Study	Combined Methodology	Key Strengths	Research Gaps
AHP + Monte Carlo Simulation	AHP-derived weights combined with Monte Carlo–based probabilistic sensitivity analysis.	Enhances reliability through probabilistic evaluation; measures ranking stability under uncertainty.	Computationally demanding; results depend heavily on assumed probability distributions.
DEMATEL + Stability Index Models	Causal weights obtained via DEMATEL validated using stability indices and perturbation techniques.	Effectively captures interrelationships and verifies robustness of influence weights.	Primarily reliant on expert judgment; less effective in data-driven contexts.
Fuzzy AHP + Scenario-Based Sensitivity Analysis	Fuzzy pairwise comparisons integrated with scenario-based adjustments of criteria.	Efficiently manages ambiguity and uncertainty; suitable for qualitative environments.	Scenario formulation may introduce subjectivity; limited generalizability across applications.
ANP + Cross-Method Triangulation	ANP results validated by comparing rankings with methods such as TOPSIS and VIKOR.	Improves confidence through consistency across multiple methods.	Interpretation of conflicting results can be complex; lacks standardized comparison frameworks.
TOPSIS + Entropy + Rank Reversal Analysis	Entropy-based objective weights combined with rank reversal and perturbation validation tests.	Promotes ranking stability; identifies sensitivity to normalization and distance measures.	Rank reversal issues may still occur; outcomes influenced by normalization techniques.
VIKOR + Statistical Validation	VIKOR results statistically validated against alternative MCDM outputs using correlation and ANOVA.	Provides a quantitative validation framework; identifies significant ranking differences.	Requires sufficient data samples; less applicable to purely qualitative decision problems.

Table 5
Continued

Key Study	Combined Methodology	Key Strengths	Research Gaps
Hybrid Fuzzy–Probabilistic Validation	Integration of fuzzy weighting approaches with probabilistic Monte Carlo-based robustness analysis.	Offers comprehensive uncertainty handling; well-suited for complex real-world scenarios.	Increased model complexity; interpretation may be difficult for practitioners.
Rough Set Weighting + Sensitivity Index Analysis	Rough set–based objective weights evaluated using sensitivity index variations.	Effective for handling incomplete or imprecise data; minimizes reliance on expert input.	Dependent on discretization techniques; lacks standardized validation procedures.

6. Applications Across Domains

Sensitivity analysis and validation methods have been extensively incorporated in the MCDM application in various fields such that decisions are not biased even when the data is complicated and uncertain conditions are present. MCDM models AHP, TOPSIS and MOORA are also commonly applied in manufacturing to select materials, optimize machining parameters, evaluate equipment, and control quality [16,17]. The sensitivity analysis is used to determine which criteria have the greatest impact on the ultimate selections, including cost versus durability versus precision, and validation by expert evaluation or benchmarking the proposed solution is necessary to ensure that it is within the industry standard [14]. The same is applied to the supply chain management whereby MCDM aids in the analysis of suppliers, optimization in logistics, warehouse layout, analysis of risks and various other areas. In this case, sensitivity analysis on parameters such as lead time, reliability, and sustainability are used to determine how the supply chain decisions are resilient to dynamic conditions.

MCDM approaches have been used to prioritize renewable technologies, grid modernization plans, and energy-saving investments in the energy industry [21]. Since data relating to energy projects are usually uncertain due to changeable demand, unstable environmental conditions and policy restrictions, probabilistic sensitivity and cross-method validation are common in ensuring robustness. Applications in the environment, including waste management planning, mitigation of pollution and assessment of the ecosystem, are well served by fuzzy or interval-based sensitivity tests that can use inaccurate ecological data, and expert validation can be used to test ecological viability [23,24]. Sensitivity analysis is a common health care decision tool, used to evaluate the performance of hospitals, the type of medical equipment to use, or the priorities of the treatment, and is backed through statistical validation to determine the reliability of evidence-based setting decisions.

Sensitivity frameworks are essential in financial decision-making and especially in portfolio selection, credit risk management, and investment prioritization to understand the impact of market condition changes, preference of risk, or economic indicators on the rankings of MCDM. Backtesting or benchmarking against history or financial standards increases belief in the output of models [16,17]. MCDM is used in the selection of a contractor in construction management, sustainability evaluation of building materials, site selection, and the prioritization of infrastructure. The sensitivity analysis is vital in investigating the changes of the cost, safety and project duration and validation checks that it complies with the regulatory and engineering requirements. Another area of MCDM that is fast growing is smart city planning, which allows making decisions regarding mobility systems, digital infrastructure, environmental quality, and urban innovation [25]. Since urban data are non-uniform and dynamic, hybrid sensitivity measures, consisting of deterministic, fuzzy, and simulation-based methods, are employed to reflect uncertainty, and to triangulate the results of several MCDM methods are used to authenticate the soundness of intricate urban planning choices. Table 6 pointed out some of the domain-based applications of sensitivity methods and validation methods.

In all these areas, the successive combination of sensitivity analysis and validation underscores the necessity of the two methods in making MCDM-based solutions sound, reasonable, and viable.

Table 6
Domain-wise use of sensitivity and validation methods

Domain	Role of Sensitivity Analysis	Role of Validation
Manufacturing	Tests robustness of material, machining, and equipment decisions under varying cost or performance criteria.	Ensures alignment with industry standards through expert or benchmark checks.
Supply Chain	Evaluates how supplier rankings and logistics priorities shift with changing operational conditions.	Confirms decision reliability using expert feedback or comparative methods.
Energy	Captures the impact of demand fluctuations, environmental variability, and policy uncertainty.	Verifies feasibility of renewable and efficiency strategies through technical validation.
Environment	Handles imprecise ecological data using fuzzy or interval-based perturbations.	Uses expert assessments to confirm ecological appropriateness of solutions.
Healthcare	Tests stability of treatment, device, or hospital rankings under shifting clinical priorities.	Applies statistical validation to support evidence-based decision-making.
Finance	Explores market volatility impacts on portfolio or investment rankings.	Uses backtesting and benchmark comparisons for reliability.
Construction	Assesses how cost, safety, or duration variations influence project choices.	Validates compliance with engineering standards and regulatory norms.
Smart City Planning	Checks robustness of mobility, infrastructure, and sustainability decisions under dynamic urban data.	Uses triangulation across methods to ensure consistent and defensible outcomes.

7. Recent Advancements and Emerging Trends

An analogous tendency is the development of AI and machine learning-based sensitivity and validation frameworks, automating the weight tuning process, identifying unstable patterns in decisions, and using prediction models as the means of validating the results, based on either previous or real-time data [26, 27]. The machine learning algorithms are capable of simulating thousands of scenarios and recognition of influential parameters and the weighting of the criteria minimizes the use of judgments that are subjective in nature. Likewise, MCDM based on big data has become common because the issues faced by decision-makers are becoming more based on large-scale, heterogeneous data [25,26]. By combining the big data analytics and MCDM, it is possible to achieve dynamic weighing, the performance evaluation in real-time, and scalability of validation in areas that include smart cities, financial markets, and digital healthcare.

The other direction is also the advanced probabilistic and fuzzy uncertainty modeling, which improves the capabilities of MCDM in managing imprecision, vagueness and variability of data [28,29]. Probabilistic models of uncertainty are based on distributions of uncertainty, as opposed to fixed values, and fuzzy models, interval-based models, and type-2 fuzzy models provide a more comprehensive flexibility in linguistic, or expert-based judgments. Lastly, there are numerous domain-specific innovations, which are aimed at meeting specific needs of industries, including energy optimization, environmental friendliness, intelligent transportation, risk control, healthcare diagnostics, and infrastructure planning [30-32].

8. Challenges and Research Gaps

Although the sensitivity analysis and validation have been developed significantly in the context of MCDM studies, it is important to mention that a number of essential challenges and gaps in the field are still unaddressed [33]. One of the key problems is subjectivity that remains in the judgments of experts, attaching weights, and the evaluation of criteria. Subjective biases can still have an effect even with fuzzy or probabilistic additions and there remains no commonly agreed on mechanism to remove or systematically measure these effects [34,35].

Computational complexity is another issue that is raised prominently, particularly when multiple MCDM techniques are combined in a hybrid model or when robustness testing is carried out through simulation [30,31]. The more complex a model is, e.g., with interdependent criteria, large data, or probabilistic models, the more computationally costly it becomes, and thus the techniques are not easily useable in real-time or when resources are limited. Moreover, a standard format of literature on how sensitivity analysis and validation is done and reported does not exist [29, 30]. The range of perturbation, statistical tests or validation standards is inconsistently used in different studies, and thus, results cannot be compared across applications or recreations of decision processes.

There are also a small number of validation models in the field, with a large number of studies based on simple consistency checks or on expert judgments as opposed to rigorous statistical or cross-method validation. This limited range limits the richness and reliability of robustness testing, especially in information-consuming or unpredictive space [32,34,35]. Lastly, the issue of reproducibility still exists as most MCDM papers lack full datasets, parameterization, and algorithm descriptions.

9. Future Directions and Conclusions

Future MCDM studies are anticipated to change towards more intelligent, adaptive, automation-based paradigms in response to the increasing complexity of the real-world decision environments. Among these directions is the trend of more and more automating the model development, with intelligent algorithms that can autonomously generate decision hierarchies, and choose the best weighting strategies, and also conduct real-time validation with minimal human intervention required [36]. This phenomenon is in line with the growing demand of smart validation approaches that can constantly examine consistency, strength, stability particularly on large-scale or dynamic applications. The other significant direction is to develop uniform sensitivity analysis procedures. At this point, the sensitivity process is diverse in different studies, which is one of the factors that lead to challenges in reproducibility [34,35]. Formulating universally used guidelines to perturbation design, to variation of parameters and to robustness scoring will make sure that similar and transparent and repeatable results on different domains can be achieved.

It is also likely that emerging studies will aim at combining MCDM with recent AI-based uncertainty quantification algorithms, with probabilistic deep learning, Bayesian networks, and ensemble learning. Such methods have the advantage of being able to represent more realistically the sources of complex uncertainty, which may be ambiguity, variability, and incomplete information, and, in the end, enhance the accuracy of recommendations about decisions [367]. Moreover, interest is increasing in the dynamic and real-time MCDM systems that can accept real-time data, refresh priorities immediately, and generate responsive rankings in the fast-changing contexts such as financial markets, intelligent manufacturing, and disaster management. Big-data pipelines and high-performance computers architectures will be used to support such real-time systems.

Lastly, there are great possibilities of domain-specific methodological innovations. Such innovations can comprise multi-layered weighting system, context performance measures, and domain sensitivity engine to capture sectoral uncertainties [37]. As a combination, these future directions put MCDM research in a position to evolve into more intelligent, transparent, scalable and context sensitive decision support systems that can support the ever more complex challenges presented by industries and other areas of the society.

This review provides the growing sophistication and methodological development of the modern multi-criteria decision-making, and the key role of the weighting techniques to generate sound and credible results. The results confirm that sensitivity analysis and validation are not just optional procedures but key components without which the credibility, strength as well as transparency of MCDM results cannot be guaranteed in the context of a broad spectrum of application fields. With the increasing uncertainty and data-heavy and computationally expensive decision environments, there is a necessity to implement hybrid frameworks, intelligent automation, and sophisticated uncertainty modeling. The presented insights support the main thesis that effective multi-criteria decision-making in current and future research is based on strong weighting strategies, systematized sensitivity and validation practices.

Acknowledgement
This research was not funded by any grant.

Conflicts of Interest
Authors declare that this study has no known competing.

References
[1] Sahoo, S. K., & Goswami, S. S. (2023). A comprehensive review of multiple criteria decision-making (MCDM) methods: advancements, applications, and future directions. *Decision Making Advances, 1*(1), 25-48. https://doi.org/10.31181/dma1120237
[2] Więckowski, J., Sałabun, W., Kizielewicz, B., Bączkiewicz, A., Shekhovtsov, A., Paradowski, B., & Wątróbski, J. (2023). Recent advances in multi-criteria decision analysis: A comprehensive review of applications and trends. International Journal of Knowledge-based and Intelligent Engineering Systems, 27(4), 367-393. https://doi.org/10.3233/KES-230487
[3] Kumar, R., & Pamucar, D. (2025). A comprehensive and systematic review of multi-criteria decision-making (MCDM) methods to solve decision-making problems: two decades from 2004 to 2024. *Spectrum of Decision Making and Applications, 2*(1), 178-197. https://doi.org/10.31181/sdmap21202524
[4] Demir, G., Chatterjee, P., & Pamucar, D. (2024). Sensitivity analysis in multi-criteria decision making: A state-of-the-art research perspective using bibliometric analysis. *Expert Systems with Applications, 237*, 121660. https://doi.org/10.1016/j.eswa.2023.121660
[5] Moktadir, M. A., Paul, S. K., Bai, C., & Santibanez Gonzalez, E. D. (2025). The current and future states of MCDM methods in sustainable supply chain risk assessment. *Environment, Development and Sustainability, 27*(3), 7435-7480. https://doi.org/10.1007/s10668-023-04200-1
[6] Więckowski, J., Hernes, M., & Sałabun, W. (2025). Comparison of Multi-Criteria Decision Analysis methods under comprehensive sensitivity analysis. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3588166
[7] Sahoo, S. K., Pamucar, D., & Goswami, S. S. (2025). A review of multi-criteria decision-making (MCDM) applications to solve energy management problems from 2010-2025: Current state and future research. *Spectrum of Decision Making and Applications, 2*(1), 219-241. https://doi.org/10.31181/sdmap21202525
[8] Ismail, M. M., Abdelhady, H. R., & Emad, M. (2024). Multi-criteria decision-making techniques: a comprehensive review of methodologies and applications. *International Journal of Computers and Informatics (Zagazig University), 2*, 27-38. https://www.ijci.zu.edu.eg/index.php/ijci/article/view/70
[9] Khan, N. A., Kumar, A., & Rao, N. (2025). An Insight into Multi-Criteria Decision Methods for the Selection of Robot: A Comprehensive Review. *SN Computer Science, 6*(6), 612. https://doi.org/10.1007/s42979-025-04143-6
[10] Rishabh, R., & Das, K. N. (2025). A critical review on metaheuristic algorithms based multi-criteria decision-making approaches and applications. *Archives of Computational Methods in Engineering, 32*(2), 963-993. https://doi.org/10.1007/s11831-024-10165-9

[11] Avramova, T., Peneva, T., & Ivanov, A. (2025). Overview of Existing Multi-Criteria Decision-Making (MCDM) Methods Used in Industrial Environments. *Technologies, 13*(10), 444. https://doi.org/10.3390/technologies13100444

[12] Singh, R., Pathak, V. K., Kumar, R., Dikshit, M., Aherwar, A., Singh, V., & Singh, T. (2024). A historical review and analysis on MOORA and its fuzzy extensions for different applications. *Heliyon, 10*(3). https://doi.org/10.1016/j.heliyon.2024.e25453

[13] Gyani, J., Ahmed, A., & Haq, M. A. (2022). MCDM and various prioritization methods in AHP for CSS: A comprehensive review. *IEEE Access, 10*, 33492-33511. https://doi.org/10.1109/ACCESS.2022.3161742

[14] Singh, S. P., Mehta, A., & Vasudev, H. (2025). Application of sensitivity analysis for multiple attribute decision making in lean production system. *Engineering Management Journal*, 1-24. https://doi.org/10.1080/10429247.2024.2383855

[15] Ouhmida, S., Moulay Abdelali, H., & Lamdouar, N. (2025). Revolutionizing bridge rehabilitation through artificial intelligence: a comprehensive review and future directions. *Asian Journal of Civil Engineering*, 1-15. https://doi.org/10.1007/s42107-025-01322-x

[16] Murugan, R. S., & Vinodh, S. (2025). Holistic review on design for additive manufacturing. *Progress in Additive Manufacturing, 10*(8), 4497-4532. https://doi.org/10.1007/s40964-024-00887-4

[17] Doost, Z. H., Alsuwaiyan, M., & Yaseen, Z. M. (2024). Runoff management based water harvesting for better water resources sustainability: a comprehensive review. Knowledge-Based Engineering and Sciences, 5(1), 1-45. https://doi.org/10.51526/kbes.2024.5.1.1-45

[18] Ray, S. K. (2025). Integrating Geographic Information System, Artificial Intelligence, and Multi-Criteria Decision Analysis: A Comprehensive Review for Sustainable Urban Settlement Planning. *Applied Spatial Analysis and Policy, 18*(4), 155. https://doi.org/10.1007/s12061-025-09762-3

[19] Gacu, J. G., Monjardin, C. E. F., Mangulabnan, R. G. T., Pugat, G. C. E., & Solmerin, J. G. (2025). Artificial Intelligence (AI) in Surface Water Management: A Comprehensive Review of Methods, Applications, and Challenges. *Water, 17*(11), 1707. https://doi.org/10.3390/w17111707

[20] Abirami, K. M., Veena, N., Srikanth, R., & Dhanasekaran, P. (2024). An extensive review of the literature using the Diophantine equations to study fuzzy set theory. *International Journal of Mathematics and Mathematical Sciences, 2024*(1), 5014170. https://doi.org/10.1155/2024/5014170

[21] Karatzinis, G. D., & Boutalis, Y. S. (2025). A review study of fuzzy cognitive maps in engineering: applications, insights, and future directions. *Eng, 6*(2), 37. https://doi.org/10.3390/eng6020037

[22] Cao, Y., Cui, J., Liu, S., Li, X., Zhou, Q., Hu, C., ... & Liu, Z. (2023). A holistic review on e-mobility service optimization: Challenges, recent progress, and future directions. *IEEE Transactions on Transportation Electrification, 10*(2), 3712-3741. https://doi.org/10.1109/TTE.2023.3311410

[23] El Madou, K., Marso, S., El Kharrim, M., & El Merouani, M. (2024). Evolutions in machine learning technology for financial distress prediction: A comprehensive review and comparative analysis. *Expert Systems, 41*(2), e13485. https://doi.org/10.1111/exsy.13485

[24] Więckowski, J., & Sałabun, W. (2025). Comparative sensitivity analysis in composite material selection: Evaluating OAT and COMSAM methods in multi-criteria decision-making. *Spectrum of Mechanical Engineering and Operational Research, 2*(1), 1-12. https://doi.org/10.31181/smeor21202524

[25] Bilquise, G., Shaalan, K., & AlKhatib, M. (2025). A Comprehensive Review of Virtual Commerce Applications for the Metaverse: Open Issues, Challenges and Recommended Solution for Benchmarking. *International Journal of Human–Computer Interaction*, 1-27. https://doi.org/10.1080/10447318.2025.2499662

[26] Kuhaneswaran, B., Chamanee, G., & Kumara, B. T. G. S. (2025). A comprehensive review on the integration of geographic information systems and artificial intelligence for landfill site selection: A systematic mapping perspective. *Waste Management & Research, 43*(2), 137-159. https://doi.org/10.1177/0734242X241237100

[27] Losada-Agudelo, M., & Souyris, S. (2024). Sustainable operations management in the energy sector: A comprehensive review of the literature from 2000 to 2024. *Sustainability, 16*(18), 7999. https://doi.org/10.3390/su16187999

[28] Yu, S., & Mu, Y. (2022). Sustainable agricultural development assessment: A comprehensive review and bibliometric analysis. *Sustainability, 14*(19), 11824. https://doi.org/10.3390/su141911824

[29] Adem, A., Çakit, E., Dağdeviren, M., Szopa, A., & Karwowski, W. (2025). A Symbiosis of Multi-Criteria Decision Making and Electroencephalography: A Review of Techniques, Applications, and Future Directions. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3562099

[30] Anbari Moghadam, M., & Besiktepe, D. (2025). Synthesis of multi-criteria decision-making applications in facilities management and building maintenance: Trends, methods, and future research directions. *Buildings, 15*(18), 3258. https://doi.org/10.3390/buildings15183258

[31] Mushthofa, M., Thedy, J., Teguh, M., Purwanto, Pratama, A. G., & Han, A. L. (2025). Artificial Intelligence in Geopolymer Concrete Mix Design: A Comprehensive Review of Techniques and Applications. *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, 1-33. https://doi.org/10.1007/s40996-025-01873-8

[32] Abdel-Basset, M., Mohamed, R., & Chang, V. (2025). A multi-criteria decision-making framework to evaluate the impact of industry 5.0 technologies: case study, lessons learned, challenges and future directions. *Information Systems Frontiers, 27*(2), 791-821. https://doi.org/10.1007/s10796-024-10472-3

[33] Lu, Z., Liu, G., Song, Z., Sun, K., Li, M., Chen, Y., Zhao, X., & Zhang, W. (2024). Advancements in technologies and methodologies of machine learning in landslide susceptibility research: current trends and future directions. *Applied Sciences, 14*(21), 9639. https://doi.org/10.3390/app14219639

[34] Kut, P., & Pietrucha-Urbanik, K. (2024). Bibliometric Analysis of Multi-Criteria Decision-Making (MCDM) Methods in Environmental and Energy Engineering Using CiteSpace Software: Identification of Key Research Trends and Patterns of International Cooperation. *Energies, 17*(16), 3941. https://doi.org/10.3390/en17163941

[35] Shah, H. M., Gardas, B. B., Narwane, V. S., & Mehta, H. S. (2023). The contemporary state of big data analytics and artificial intelligence towards intelligent supply chain risk management: a comprehensive review. *Kybernetes, 52*(5), 1643-1697. https://doi.org/10.1108/K-05-2021-0423

[36] Viriyasitavat, W., Da Xu, L., Niyato, D., Bi, Z., & Hoonsopon, D. (2022). Applications of blockchain in business processes: A comprehensive review. *IEEE Access, 10*, 118900-118925. https://doi.org/10.1109/ACCESS.2022.3217794

[37] Tesic, D., Pamučar, D., Demir, G., Puška, A., & Božanić, D. (2026). Aggregation of Expert Ranking Opinions Using Multi-Criteria Decision-Making Methods. *Spectrum of Operational Research*, 1-14. https://doi.org/10.31181/sor202780