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A Comprehensive Review: The Novel Weighting Methods For Multi-Criteria Decision-Making (MCDM)

Arkyadeep Sarkar[1], Shankha Shubhra Goswami[1,*]

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

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ABSTRACT

In Multi-Criteria Decision-Making (MCDM), the importance of the criteria, interpreted relative to each other, defines a key factor that directly determines the accuracy, transparency, and reliability of the final assessment. In the past ten years, there have been tremendous changes in the fields of computational intelligence, uncertainty modelling, and multi-faceted decision frameworks, and the number of novel weighting approaches has gone beyond the constraints of traditional subjective and objective models. This paper provides an in-depth overview of these new methods, including current subjective schemes, objective models derived from data, integrations, fuzzy and probabilistic developments, and artificial intelligence weighting schemes. The review identifies how these methods help enhance robustness, minimize bias, improve uncertainty management, and enable flexibility when faced with complex situations by analyzing peer-reviewed articles published between 2010 and 2025. Comparative reflections are used to identify the methodological strengths, practical limitations, and implementation issues of each group of these weighting strategies. Another important area is the increasing popularity of explainability, universal benchmarking, and big-data integration as key future trends, which are highlighted in the review. On balance, the current research summarizes the dynamic nature of weighting procedures and contributes useful insights regarding their use by researchers, practitioners, and policymakers in search of more reliable and intelligent decision support systems.

1. Introduction

The concept of Multi-Criteria Decision-Making (MCDM) has become one of the main analytical tools that are used to find solutions to complex problems when the decisions should meet a number of criteria, which are often conflicting and sometimes incomparable [1]. With the contemporary decision environments becoming ever-complex, such as sustainable energy planning, industrial optimization, or healthcare prioritization and intelligent transportation systems, the importance of MCDM gains more and more importance as indispensable. The fact that it is also

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

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able to organize problems, measure preferences and rank preferences and to rank alternatives makes it one of the most common methods of decision science that have been applied [2].

Owing to multiple years of development, the list of MCDM techniques has become rich but the accuracy and reliability of the techniques remain to be strongly dependent on the way the relative importance of criteria is calculated. The central part of every MCDM model is criteria weighting since weighting determines the contribution of each factor in the ultimate choice. The change in the allocation of weight by just a little bit prevents the ranking of the alternatives to shift and as a consequence of this, weight determination is a sensitive and critical process [3,4]. The conventional weighting methods like AHP, Entropy and CRITIC have furnished ground on the beliefs of subjectivity and objective patterns of data. This, however, does not hold in decision environments today which are more uncertain and have more dimensions and dynamic relationships among criteria that is challenging to the assumptions of the weighting techniques of the past [5]. As a consequence, there is the increased focus on innovative approaches that can help to strengthen, increase transparency, and flexibility.

The intensive growth of data-driven analytics, artificial intelligence, and fuzzy uncertainty modeling has brought a tidal change in the weighting techniques that provide more accuracy and adaptability. These new methods combine human judgments and computational learning processes and focus on consistency, slower bias, and better representation of the multidimensional relationships [3,6]. As much as these approaches are being applied in different fields, absence of a unified review that explicitly generalises their conceptual premises, methodological contributions and application relevance exist. The existing literature is more inclined to investigate each of these methods separately or small categories and the scholars have not reached a unified picture of how these new techniques are compared to each other or how they are developed.

In this review, this gap is addressed by thoroughly studying the most recent developments of methods of weighting adopted in MCDM research. The aim is to offer a thorough review of recently emerging subjective, objective, hybrid, uncertainty-driven and AI-enhanced weighting schemes [7,8]. The study will also seek to chart their trends of development, determine any limitations in their methodology and determine their appropriateness in the real- world decision-making issues. Because it provided an overarching view of the current state and the direction of the field by synthesizing information scattered across various areas of study, the review provides a comprehensive view of the current state and direction that the field was moving.

There are fourfold contributions of this review. First, it gives a logical summary of new weighting strategies that have emerged in the past couple of years, allowing the reader to get the conceptual heterogeneity of these approaches. Second, it contrasts the approaches with previously existing methods to point out the advancement in consistency, efficacy, and bias reduction [9]. Third, it comes with important perspectives of realistic issues, gaps in research, and future developments to influence the future course of MCDM weighting. Lastly, it is a good source of information to researchers and practitioners trying to understand how to make the right decisions in choosing a suitable weighting strategy within particular decision scenarios. With these contributions, there is high chance of reliable and informed decision-making on contemporary multi-criteria problems.

2. Methodology of the Review

The methodological framework followed in the present case of this review was so aimed as to result in the holistic, transparent, and systematic evidence of the studies that concerned the innovative weighting methodology in the greater framework of MCDM [10,11]. A systematic literature search and filtering process was undertaken to retrieve the available academic work in terms of the theoretical advancement, methodological developments, and application-based studies. Though in this piece, there is no meta-analysis, the study follows the rigor of the existing review guidelines in ensuring that there is clarity, reliability, and reproducibility of the results.

Search was initiated with a narrow search in major scholarly databases that contained vast amount of covering engineering, management, operations research, computer science and decision sciences literature. The consulted databases were Scopus, Web of science core collection, ScienceDirect, IEEE Xplore and SpringerLink and Taylor and Francis Online. These sources have been chosen because they have high indexing of peer-reviewed journals and conference proceedings deemed to be applicable to MCDM and computational decision modelling [11,12]. The search competed several databases, which guaranteed that the research material conducted in both domains of methodological and interdisciplinary application was not filtered into a specific publisher or field.

In order to find out the most suitable literature, a list of precisely selected keywords and Boolean constructs were used. Some of the keywords that were searched were: multi-criteria decision-making, criteria weighting, novel weighting methods, subjective weights, objective weights, hybrid weighting, fuzzy weighting, AI-based weighting, machine learning weighting, and MCDM weighting techniques. The keywords were modified using synonyms that broadened the search to the use of multi-attribute, importance weighting, and decision support models. The results were refined with the help of Boolean operator AND, OR, and NOT to guarantee that only the studies concerned methodological contribution or new weighting concept concepts were obtained [10,13]. Such a strategy enabled the discovery of various articles, such as theoretical advancements, and algorithmic and application-oriented assessments. Table 1 is a summary of the inclusion and exclusion criteria used to guarantee that the studied chosen articles were not obsolete, practical, and concentrated on new approaches to weighting used in the realm of MCDM.

Table 1
Inclusion and exclusion criteria

Criteria type	Specific requirement
	Inclusion criteria
Publication type	Peer-reviewed journal articles, conference papers, and book chapters presenting methodological developments or applications involving novel weighting methods.
Time range	Studies published between 2010 and 2025, covering the period of rapid advancements in hybrid, fuzzy, and AI-enhanced weighting approaches.
Focus area	Articles specifically discussing weighting techniques within the context of MCDM or MADM (Multi-Attribute Decision-Making).
Language	Publications written in English.
	Exclusion criteria
Traditional methods only	Articles focusing solely on conventional weighting methods without proposing any new extensions or modifications.
Irrelevant focus	Studies unrelated to decision-making, despite containing relevant keywords.
Non-peer-reviewed materials	Editorials, theses, dissertations, magazine articles, or other non-peer-reviewed content.
Methodological clarity	Publications lacking detailed explanation of the weighting process or sufficient methodological rigor.

Inclusion and exclusion criteria were used after retrieving the original pool of documents in order to be relevant and of high academic quality. The procedure was done in three phases of screening: initial retrieval screening, title and abstract screening and full-text screening [12,14]. Duplicates analyse was carried out by deleting duplicates with the help of database tools. In the abstract screening stage, the papers that only implemented the usual methods in general, but not made a contribution to the methods, were eliminated. The rest of the articles were subjected to full-text evaluation in order to establish that new or longer weighting methodologies were used. Finally, the review was based on a set of refined publications at the conclusion of the process [13,15]. The systematic selection practice and filtering of relevant studies are illustrated in Figure 1.

To enhance methodological transparency and ensure reproducibility, the literature review process was structured in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. The selection procedure followed four sequential stages.

i. Identification: During the identification stage, a comprehensive search across major academic databases, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, and Taylor & Francis Online, resulted in an initial pool of publications. The search strategy incorporated carefully selected keywords and Boolean operators to capture relevant studies on novel weighting methods in MCDM.

ii. Screening: In the screening phase, duplicate records were removed using database management tools, followed by title and abstract screening to exclude studies that did not focus on methodological contributions to criteria weighting. Articles limited to conventional methods without extensions or innovations were also excluded at this stage.

iii. Eligibility assessment: The remaining studies were subjected to full-text eligibility assessment, where each publication was evaluated based on predefined inclusion and exclusion criteria, including methodological rigor, relevance to MCDM weighting, and clarity of the proposed approach.

iv. Final inclusion: Finally, a refined set of high-quality studies was retained for qualitative synthesis and analysis. The complete selection process, along with the number of records at each stage, is illustrated in the PRISMA flow diagram presented in Figure 1.

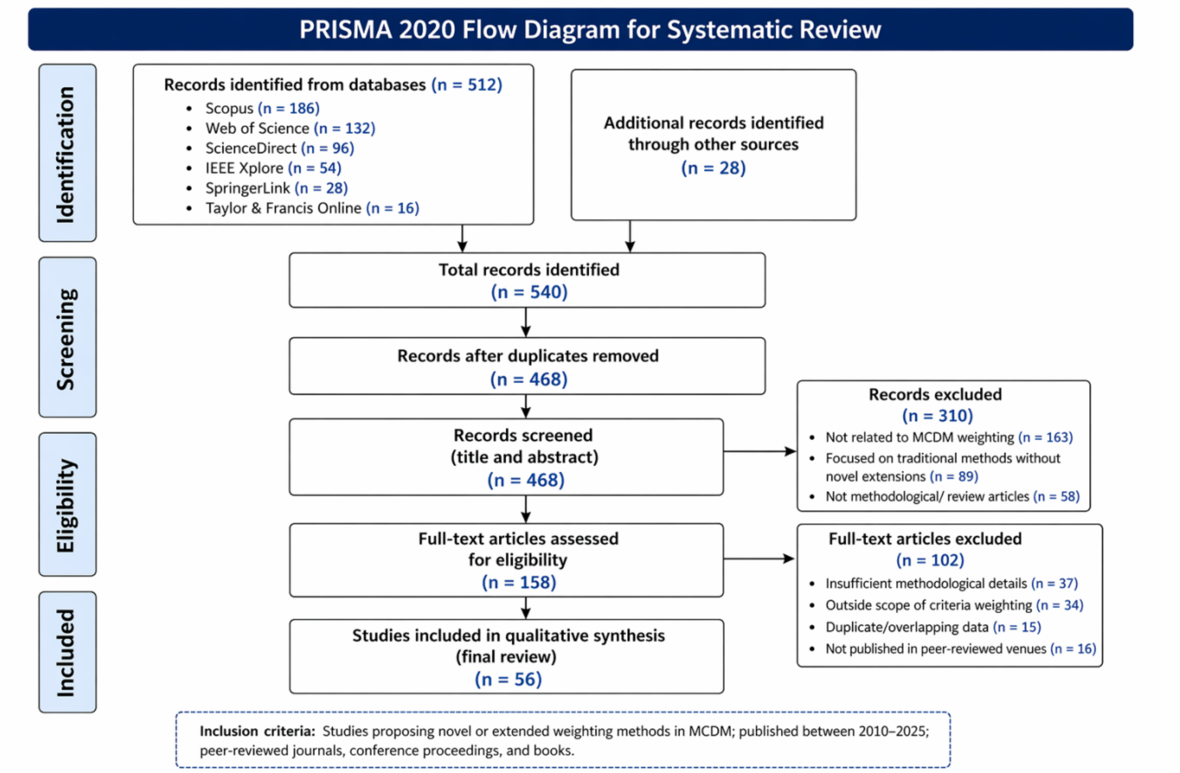


Fig. 1. PRISMA flow diagram illustrating the systematic literature selection process for identifying relevant studies on novel weighting methods in MCDM

The PRISMA flow diagram provides a transparent and structured representation of the literature selection process adopted in this study. It systematically outlines the progression of studies through four key stages: identification, screening, eligibility, and inclusion, thereby ensuring methodological rigor and reproducibility.

In the identification stage, a comprehensive search was conducted across multiple academic databases, resulting in an initial pool of 512 records, supplemented by 28 additional records identified through other sources such as reference lists and manual searches. This yielded a total of 540 potentially relevant studies. During the screening phase, duplicate entries were removed, reducing the dataset to 468 unique records. These records were then subjected to title and abstract screening, leading to the exclusion of 310 studies. The primary reasons for exclusion at this stage included lack of relevance to MCDM weighting methods, focus on purely traditional approaches without methodological advancements, and non-methodological or review-based content. Subsequently, in the eligibility stage, the remaining 158 full-text articles were carefully assessed against predefined inclusion criteria. A total of 102 studies were excluded after full-text evaluation due to factors such as insufficient methodological detail, lack of relevance to criteria weighting, duplication or overlapping contributions, and absence of publication in peer-reviewed venues. Finally, in the inclusion stage, a total of 56 high-quality studies were selected for detailed qualitative synthesis. These studies form the core dataset for the review and underpin the subsequent analysis of traditional, advanced, and emerging weighting methods in MCDM.

Overall, the PRISMA framework ensures that the selection process is systematic, unbiased, and reproducible, thereby enhancing the credibility and scientific robustness of the review.

3. Overview of Weighting Methods in MCDM

In Multi-Criteria Decision-Making (MCDM), the determination of criteria weights constitutes a foundational step that directly influences the evaluation and ranking of alternatives. Each criterion represents a distinct dimension of performance, and the relative importance assigned to these criteria governs the aggregation of decision outcomes. Consequently, even minor variations in weight allocation can significantly alter final rankings, highlighting the sensitivity and criticality of the weighting process [9,10]. A robust weighting framework must therefore accurately reflect decision-maker priorities, contextual requirements, and intrinsic data characteristics to ensure credible and transparent decision support.

To enhance conceptual clarity and methodological coherence, weighting approaches in MCDM can be systematically classified into two primary categories: subjective weighting methods and objective weighting methods [15,16]. This classification forms the theoretical basis for understanding both traditional and emerging hybrid and advanced weighting techniques.

3.1 Subjective Weighting Methods

Subjective weighting methods derive criteria importance based on the judgments, preferences, and experiential knowledge of decision-makers or domain experts [8,9,11]. These approaches are particularly relevant in situations where quantitative data is limited or where strategic, qualitative, or context-specific considerations play a dominant role. Well-established techniques such as the Analytic Hierarchy Process (AHP), Best-Worst Method (BWM), and Stepwise Weight Assessment Ratio Analysis (SWARA) rely on structured elicitation of expert opinions through pairwise comparisons, ranking procedures, or ratio-based assessments [17,18]. These methods enable the incorporation of human intuition, tacit knowledge, and contextual understanding into the decision-making process, thereby capturing nuanced preferences that may not be evident from raw data alone.

However, subjective approaches are inherently susceptible to certain limitations. Variability in expert opinions, cognitive biases, and inconsistencies in judgment can affect the reliability of the derived weights. Although modern extensions such as BWM and FUCOM aim to reduce inconsistency and cognitive burden, the dependence on human input remains a critical consideration [15]. Despite these challenges, subjective methods continue to play a vital role in policy analysis, strategic planning, and domains where expert insight is indispensable.

3.2 Objective Weighting Methods

In contrast, objective weighting methods determine criteria importance based on the intrinsic characteristics of the data, eliminating reliance on human judgment. These approaches utilize statistical, mathematical, or information-theoretic measures to evaluate the contribution of each criterion in distinguishing among alternatives. Prominent objective techniques include the Entropy method, CRITIC (Criteria Importance Through Intercriteria Correlation), and principal component-based approaches, which assess criteria significance based on variability, dispersion, and inter-criteria relationships [11,13,17–19]. For instance, entropy-based methods assign higher weights to criteria exhibiting greater informational diversity, while CRITIC incorporates both contrast intensity and correlation structure to capture discriminative power.

The primary advantage of objective methods lies in their consistency, transparency, and reproducibility, as they are grounded in quantitative data analysis. These methods are particularly effective in data-rich environments such as financial evaluation, industrial performance analysis, and large-scale benchmarking problems [14]. Nevertheless, their exclusive reliance on data may lead to the omission of contextual priorities or strategic considerations, which are often critical in real-world decision-making scenarios.

3.3 Integration toward Hybrid and Advanced Methods

While subjective and objective methods represent two fundamental paradigms of weighting, their individual limitations have led to the emergence of hybrid approaches that integrate both perspectives [19,20]. By combining expert judgment with data-driven insights, hybrid models aim to achieve a balanced and more robust estimation of criteria importance. Furthermore, recent advancements have extended these foundations into more sophisticated frameworks, including fuzzy, probabilistic, and artificial intelligence-based weighting methods [21]. These approaches address uncertainty, ambiguity, and dynamic decision environments, thereby enhancing the adaptability and realism of MCDM models.

Overall, the structured classification into subjective and objective weighting methods provides a coherent conceptual framework for understanding the evolution of weighting techniques [19]. This taxonomy not only improves methodological transparency but also establishes a logical foundation for the detailed review of novel weighting approaches presented in subsequent sections.

4. Review of Novel Weighting Methods

The past few years have seen the emergence of a number of new weighting techniques to make models more accurate, less biased, and also to increase the power of representation of the MCDM models. Among the significant developments, there has been the establishment of novel subjective methods, which focus more on the enhancement of expert judgment and structure [15,18,19]. Other means like the Best-Worst Method (BWM), Full Consistency Method (FUCOM) and Stepwise Weight Assessment Ratio Analysis (SWARA) are much better preference elicitation mechanisms than conventional methods. They mitigate the impact of inconsistency and decision fatigue through these models which minimize the number of pairwise comparisons or provide ratio-based assessment which is more reflective of human judgement [22]. The advantageous fact that grants them popularity is their capability to ensure transparency and to take cognitive load off professionals, which makes them especially successful in such areas as supply chain management, environmental planning, or estimating urban infrastructure.

These developments have been accompanied by the introduction of new objective methods of weighting to be used to calculate the criterion importance based on data patterns instead of subjective preferences. Several extension of the CRITIC technique, enhanced Entropy-based models and dispersion-sensitive measures now provide elegant means of capturing the richness of information and defining criteria with robust discriminative ability [15,16]. Others use correlation correction where some methods are based on maximization of variance, some are based on normalization and some are based on normalization and improvement [23]. The use of data envelopment analysis (DEA)-based weighting techniques has also received some focus because of its capability in providing weights based on evaluating performance of alternatives giving it an analytical view of approaching performance measurement in conjunction with determining weights. These objective methods are used more and more in financial risk assessment, performance benchmarking and resource allocation problems when the data is readily available and the decision-makers tend to choose mathematically based weighting structures.

The development of hybrid weighting models is a significant change towards merging human judgment and the information-driven insights. These models tend to balance the shortcomings of the subjective and objective view by integrating complementary approaches [6,7,10]. The combinations like AHP-Entropy, BWM-CRITIC, FUCOM-Entropy and DEMATEL-ANP are popular as this allows professionals to provide primary preferences and at the same time data patterns are used to narrow down the final weights. Combinative methods aid in reducing the drawbacks of each of the separate techniques by balancing the elimination of bias, consistency and alignment with context [22,24]. They are specifically useful when dealing with complex decision-making situations in which qualitative expertise and quantitative data need to be taken into consideration at the same time like in planning a renewable energy system, designing a transportation system, analyzing suppliers and making strategic policy decisions.

On the same front as the hybrid models, fuzzy and uncertainty-based techniques have also made significant progress and prove to be robustly applicable to the decision-problem problems with vague, imprecise, or incomplete information (refer to [19] and [20] are only examples). Such techniques as fuzzy AHP, intuitionistic fuzzy weighting, hesitant fuzzy sets, rough set-based models, and grey system weighting methods are meant to effectively measure the uncertainty by capturing criteria importance in probability probability distributions or approximation bounds as a matter of membership, hesitation, probability distributions or approximation boundaries [25]. Such models come into play particularly in regions where human perceptions are involved in making a decision or where there is no definite numerical value. These are healthcare diagnosis, evaluation of environmental sustainability, risk analysis, and social policy evaluation [26]. By taking uncertainty into account in a more explicit manner, these methods provide a higher aptitude to flex and aid in making sure the decisions stand by even in cases where the information is not complete or changing.

The weighting landscape is also getting redefined through the application of artificial intelligence because automated, adaptive and data-driven optimization of weights are all feasible. Neural networks, genetic algorithms, particle swarm optimization, ant colony optimization, and reinforcement learning are machine learning approaches which are increasingly being used to generate or optimize weights [21,25]. These AI-based algorithms can be trained on previous data or use large-scale search and discover the best configurations of weights. They perform well in dynamic or high-dimensional decision environments in which the conventional techniques of weighting may fail. AI-based weighting methods are highly optimistic in predictive maintenance, portfolio optimization, smart city planning, and other complex engineering systems, and are generally more effective than various fixed weighting methods [24,26]. They are especially helpful in fast changing areas because of their capacity to revise weights continuously upon the arrival of new information.

In these families of new weighting techniques, there are a number of real-life examples of increasing trends and methodological preferences. As an example, BWM and FUCOM were widespread in recent sustainability and logistics research because of their effectiveness and minimal judgmental complexity [18,19]. Applications that use large amounts of data, e.g. environmental monitoring and analysis of industrial performance, are dominated by entropy and variants of CRITIC. Hybrid models, particularly the one where the subjective judgment is paired with fuzzy or probabilistic extensions, are becoming more preferable in socio-technical problems where the uncertainty is not less important [12]. In the meantime AI-enabled weighting systems are rapidly growing in directions where predictive modeling and decision support in real time are involved, courtesy of the greater computational power as well as the availability of huge amounts of data.

To conclude, the new perspectives of novel weighting approaches to MCDM have been more eclectic, advanced and practical. Every type of technique: subjective, objective, hybrid, fuzzy, and AI-enhanced, deals with various weaknesses of the traditional approaches that provide more flexible and context-appropriate approaches to decision issues today [26,27]. These innovations represent a definite direction of combining human knowledge and computational intelligence and focusing on managing uncertainty and methodological perfection. The increasing trends of the application of the new methods in various industries highlight the increased applicability of the method and the necessity of the ongoing research to optimize their functioning and define its usefulness.

4.1 Review of Other Objective Weighting Methods

In addition to classical objective weighting techniques, recent years have witnessed the emergence of several advanced data-driven methods that aim to overcome the inherent limitations of traditional models such as Entropy and CRITIC. These modern approaches focus on improving sensitivity, robustness, and the ability to capture complex interdependencies among criteria. One notable advancement is the Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW) method, which determines criteria weights based on the logarithmic transformation of percentage variations across alternatives. Unlike entropy, which primarily measures dispersion, LOPCOW emphasizes relative rate of change, thereby providing a more stable and scale-insensitive weighting structure. This makes it particularly effective in datasets where proportional differences are more meaningful than absolute variability. Furthermore, LOPCOW avoids excessive sensitivity to extreme values, which is a known limitation in entropy-based formulations.

Another important contribution is the Weighted Euclidean Norm Standardized Logarithmic Objective (WENSLO) method, which integrates normalization, logarithmic scaling, and Euclidean distance concepts to evaluate criteria importance. WENSLO enhances discrimination capability by combining magnitude and distributional characteristics of data, allowing it to better capture subtle variations among criteria. Compared to CRITIC, which relies heavily on correlation structures, WENSLO provides a more balanced representation of dispersion and relative influence, especially in high-dimensional decision problems. The Method based on the Removal Effects of Criteria (MEREC) represents a fundamentally different perspective by evaluating the importance of each criterion through its impact on the overall decision outcome when removed. In this approach, weights are assigned based on the degree to which the exclusion of a criterion alters the performance of alternatives. This removal-based sensitivity analysis enables MEREC to directly quantify marginal contribution, offering a more intuitive and decision-oriented interpretation of weight significance. Unlike entropy and CRITIC, which rely on statistical properties, MEREC aligns closely with the concept of functional relevance within the decision model, thereby enhancing interpretability.

Similarly, the Integrated Determination of Objective Criteria Weights (IDOCRIW) method combines entropy measures with deviation-based analysis to produce more robust and balanced weights. By integrating multiple objective perspectives—namely information content and contrast intensity—IDOCRIW mitigates the bias associated with relying on a single statistical metric. This hybridization within the objective framework improves stability and reduces the risk of over- or under-weighting criteria due to isolated data characteristics. Collectively, these contemporary methods represent a significant advancement over traditional objective weighting techniques. While entropy focuses primarily on information dispersion and CRITIC incorporates correlation structure, newer approaches such as LOPCOW, WENSLO, MEREC, and IDOCRIW introduce enhanced sensitivity analysis, multi-dimensional data interpretation, and improved robustness against data irregularities. Moreover, they are better suited for modern decision environments characterized by high dimensionality, non-linearity, and complex interdependencies among criteria. The growing adoption of these methods in recent literature highlights a clear shift toward more adaptive and analytically sophisticated objective weighting frameworks. Their inclusion in this review not only strengthens its comprehensiveness but also provides a more accurate representation of current research trends in MCDM weighting methodologies.

4.2 Review of Other Subjective Weighting Methods

In addition to classical subjective weighting methods such as AHP, BWM, and SWARA, recent years have seen the development of several advanced approaches that aim to improve consistency, reduce cognitive burden, and enhance the reliability of expert-driven weight elicitation processes. One such method is the Level-Based Weight Assessment (LBWA) approach, which introduces a structured mechanism for assigning weights based on hierarchical grouping of criteria into different importance levels. Unlike pairwise comparison-based techniques, LBWA reduces the number of required judgments by allowing decision-makers to classify criteria into predefined levels and then assign relative importance within each level. This significantly minimizes cognitive complexity and inconsistency, making LBWA particularly suitable for large-scale decision problems with numerous criteria. Furthermore, LBWA enhances transparency by providing a clear and intuitive mapping between qualitative importance levels and quantitative weights.

Another notable advancement is the Defining Interrelationships Between Rankings (DIBR) method, which determines criteria weights based on the relative ranking positions assigned by decision-makers. Instead of relying on exhaustive pairwise comparisons, DIBR utilizes ranking-based information to construct weight vectors, thereby simplifying the elicitation process. The method captures the ordinal relationships among criteria and transforms them into quantitative weights through structured mathematical formulations. This approach reduces subjectivity-induced inconsistencies while maintaining alignment with expert preferences. Building upon this foundation, the DIBR II method represents an enhanced version that incorporates improved normalization and aggregation mechanisms to produce more stable and discriminative weight distributions. DIBR II addresses certain limitations of the original DIBR method, such as sensitivity to ranking ties and limited differentiation among closely ranked criteria. By refining the transformation process from ordinal rankings to cardinal weights, DIBR II achieves greater robustness and improved sensitivity, making it more suitable for complex decision environments where subtle distinctions among criteria are critical.

These contemporary subjective weighting methods offer several advantages over traditional approaches. While AHP provides a comprehensive pairwise comparison framework, it often suffers from consistency issues and high cognitive load, especially in large decision problems. BWM reduces the number of comparisons but still requires structured pairwise judgments. SWARA simplifies the process through stepwise evaluation but remains dependent on sequential subjective assessments. In contrast, LBWA, DIBR, and DIBR II introduce more efficient elicitation mechanisms, reduce the burden on decision-makers, and enhance consistency without compromising the representation of expert knowledge. Moreover, these methods are increasingly being adopted in recent applications across supply chain management, sustainability assessment, risk analysis, and engineering decision-making, reflecting their practical relevance and methodological maturity. Their integration into the present review ensures a more comprehensive and up-to-date representation of subjective weighting techniques, aligning the manuscript with current advancements in the MCDM domain.

To enhance the clarity and comparative understanding of the diverse weighting methods discussed in this review, a systematic synthesis is presented in Table 2. The table categorizes major weighting approaches based on their methodological type, input requirements, computational complexity, strengths, limitations, and typical application domains. This structured representation enables a direct comparison between classical and contemporary methods, highlighting their relative advantages and suitability under different decision-making scenarios. From the synthesis, it is evident that subjective methods such as AHP, BWM, and their recent extensions (LBWA, DIBR, DIBR II) primarily emphasize expert knowledge but vary in terms of cognitive complexity and consistency. Objective methods, including both traditional (Entropy, CRITIC) and modern approaches (LOPCOW, WENSLO, MEREC, IDOCRIW), differ in their ability to capture data variability, interdependencies, and sensitivity to changes. Hybrid and advanced methods further extend these capabilities by integrating multiple perspectives or leveraging computational intelligence.

This comparative framework not only improves readability but also provides practical guidance for selecting appropriate weighting techniques based on problem characteristics, data availability, and required analytical depth.

Table 2
Comparative synthesis of major weighting methods in MCDM

Method	Type	Input requirements	Computational complexity	Key strengths	Limitations	Typical applications
AHP	Subjective	Pairwise comparison matrix	High (consistency checks)	Structured, intuitive, widely accepted	Inconsistency, high cognitive load	Policy analysis, engineering decisions
BWM	Subjective	Best & worst criteria comparisons	Moderate	Reduced comparisons, improved consistency	Still dependent on expert judgment	Supplier selection, logistics
SWARA	Subjective	Sequential expert evaluation	Low	Simple, flexible	Order-dependent bias	Sustainability assessment
LBWA	Subjective	Criteria grouping into levels	Low	Reduced cognitive burden, scalable	Less precise for close criteria	Large-scale decision problems

Table 2
Continued

Method	Type	Input requirements	Computational complexity	Key strengths	Limitations	Typical applications
DIBR	Subjective	Ranking of criteria	Low	Simple, avoids pairwise comparisons	Limited differentiation sensitivity	Risk analysis, evaluation problems
DIBR II	Subjective	Ranked criteria with refinement	Low–Moderate	Improved robustness over DIBR	Still ranking-dependent	Complex decision environments
Entropy	Objective	Decision matrix	Low	Data-driven, objective	Ignores inter-criteria relationships	Performance evaluation
CRITIC	Objective	Decision matrix + correlation	Moderate	Considers contrast & correlation	Sensitive to data scaling	Financial analysis
LOPCOW	Objective	Decision matrix (log variation)	Low–Moderate	Stable, less sensitive to extremes	Limited interpretability	Engineering, benchmarking
WENSLO	Objective	Normalized data + log scaling	Moderate	Captures magnitude & distribution	Computationally involved	High-dimensional datasets
MEREC	Objective	Decision matrix (removal effect)	Moderate	Measures marginal contribution	Sensitive to dataset structure	Decision sensitivity analysis
IDOCRIW	Objective	Entropy + deviation measures	Moderate	Balanced weighting, robust	Hybrid complexity within objective domain	Industrial decision-making
AHP-Entropy	Hybrid	Expert judgment + data	Moderate–High	Balanced subjective-objective	Increased complexity	Energy planning
DEMATEL-ANP	Hybrid	Influence relationships + expert input	High	Captures interdependencies	Computationally intensive	Strategic planning
Fuzzy AHP	Uncertainty-based	Fuzzy pairwise comparisons	High	Handles ambiguity	Complex parameter selection	Healthcare, environment
Grey weighting	Uncertainty-based	Incomplete data	Moderate	Effective under uncertainty	Limited precision	Risk analysis
AI-based (ML/GA/PSO)	Advanced	Large datasets	High	Adaptive, handles non-linearity	Black-box nature	Smart systems, finance

5. Bibliometric Analysis of Weighting Methods in MCDM

To complement the qualitative synthesis and provide a quantitative perspective on the evolution of weighting methods in MCDM, a bibliometric analysis was conducted using VOSviewer. The analysis was based on the final set of selected publications obtained through the systematic review process. Bibliometric techniques enable the identification of research trends, influential authors, collaborative networks, and thematic structures within a research domain. By mapping relationships among publications, keywords, and citations, this approach provides deeper insight into the intellectual development and emerging directions of the field.

The results are presented through network visualization maps shown in Figure 2 are critically interpreted to identify emerging trends, research clusters, and methodological evolution in MCDM weighting techniques. The dataset was analyzed using three key bibliometric approaches as follows.

- Keyword co-occurrence analysis to reveal dominant research themes
- Co-authorship analysis to identify influential researchers
- Citation and co-citation analysis to highlight foundational works and intellectual structure

First, a keyword co-occurrence analysis was conducted to identify dominant research themes and evolving topics. The visualization reveals several major clusters, including:

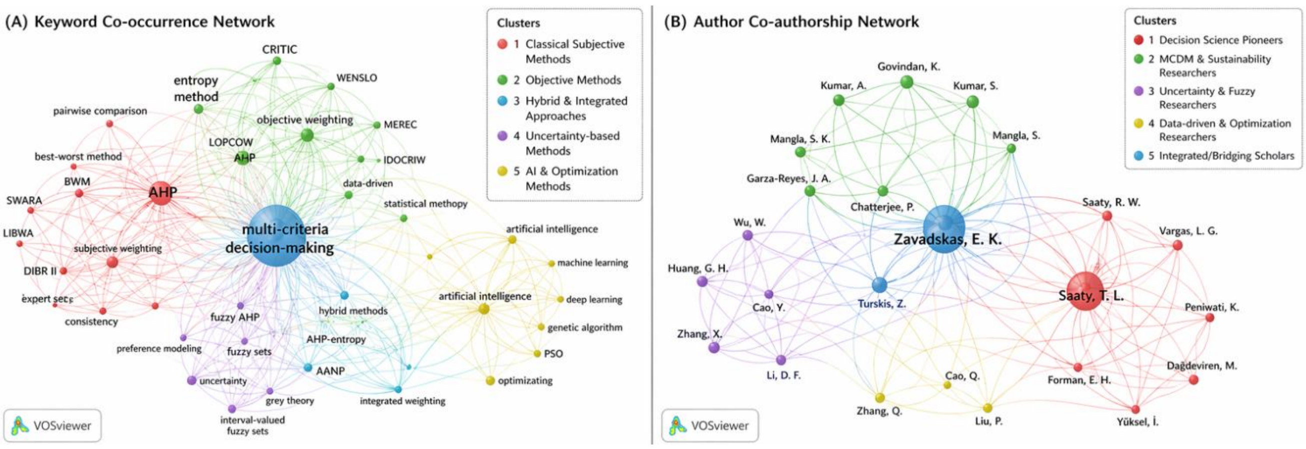
- Classical weighting methods (AHP, Entropy, CRITIC)
- Hybrid and integrated approaches (AHP-Entropy, DEMATEL-ANP)
- Uncertainty-based methods (fuzzy, grey systems, rough sets)
- AI-driven approaches (machine learning, optimization-based weighting)

The prominence of keywords related to artificial intelligence, uncertainty modeling, and hybrid frameworks indicates a clear shift toward more advanced and adaptive weighting methodologies.

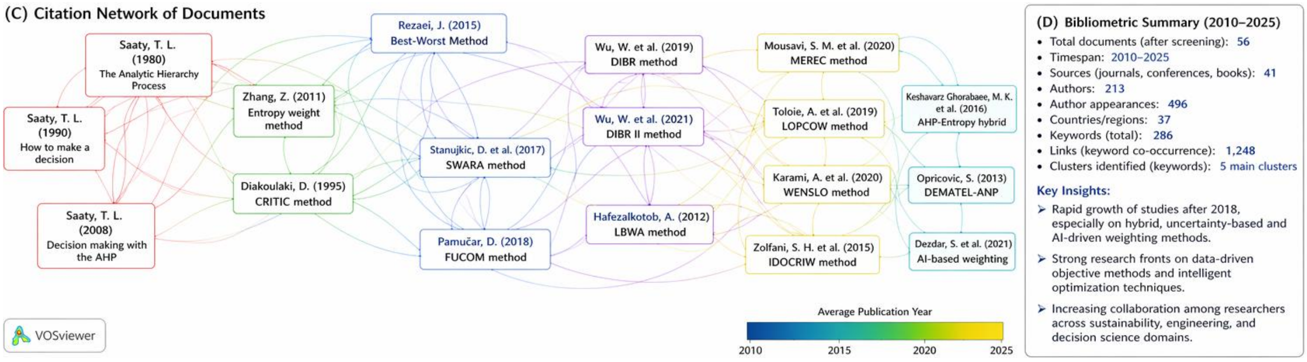
Second, a co-authorship analysis was performed to examine collaboration patterns among researchers. The resulting network visualization highlights key contributors and research groups that have significantly influenced the development of MCDM weighting methodologies. It was observed that the field is characterized by clustered collaboration networks, with several prominent authors contributing extensively to hybrid, fuzzy, and AI-based weighting techniques.

Third, a citation and co-citation analysis was carried out to identify influential publications and the intellectual structure of the field. The results show that foundational works on AHP, entropy-based weighting, and CRITIC continue to serve as core references, while more recent studies on hybrid and AI-based methods are gaining increasing attention.

Overall, the bibliometric findings strongly support the qualitative observations presented in this review. The transition from traditional subjective and objective methods toward hybrid, uncertainty-based, and AI-enhanced approaches is clearly reflected in both keyword trends and citation patterns. This confirms that the development of weighting methods in MCDM is moving toward greater complexity, adaptability, and data integration.



(a) Keyword co-occurrence network (b) Author co-authorship network



(c) Citation network of documents

(d) Overall bibliometric summary and key insights

Fig. 2. Bibliometric analysis of novel weighting methods in MCDM using VOSviewer

The bibliometric visualization generated using VOSviewer provides a quantitative mapping of the intellectual structure, research trends, and collaborative patterns in the domain of weighting methods within MCDM. The figure is organized into four complementary panels: (A) keyword co-occurrence network, (B) author co-authorship network, (C) citation network of documents, and (D) bibliometric summary and insights. The VOSviewer-based bibliometric analysis reveals distinct thematic clusters, evolving research trends, and strong collaboration networks within MCDM weighting methods. The results indicate a clear transition from classical approaches toward hybrid, uncertainty-based, and AI-driven techniques, thereby quantitatively supporting the methodological advancements discussed in this review.

5.1 Keyword Co-occurrence Network

Panel (A) illustrates the co-occurrence relationships among frequently used keywords, where each node represents a keyword and the links indicate the frequency with which two keywords appear together in the same publication. The size of each node reflects its occurrence frequency, while colors denote distinct thematic clusters. The visualization reveals five major research clusters.

i. Classical subjective methods cluster (e.g., AHP, BWM, SWARA): representing foundational decision-making frameworks driven by expert judgment.
ii. Objective methods cluster (e.g., Entropy, CRITIC, LOPCOW, MEREC, IDOCRIW): highlighting data-driven approaches focused on statistical and informational measures.
iii. Hybrid and integrated approaches cluster (e.g., AHP-Entropy, ANP, DEMATEL): emphasizing the integration of subjective and objective paradigms.
iv. Uncertainty-based methods cluster (e.g., fuzzy sets, grey theory): capturing research addressing vagueness and imprecision.
v. AI and optimization cluster (e.g., machine learning, genetic algorithms, PSO): representing the most recent trend toward intelligent and adaptive weighting mechanisms.

The central positioning of “multi-criteria decision-making” indicates its role as the core unifying domain, while the increasing density around AI-related keywords reflects a shift toward advanced computational approaches.

5.2 Author Co-authorship Network

Panel (B) presents the collaborative structure among researchers, where nodes represent authors and links denote co-authorship relationships. Larger nodes correspond to more influential or highly connected authors, and colors indicate collaborative clusters. The network demonstrates that the field is characterized by distinct research communities, including.

i. A cluster of decision science pioneers, contributing foundational works
ii. A group focused on MCDM applications in sustainability and engineering
iii. A cluster specializing in uncertainty modeling (fuzzy/grey systems)
iv. Emerging researchers working on data-driven and optimization-based methods

Highly connected authors (e.g., central nodes in the network) act as bridging figures, linking different research domains and facilitating interdisciplinary knowledge transfer. This indicates a moderate-to-high level of collaboration, which has intensified in recent years.

5.3 Citation Network of Documents

Panel (C) depicts the citation relationships among key publications, thereby revealing the intellectual backbone of the field. Nodes represent individual studies, and directed links indicate citation flows. The network highlights a clear evolutionary trajectory.

i. Foundational works (e.g., early AHP and entropy-based studies) form the core knowledge base
ii. Intermediate developments (e.g., SWARA, FUCOM, hybrid models) extend methodological capabilities
iii. Recent contributions (e.g., LOPCOW, MEREC, WENSLO, IDOCRIW, DIBR II) emerge as innovative nodes, indicating growing scholarly attention

The clustering of newer methods around recent years confirms the rapid expansion of advanced and specialized weighting techniques, reinforcing the argument that the field is transitioning toward more sophisticated models.

5.4 Bibliometric Summary and Key Insights

Panel (D) provides a quantitative summary of the dataset, including total publications, authors, sources, keywords, and identified clusters. It also highlights key trends:

i. A significant increase in publications post-2018, indicating accelerated research activity
ii. Growing emphasis on hybrid, uncertainty-based, and AI-driven methods
iii. Expansion of interdisciplinary applications across engineering, sustainability, and decision sciences
iv. Increasing collaboration among international research groups

These observations quantitatively validate the qualitative findings of the review, particularly the shift from traditional static models to adaptive, data-driven, and intelligent weighting frameworks.

5.5 Overall Interpretation and Contribution

The integrated analysis of these four panels demonstrates that the field of MCDM weighting methods has evolved along three major dimensions.

1. Methodological sophistication – from simple deterministic models to hybrid and AI-based approaches
2. Thematic diversification – from classical methods to uncertainty handling and intelligent systems
3. Collaborative expansion – increasing interaction among researchers across domains

Importantly, the bibliometric results strongly support the central argument of this review: that recent weighting methods do not merely extend traditional techniques but fundamentally enhance robustness, adaptability, and analytical depth in complex decision-making environments.

6. Comparative Discussion

The concept of new weighting means in MCDM has dramatically widened the analytical properties of decision-making models, although their merits and weaknesses are more easily understood when compared to the previous approaches [23,24]. Classical approaches like AHP, Entropy and CRITIC have served as such exceptable grounds because of their simplicity, intuitive design and their convenient application in various disciplines. Nonetheless, their reliance on either completely subjective assessments or purely data-driven trends frequently predetermines their inability to model the complex relationships, uncertainty and changing decision conditions [28]. New strategies are trying to fill in these voids with more flexible models that feature expert knowledge, data properties, and computational intelligence thus allowing a better representation of criterion significance.

One of the main advantages of new subjective methods, such as BWM, FUCOM, and SWARA, is greater methodological consistency and less mental load than their aging counterparts based on a pairwise comparison. These methods facilitationly simplify preference elicitation and generate more stable weight vectors using a fewer number of judgments required [27,28]. On the other hand, they have the downside of being dependent on expert knowledge, which has the potential of bringing individual bias to it particularly where two or more parties are involved or when there is a clash of opinions. The new objective techniques, especially those based on the extensions of the CRITIC or Entropy, are good at uncovering concealed trends and entailing discriminative features, but they can disregard contextual peculiarities that are essential according to specialists [29]. There is also the possibility of lack of human influence on the purely objective methods that could lead to weights that may look mathematically well but not adjusted to the real-world priorities.

This gap is filled by hybrid models which seek to combine the interpretive power of subjective methods with the mathematical accuracy of objective [28]. Their significant strength is in their balance; they seize human judgment where it is needed, and rely the ultimate weights on statistical evidences. The literature keeps demonstrating that such models tend to generate stronger and satisfactory results in comparison with single methodologies, particularly in complicated sectors as environmental sustainability, the transportation strategy, and optimization of supply chain [29,30]. Yet, hybrid structures are occasionally computationally heavy, and their complexity of methodology sometimes makes them hard to implement especially by practitioners who find it easier to use simpler tools.

Uncertainty-oriented approaches, such as fuzzy logic, rough sets, grey systems, and probabilistic weighting are used to overcome one of the major limitations of both classical and modern crisp approaches: they clearly describe the sense of ambiguity in human perception and data. These procedures are especially useful when the express linguistic preferences of decision-maker or when the characteristics of key attributes have no accurate numerical values [26,27]. This flexibility qualifies them to domains of high uncertainty e.g. evaluating risk, medical diagnosis, and assessing social welfare. However, it is difficult to deal with model parameters properly, since inadequate membership functions or ambiguous linguistic scale might cast a novel form of uncertainty on them, which may compromise the intended power of the latter.

Weighting methods that apply AI and machine learning are a step ahead since they can be used to estimate weights adaptively, automatically, and with an optimization-oriented methodology [31]. These algorithms are most effective with large-scale, data-intensive problems, and are able to identify nonlinear relationships and obscure dependencies that are not noticeable by traditional algorithms. The fact that they can also update weights dynamically as new information is available is a significant improvement in fast changing environments decision-making [30]. Nevertheless, interpretability and computational complexity are the main limitations of them. Most AI-based models are considered black boxes and are not easily explainable on how the weights are obtained and this could decrease transparency and acceptance among decision-makers with interpretability inherent in their paradigm.

Information gained in recent literature shows that the choice of the method of weighting is becoming dependent on rather the nature of the decision situation than on the tradition of methods [31,32]. Research always emphasizes that a particular technique is not applicable in all circumstances and thus, every technique works best in particular circumstances. As an example, the subjective models have been maintained in the areas of policy analysis and strategy formulation where they are a source of indispensable knowledge among experts. Objective models are better in the inherent performance of industry and financial assessment as there is sufficient information available [29,30]. Far less predictable and more uncertain hybrid and uncertainty-based models can be most effectively utilized in areas that require a combination of quantitative and qualitative elements, whereas AI-enhanced approaches are rapidly finding their way into the realms of predictive analytics and intelligent systems.

In spite of these developments, there are still a number of challenges. The incredible application of new weighting techniques may need more knowledge of methodology and, in particular, the complicated parameter calibration. Lack of standardization in terms of choosing the right methods of weighting leads to discrepancies in the studies and restricts comparability [33]. In addition, creating a bias reduction model using advanced models can accidentally introduce new types of computation or structure biasness. The question of reliability is also a concern in the case where sophisticated models rely on the quality of data, human calibration, or the stability of an algorithm.

Essentially, the history of the development of the weighting techniques is a process of constant compromising of simple and sophisticated, interpretable and computational accuracy, and of human intuition and systemic intelligence. Although new methods provide greater flexibility, greater uncertainty modelling and power of analysis, they can be implemented successfully only when a careful method selection, transparency, and comprehension of the characteristics of the decision problem are taken into account [34]. The increasing variety of approaches promotes the significance of more extensive comparative assessments and the necessity of standardized systems according to which the practitioners should be led to the reliable and context-specific strategies of weighting.

6.1 Conceptual Evolution Framework of MCDM Weighting Methods

The rapid expansion of weighting methodologies in Multi-Criteria Decision-Making (MCDM) reflects a clear transition from static, assumption-driven models toward adaptive, data-integrated, and uncertainty-aware frameworks. A rigorous comparative analysis reveals that this evolution is not merely incremental but represents a fundamental shift in how criteria importance is conceptualized and quantified. From the perspective of consistency and reliability, traditional subjective methods such as AHP rely heavily on pairwise comparisons, which are prone to inconsistency, especially as the number of criteria increases. Although consistency ratios are used as corrective measures, they do not eliminate the inherent cognitive burden. In contrast, modern approaches such as LBWA and DIBR II significantly reduce the number of required judgments by employing level-based or ranking-based mechanisms. This structural simplification leads to more stable weight estimations while preserving alignment with expert preferences, thereby representing a clear methodological advancement.

In terms of sensitivity and robustness, classical objective methods such as Entropy primarily depend on data dispersion, making them sensitive to extreme values and scale variations. CRITIC improves upon this by incorporating correlation structures, yet it still assumes linear relationships among criteria. Contemporary methods such as LOPCOW and MEREC introduce more refined sensitivity mechanisms. LOPCOW captures logarithmic variation, which stabilizes weight computation across heterogeneous datasets, while MEREC evaluates the marginal contribution of each criterion through removal-based analysis. These innovations enable a more realistic assessment of criterion importance, particularly in complex and non-uniform datasets. The treatment of uncertainty represents another critical dimension of advancement. Traditional weighting methods operate under deterministic assumptions, which limit their applicability in real-world scenarios characterized by vagueness and incomplete information. The introduction of fuzzy, intuitionistic, and grey-based weighting approaches allows for the explicit modeling of ambiguity and linguistic preferences. These methods significantly enhance the representational capability of MCDM models, although they introduce additional complexity in parameter selection and interpretation.

With regard to computational complexity and scalability, earlier methods such as AHP become increasingly inefficient as the number of criteria grows due to exponential increases in pairwise comparisons. Modern subjective methods (e.g., LBWA, DIBR) and objective methods (e.g., IDOCRIW) are specifically designed to reduce computational burden while maintaining analytical rigor. However, advanced AI-based approaches, including machine learning and metaheuristic optimization, often introduce high computational costs despite their superior performance in handling large-scale and nonlinear problems. This highlights an important trade-off between analytical power and computational feasibility. Another key dimension is interpretability and transparency, which are essential for decision-maker acceptance. Traditional methods are generally more transparent due to their structured formulations and explicit calculations. In contrast, AI-based weighting methods, while highly adaptive and accurate, often function as "black-box" models. This lack of explainability can limit their adoption in sensitive domains such as policy-making and healthcare. Consequently, recent research has emphasized the integration of explainable AI (XAI) techniques to address this limitation.

From an adaptability perspective, modern weighting methods clearly outperform traditional approaches. Classical methods assume static decision environments, whereas contemporary techniques—particularly hybrid and AI-driven models—are capable of dynamically updating weights based on new data or changing conditions. This is especially relevant in applications such as smart systems, financial forecasting, and real-time decision support.

Overall, the evolution of weighting methods can be interpreted as a progression across three stages.

(i) Foundational methods, focused on simplicity and interpretability (AHP, Entropy, CRITIC),
(ii) Refined methods, aimed at improving consistency and robustness (BWM, LBWA, LOPCOW, MEREC), and
(iii) Advanced methods, emphasizing adaptability, uncertainty handling, and computational intelligence (fuzzy models, hybrid frameworks, AI-based approaches).

Despite these advancements, no single method can be considered universally superior. Each approach exhibits inherent trade-offs between accuracy, complexity, interpretability, and applicability. Therefore, the selection of an appropriate weighting method must be context-dependent, guided by the nature of the decision problem, availability of data, and the required level of analytical sophistication. This nuanced comparative analysis demonstrates that recent weighting techniques do not merely extend traditional models but fundamentally enhance the robustness, flexibility, and realism of MCDM frameworks, thereby offering substantial added value in addressing complex decision-making challenges. The conceptual framework shown in Figure 3 illustrates the evolutionary trajectory of weighting methods in MCDM, structured across five distinct stages. Each stage represents a progressive shift in methodological sophistication, computational capability, and decision-making realism, reflecting how the field has responded to increasing complexity, uncertainty, and data availability.

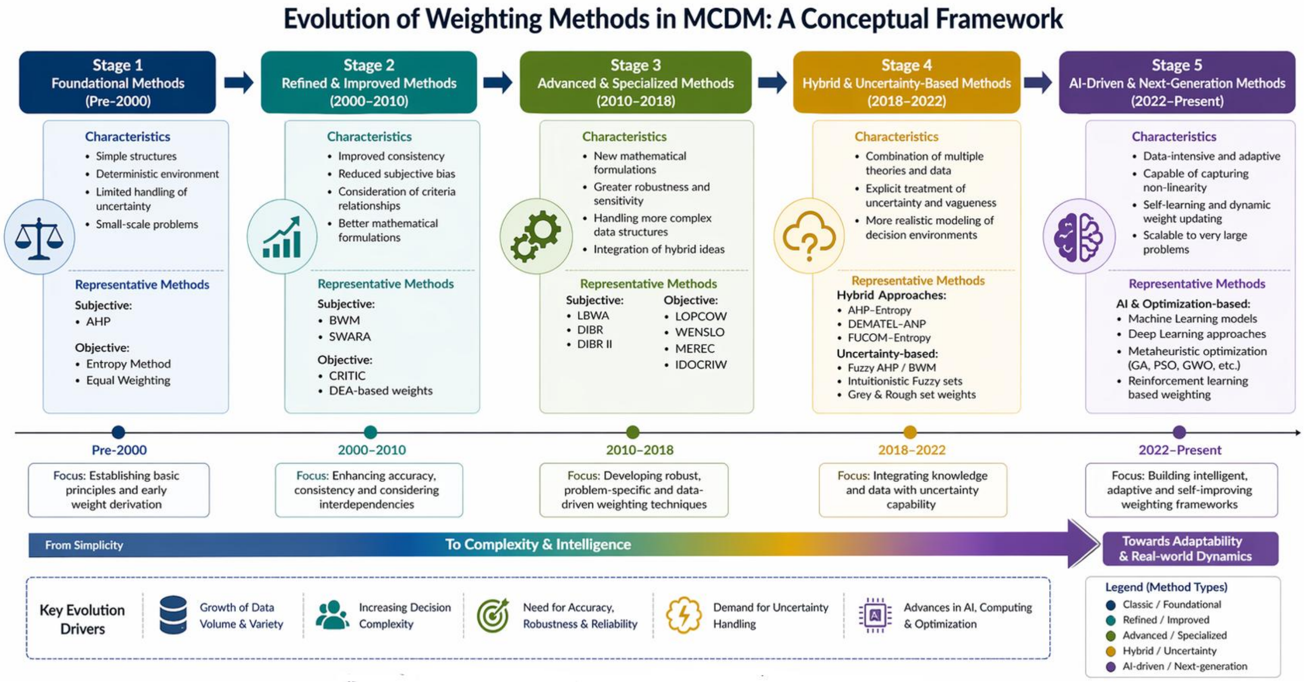


Fig. 3. Conceptual framework showing the evolutionary timeline of weighting methods in MCDM

6.1.1 Stage 1: Foundational methods (Pre-2000)

The first stage represents the origin of weighting methodologies, characterized by relatively simple, deterministic frameworks. Methods such as AHP and basic entropy-based approaches dominate this phase, focusing on establishing fundamental principles of criteria importance and decision structuring. These methods assume the following.

i. Stable and well-defined decision environments
ii. Limited number of criteria
iii. Minimal consideration of uncertainty or interdependencies

While highly interpretable and easy to implement, their limited ability to handle complexity and ambiguity restricts their applicability in modern decision contexts. Nevertheless, this stage forms the theoretical backbone of all subsequent developments.

6.1.2 Stage 2: Refined and improved methods (2000–2010)

The second stage reflects efforts to enhance consistency, reduce subjectivity bias, and incorporate inter-criteria relationships. Methods such as BWM, SWARA, and CRITIC emerged during this period, addressing key limitations of earlier techniques. Key advancements include.

i. Reduction in pairwise comparison burden (e.g., BWM)
ii. Improved mathematical formulations for weight derivation
iii. Initial consideration of criteria correlation and variability (CRITIC)

This stage marks a transition from purely conceptual models to more mathematically robust frameworks, though methods still largely operate under deterministic assumptions.

6.1.3 Stage 3: Advanced and specialized methods (2010–2018)

In this stage, weighting methods become more problem-specific, data-sensitive, and analytically refined. New approaches such as LBWA, DIBR, DIBR II (subjective), and LOPCOW, WENSLO, MEREC, IDOCRIW (objective) are introduced. The defining characteristics of this phase include.

i. Development of alternative elicitation mechanisms (e.g., ranking-based, level-based methods)
ii. Enhanced robustness and sensitivity analysis
iii. Better handling of heterogeneous and high-dimensional datasets

Unlike earlier methods, these approaches are designed to directly address specific methodological limitations, such as inconsistency, sensitivity to extreme values, and computational inefficiency. This stage represents a clear move toward methodological optimization and diversification.

6.1.4 Stage 4: Hybrid and uncertainty-based methods (2018–2022)

The fourth stage reflects a significant paradigm shift toward integration and uncertainty modeling. Researchers increasingly combine subjective and objective methods (e.g., AHP-Entropy, DEMATEL-ANP) while incorporating uncertainty frameworks such as fuzzy sets, intuitionistic fuzzy sets, grey theory, and rough sets. Key features include.

i. Explicit modeling of ambiguity, vagueness, and incomplete information
ii. Integration of multiple methodologies to leverage complementary strengths
iii. More realistic representation of complex decision environments

This stage addresses one of the most critical limitations of earlier methods—the inability to capture real-world uncertainty—thereby significantly enhancing the applicability of MCDM models.

6.1.5 Stage 5: AI-Driven and next-generation methods (2022–Present)

The final stage represents the current frontier of weighting methodologies, characterized by the integration of artificial intelligence, machine learning, and optimization techniques. Methods in this category include deep learning-based weighting, metaheuristic optimization (e.g., genetic algorithms, particle swarm optimization), and reinforcement learning approaches. These methods exhibit.

i. Ability to capture non-linear and complex relationships
ii. Dynamic and adaptive weight updating mechanisms
iii. Scalability to large and real-time datasets

However, this advancement comes with trade-offs, particularly in terms of interpretability and computational complexity, as many AI-based models function as black-box systems.

The conceptual framework illustrated in Figure 3 reveals a set of interrelated evolutionary trends that collectively characterize the transformation of weighting methods in MCDM. Initially, early approaches were developed with an emphasis on simplicity and interpretability, relying on structured yet relatively straightforward formulations. However, contemporary methods prioritize higher levels of accuracy, robustness, and analytical depth, even at the expense of increased computational and methodological complexity. This progression is closely associated with a fundamental shift from deterministic models toward uncertainty-aware frameworks, where ambiguity, vagueness, and incomplete information are explicitly incorporated into the decision-making process, thereby enhancing real-world applicability.

Simultaneously, the evolution reflects a transition from static to dynamic paradigms. Traditional weighting techniques typically assume fixed and invariant criteria weights, whereas modern approaches—particularly those driven by artificial intelligence and optimization—enable adaptive, data-responsive, and real-time weight adjustments. In parallel, there has been a notable movement from isolated methodological structures toward integrated and hybrid frameworks. Contemporary models increasingly combine subjective judgment, objective data-driven insights, and computational intelligence, resulting in more balanced and comprehensive weighting mechanisms. These transformations are driven by several critical factors, including the exponential growth in data volume and diversity, increasing complexity and interdependencies within decision systems, the demand for greater accuracy and robustness, and the necessity to effectively handle uncertainty and ambiguity. Additionally, rapid advancements in computational intelligence, machine learning, and optimization techniques have provided the technical foundation for developing more sophisticated and adaptive weighting models.

Overall, the evolution of weighting methods in MCDM can be understood as a progressively transformative process rather than a linear progression. Modern approaches do not merely extend traditional techniques but fundamentally redefine the weighting paradigm by incorporating adaptability, intelligence, and enhanced uncertainty modeling. The proposed conceptual framework thus offers a unified and systematic perspective on this evolution, enabling researchers and practitioners to better understand the current state of the field, trace the trajectory of methodological advancements, and identify the most appropriate weighting approaches for specific decision-making contexts. In essence, the framework highlights a clear transition from foundational deterministic models to advanced, adaptive, and AI-driven methodologies, reflecting the increasing complexity and dynamic nature of contemporary decision environments.

7. Practical Implications

This has a direct practical contribution in the Multi-Criteria Decision Making (MCDM) framework on novel methods of weighting in the region of contemporary multi-technology particularly toward the design, justification and implementation of multi-faceted decisions as uncertainty grows [23,25,29]. To researchers, the widening range of subjective, objective, hybrid, fuzzy, probabilistic, and AI-driven weighting methods can be found to offer a more analytic level of research on the study of preference structures, ambiguous data management, and enhancing reliability within multi-criteria assessments. These sophisticated techniques enable researchers to simulate the human judgment in a more realistic manner, reduce biases that have traditionally corrupted the pairwise comparisons, and combine various information sources at the same time [31]. Consequently, scholars can acquire the ability to come up with more rigorous models, justify cross-method consistency and also be involved in the creation of methodological innovation. This increasing methodological heterogeneity even brings about possibilities of comparative research, meta-analyses and the construction of domain specific weighting models that suit the application of specific uses in engineering, climate research, healthcare and finance.

To the industry practitioners, the new weighting strategies introduce a lot of operational importance thanks to the better transparency, defensibility and flexibility of the decision-making models. Companies are able to assess their suppliers, technologies, risk portfolio, product design, and sustainability plans more accurately, especially in situations where the market changes fast or the information is incomplete [32,35]. The use of fuzzy and probabilistic weighting as allows companies to include expertise ambiguity, but without reducing analytical rigor, and machine-learning-based models can determine unobservable trends in operational data affecting the criteria importance. These increased capabilities minimize errors in decisions, smart allocation of resources and make strategic planning strong [33]. Furthermore, hybrid weighting are the methods that combine the human judgment with quantitative evidence to help organizations to make balanced and responsible decision making that cannot be subject to managerial analysis, regulatory demands and market competition.

The practical consequences are especially important to the policymakers because any decision made by the populace has routinarily encountered the issues of uncertainty, competing interests, conflicting priorities, and myriad of stakeholder interests [26,27]. The new form of weighting gives governments and regulatory authorities consistent, transparent means of evaluating trade offs, e.g., in planning infrastructure, evaluating environmental impacts, implementing interventions to promote the health of the population, making transitions to energy, and developing socioeconomic development plans. A possibility to introduce the expert consensus, objective data, and algorithmic insights benefits the legitimacy and fairness of policy decisions [36,37]. Moreover, the usage of the advanced weighting models will allow the incorporation of the long-term risk situations, equity aspects, and sustainability indicators, which will make the process of policymaking more inclusive and future-oriented. Such approaches also facilitate evidence-based governance through the minimization of subjectivity, strengthening of cross-stakeholder discussion, and augmentation of the strength of evaluations in the public sector.

In general, the applied implications of innovative weighting approaches speak of a scale-shifting change in the process of the decision-making construction and rationalization in the academic, industrial, and policy spheres [34]. These sophisticated techniques of weighting should become common tools that can enhance efficiency, neutrality, and trustworthiness of stakeholders in complicated epistemic settings as MCDM applications proliferate to other fields like smart cities, renewable energy design, digital transformation, and AI governance.

8. Limitations of the Review

Although the review presents an extensive report on the recent developments in weighting approaches to Multi-Criteria Decision-Making (MCDM), it is important to admit that various drawbacks need to be considered to bring their conclusions to context and interpret the results. To begin with, the limits of the review were deliberately narrowed down to methodological advances in weighting methods and those that have been developed since 2010 to 2025 [32,33]. Though this period represents the latest innovations, it could do away with earlier research that establishes the basis of the specific hybrid or AI models. Moreover, it is clear that most of the approaches introduced in the review are clearly defined as new in the literature, which may ignore more incremental or domain-specific adaptations, which might yield extra knowledge, but that were not discussed in the same terms [31,36]. In turn, the purpose of the review is to be full, whereas it does not cover all weighting methods that have been employed historically or in very specialized versions.

Second, the choice of the database is limited in itself. Despite the systematic search of such large scholarly databases as Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink and Taylor and Francis Online with the scope of papers published in the past decade, the review might have missed some relevant studies that have been indexed in regional or less popular repositories, and non-English ones [36,37]. Certain studies, especially in new areas or interdisciplinary use might not be published in a journal, and may instead be found only in conference proceedings, technical reports or grey literature and this was omitted to ensure that the methodology of the research was rigorous. This selection bias may affect the coverage of the representation of some of the weighting methods or weighting applications, particularly those created in a non-Western environment or within a niche industry.

Third, the review is limited to mathematical consistency checks and standardization standard studies. Although other weighting schemes mainly extrapolations of subjective or hybrid schemes incorporate formal consistency indicators or checking processes, other schemes have no explicit constraints that define the internal consistency or strength [14,15]. The variability in the reporting of these methodology details, sensitivity analysis, and the comparison between the methods used by the studies and those of traditional methods restricts the capability to compare effects in various publications quantitatively. Consequently, the scope of the analysis can be limited in some respects, the review is greatly based on descriptive and qualitative synthesis, as opposed to statistical meta-analysis.

Overall, the limitations in the scope, restriction of databases, and changeability in the rigor of the methods are to be taken into account when the results of this review are interpreted [9,13]. Nevertheless, these limitations are balanced by a systematic, current, and thought-provoking review of the recent developments in the weighting procedures, being instructive of the tendency, uses, and prospective research. The identification of these shortcomings also highlights the necessity of additional systematic reviews, inclusion of more databases and the adoption of uniformed reporting procedures in enhancing the cumulative knowledge on the MCDM weighting methods.

9. Future Research Directions

The fast development of new ways of weighting in MCDM renders a number of prospective studies bound to improve their relevance, credibility, and validity. The introduction of the artificial intelligence and big data analytics in the process of weighting can be considered one of the primary directions [31]. The dynamically generated or refined weights of criterion can be addressed using AI-based approaches, including machine learning, deep learning, reinforcement learning, and metaheuristic optimization, as more and more massive and high-dimensional datasets and real-time information achievements become available. Future studies indicated the need to develop adaptive frameworks with the capability to constantly change the weights in accordance to the ever-changing data, provided complex nonlinear correlations and able to respond to varying decision circumstances [21,26,28]. It can contribute to the accuracy of decision making in many areas (including smart cities, predictive maintenance, healthcare management, and financial portfolio optimization) where the traditional method of static weighting can be inadequate.

The other essential direction is the ability to set the universal benchmarking criteria on the methods of weighting. There is a tendency today to base methodological comparisons on case studies or application-based studies so it is hard to perform objective comparisons of the relative performance of various approaches [13,18]. Further research ought to establish standardized data, measures of performance and testing procedures that can enable systematic benchmarking of subjective, objective, hybrid, fuzzy and AI-enhanced weighting methods. Benchmarking may assist researchers to detect strengths and limitations more seriously, enhance reproducibility, and advise practitioners how to choose methods that were appropriate to their unique decision issues.

The creation of clear and understandable weighting systems can be defined as no less significant research priorities. Although AI-based and hybrid models can provide a high accuracy rate with a high degree of adaptability, they typically serve as a black box, making them unacceptable and non-explainable by decision-makers [16,21]. Future studies can include the application of explainable AI (XAI) concepts and visualization to the weighting models so that the users can track the derivation of the weights, comprehend the behind the scenes assumptions, and make decisions. The transparency models are especially needed in high stakes areas like social policy, healthcare, and lock-in infrastructure where accountability, trust among stakeholders and ethical concerns hold the paramount importance.

Lastly, it is still a challenge to enhance the strength and uncertainty management of the weighting techniques [30]. The environments where decisions are made are often typified by unavailable, inaccurate or even conflicting information, although much of the current methodology oversimplifies uncertainty or assumes that some of the existing assumptions will no longer be true in practice. It needs to conduct future research to enlarge the applicability of the fuzzy logic, rough sets, probabilistic models, grey system theory and hybrid uncertainty models to accommodate the uncertainty of the real world better [9,13,19]. Also, to provide an assurance that weight assignments are correct even in a fluctuating environment or data sites, sensitivity tests and stability tests as well as scenario running must be systematically included. These developments will strengthen the validity, the stability and practical functionality of the MCDM methods in more complex and uncertain settings.

To conclude, the future of the methods of weighting in MCDM is to develop adjustable, transparent, robust, and unified system frameworks based on AI, big data, and uncertainty models. By following up on these research directions, the technical sophistication of the methods of weighting is not only going to improve, but also increase their applicability to more academic, industrial, and policy-oriented decision-making problems.

10. Conclusion

The current review is an in-depth analysis of the recent developments in weighting techniques of Multi-Criteria Decision-Making (MCDM) which points at the increased variety, complexity and applicability of the modern techniques. The major discoveries suggest that new methods of weighting, such as subjective, objective, hybrid, fuzzy, probabilistic, and AI-based models, have optimally increased reliability, the ability to adapt, and representational ability of MCDM models. The BWM and FUCOM subjective innovations have shown better consistency and less cognitive load during expert-based tasks. Objective models, such as refined Entropy and CRITIC extensions, have strong, data-guided weighting schemes which include intrinsic variability in measure of decision criteria. The hybrid models strike a chord between subjective and objective methods and solve uncertainties and vagueness that are usually found in reality situations. The role of AI and machine-learning-based weighting strategies continues to develop the field through the possibility to estimate weights through adaptative and dynamic approaches and to produce weight estimates based on optimization and in a complex and high-dimensional environment.

These innovative weighting techniques are important because they reduced the weaknesses of the older methods and gave better tools to the decision-maker that were more accurate and consistent and context-sensitive. These approaches increase the clarity, equity and strength of the multi-criteria assessments by admitting human opinions, statistical tendencies, ambiguity, and changing situations. They are practical in their applicability beyond research, industry and policy making, as they provide the capacity to make strategic plans, resource allocations, risk assessment and performance assessment with more confidence and accuracy.

These new technologies, besides boosting methodological developments, have a more general side effect on decision-making research, by establishing the usefulness of using computational intelligence, uncertainty modelling, and expert-driven structured judgments as part of classical MCDM methodologies. Synthesis provided in this review does not only seek to clarify the comparative advantages of various weighting approaches but also points to the emerging trends, gaps and opportunities to be looked into in the future. Such a synthesis of the state of art in weighting processes gives this work an underlying reference to the scholars and practitioners seeking to increase the quality of decision making, the rigor and applicability of methods that can be applied in different fields. Conclusively, the current progress and enhancement of new weighting methods are bound to enhance general reliability, dynamism, and influence of MCDM in solving multi-dimensional decision situations in modern situations.

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There is no conflict of interest to disclose.

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