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Criteria Weighting Methods in Multi-Criteria Decision Making: A Comprehensive Review of Subjective, Objective, and Hybrid Approaches

Arkyadeep Sarkar[1], Shankha Shubhra Goswami[1,*], Dhiren Kumar Behera[2], Darko Bozanic[3]

[1] Department of Mechanical Engineering, Abacus Institute of Engineering and Management, Hooghly, India
[2] Department of Mechanical Engineering, Indira Gandhi Institute of Technology, Sarang, India
[3] Military Academy, University of Defence in Belgrade, Belgrade, Serbia

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ABSTRACT

In Multi-Criteria Decision Making (MCDM) method, the criteria weighting is one of the most critical parameters that affect the stability of the ranks, sensitivity of the decision and the robustness of the model. A variety of methods have been developed to weight; these can be categorized as subjective, objective and hybrid. The weights derived from the statistical or information theoretic properties of the inherent data are called objective methods, while those based on expert judgment and cognitive evaluations are called subjective methods. Combining both paradigms is known as hybrid methods and provides a more reliable and unbiased approach. Although significant methodological progress has been made, there remain many different methods, variations in method selection, validation and contextual applicability. The paper comprehensively reviews and critically analyzes the most important criteria weighting techniques in MCDM. It categorizes and compares current solutions, analyzes their theory and limitations, and explores their use in different fields including engineering, energy systems, supply chain and financial decision-making. The research also identifies the new trends like fuzzy logic integration, machine learning based weighting and adaptive decision frameworks. Thirdly, the main research gaps and future research directions are suggested to lead next generation weighting models in MCDM under uncertainty.

1. Introduction

Multi-Criteria Decision Making (MCDM) is a powerful and indispensable analytical paradigm that has developed for handling complex decision problems when there are multiple, often-competing, criteria used to evaluate the problem. In the real world of making a decision, for example in engineering design, energy planning, financial investment, Supply Chain optimization or Sustainability assessment, decision makers are often faced with a range of options that cannot be assessed with a single performance measure. Instead, these alternatives need to be evaluated by a diverse range of quantitative (e.g., cost, efficiency, performance) and qualitative (e.g., risk, reliability, perception of sustainability) metrics. [1, 2] The inherent multi-dimensional nature makes

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

MCDM an important tool for structured and rational decision support. The criteria weighting process is a key and influential step in the MCDM framework. Weighting is the process of assigning relative importance to each criterion and thereby directly influences the decision landscape and hence the ranking of the alternatives. In contrast to other procedural methods of MCDM like normalization and aggregation, weighting process in MCDM has a strong subjectivity and/or data-driven bias on the model, which can significantly impact the result [3]. Consequently even moderate differences in weights can cause dramatic reordering in the ranking order, sometimes resulting in rank reversal phenomena that can introduce doubt in the outcome of the decision and its robustness.

The sensitivity of the MCDM results to weight variation has been well documented in the literature and the weight step is one of the most important and methodologically sensitive steps in the entire decision making process. The accuracy and appropriateness of the assigned weights are crucial for the classical and widely used MCDM techniques, including a technique of the Analytic Hierarchy Process (AHP), a technique of Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Complex Proportional Assessment (COPRAS), VIKOR and Weighted Aggregated Sum Product Assessment (WASPAS) [4]. Therefore, the validity of any MCDM model relies on the strength of the weighting process. There has been considerable research and development of criteria weighting methods over the last few decades. Generally, these techniques fall into three main categories: subjective, objective, and hybrid strategies. Subjective weighting methods are based on expert judgment and human cognition and rely on the decision makers' experience, intuition, or structured comparison frameworks [3,4]. These approaches are popular because they are highly interpretable and allow for the use of domain knowledge. It allows the decision maker to express their own views in the judgmental process. However, they can suffer from cognitive bias, inconsistencies and differences between experts.

Objective weighting methods, on the other hand, are methods that obtain weights from the data structure itself, without using human judgment [5]. They tend to be statistical dispersion, entropy theory, correlation measures or optimization principles, and their purpose is to capture the intrinsic informational content of each criterion. Objective approaches are good for increasing the level of reproducibility and decreasing human bias, but they do not necessarily account for the contextual relevance and decision maker preferences that are important in real world applications. In order to overcome the drawbacks of both subjective and objective paradigms, hybrid weighting methods have come into being, which are a promising research direction. The methods combine data-driven analysis and expertise to generate more balanced and robust weight estimates [5,6]. These hybrid models aim to improve decision consistency and minimize inconsistencies of subjective and objective models. The growing use of these integrated systems is indicative of a trend of more intelligent and adaptive decision-support systems.

Although there have been considerable methodological advances in this area, there is no agreed or standard weighting methodology. It has been found that different weighting methods can give different answers to the same decision problem, as can result in methodological inconsistencies, lack of comparability and sensitivity to the input assumptions [6,7]. This fluctuation is a major problem in the reliability of decisions, especially when they are used in high-stakes situations where there must be reliability and reproducibility. Moreover, under the premise of the development of modern decision-making environment, the complexity of the decision-making environment has brought new difficulties to traditional weighting methods. However, conventional static weighting has been found to be inadequate in dealing with the new paradigm of big data, uncertainty, dynamic systems, and interdependent criteria structures. In many real-world situations, the context of a decision process is not fixed and elements of a process may change over time, so that adaptive and context-sensitive weighting mechanisms are needed. It may be the case of strategic decision making where the experts are allowed to consider the factors directly or indirectly involved in the judgmental process for better output.

The conceptual integration of weighting paradigms in the overall MCDM decision making pipeline is shown in Figure 1. The Figure 1 illustrates that the criteria weighting is not a standalone process, but rather a part of MCDM pipeline. The Figure 1 depicts a single conceptual model of the criteria weighting methods of MCDM systems. The framework shows the hierarchical nature of the decision environments, weighting paradigms and downstream mechanisms for integrating MCDM. The upper level of the framework introduces the concept of deterministic, uncertain and dynamic systems, and also data-intensive systems [8]. These environmental characteristics suggest that there are different ways of weighting, namely subjective, objective, and hybrid, which are based on different methodological philosophies and computational structures. The framework also illustrates the incorporation of derived weights in common MCDM methods, including TOPSIS, VIKOR, COPRAS, WASPAS and MOORA. Lastly, it emphasizes the features of ranking generation, decision stability evaluation, and sensitivity analysis in the output layer. Overall, the figure sets out a comprehensive conceptual connection between weighting theory and 'real world' decision support.

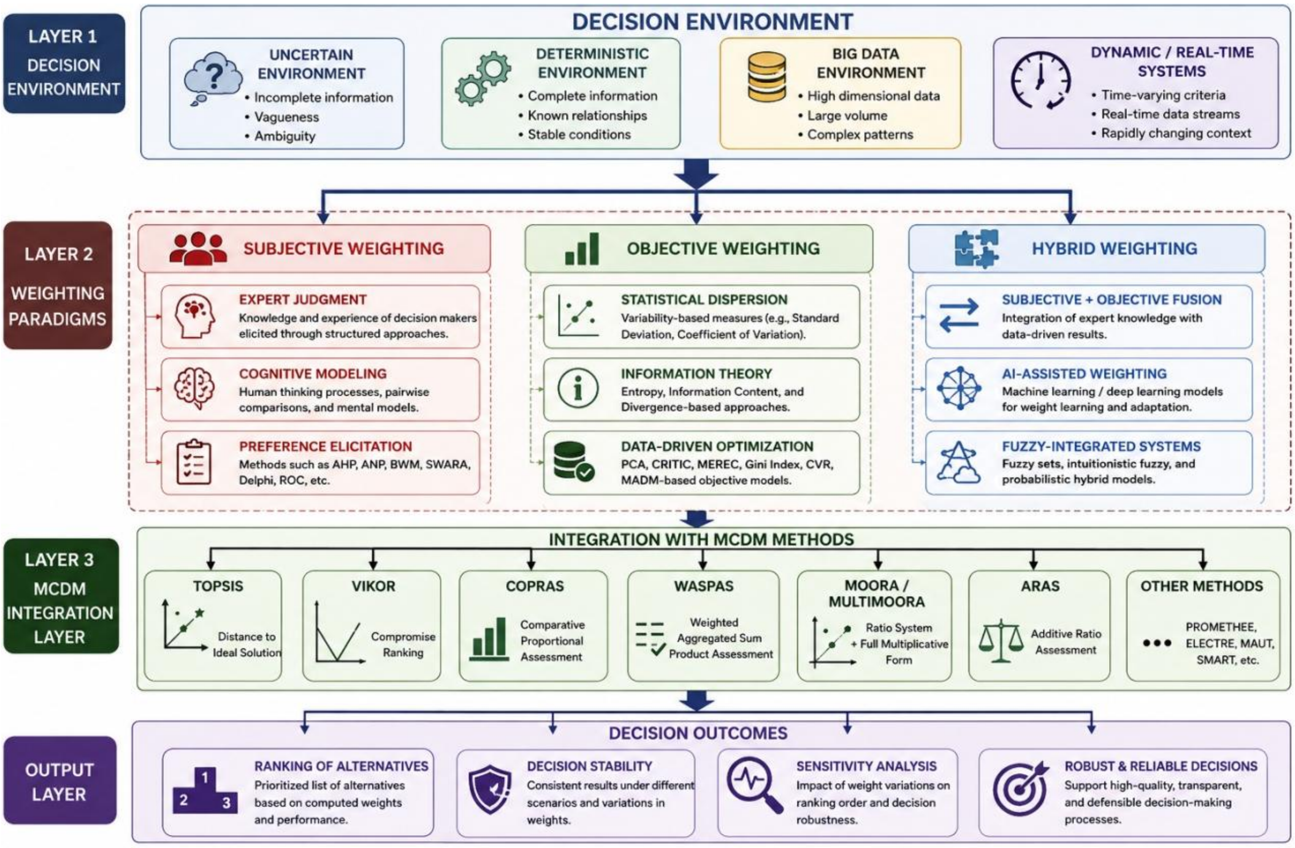

Fig. 1. Unified conceptual framework of criteria weighting methods in MCDM

Given these issues, a global and systematic knowledge of the existing criteria weighting methods is needed. Motivation of this study is the need to synthesize the fragmented research, create a proper classification framework and critically evaluate the advantages and disadvantages of various weighting methods [4,7]. The main goal of this review is to provide a structured review of subjective, objective and hybrid weighting methods in the MCDM field and their theoretical background and practical applications. Further, the paper will explore how these methods can be applied in other areas, compare their performance attributes and identify areas of methodological

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ambiguity. Specially are given importance issues like weight stability, sensitivity analysis, uncertainty handling and integration with the emerging computational intelligence techniques [3,8]. It aims to provide insights on the effects of weighting mechanisms on the decision outcome and how they can be improved in a complex and uncertain environment.

Lastly, this review provides future research avenues to develop the criteria weighting approaches. These involve the creation of adaptive weighting systems, incorporation with artificial intelligence and machine learning methods, incorporation with fuzzy uncertainty models and probabilistic uncertainty models, and the design of explainable and dynamic decision-support frameworks [8,9]. The aim of this extensive research is to offer a basic reference and a prospective view for researchers and practitioners in the field of MCDM. A summary of the chronological development of criteria weighting techniques is given in Table 1. Historical development and methodological evolution from classical weighting systems to statistical weighting systems, hybrid weighting systems, and AI-driven weighting systems are presented in Table 1.

Table 1
Evolutionary development of criteria weighting methods in MCDM

Evolutionary phase	Approximate period	Aspects	Description
Classical subjective phase	1980–2000	Dominant weighting	AHP, Rank sum, Rank reciprocal, Direct rating, Delphi
Classical subjective phase	1980–2000	Methodological characteristics	Expert-driven and manually structured weighting frameworks based on human judgment and preference elicitation
Classical subjective phase	1980–2000	Primary decision philosophy	Human cognition and expert experience
Classical subjective phase	1980–2000	Key advantages	High interpretability, easy implementation, strong contextual relevance
Classical subjective phase	1980–2000	Major limitations	High subjectivity, inconsistency, cognitive bias, limited scalability
Classical subjective phase	1980–2000	Typical application domains	Strategic planning, policy analysis, early-stage engineering design
Early objective statistical phase	1995–2010	Dominant weighting	Entropy, Standard Deviation (SD), Variance-based weighting
Early objective statistical phase	1995–2010	Methodological characteristics	Statistical and mathematical weighting approaches derived from data dispersion and information content
Early objective statistical phase	1995–2010	Primary decision philosophy	Data variability and information theory
Early objective statistical phase	1995–2010	Key advantages	Improved reproducibility, reduced human bias, mathematically rigorous
Early objective statistical phase	1995–2010	Major limitations	Ignores decision-maker preferences and contextual priorities
Early objective statistical phase	1995–2010	Typical application domains	Engineering optimization, environmental analysis, operational research
Correlation and Structural Analysis Phase	2000–2015	Dominant weighting	CRITIC, PCA-based weighting, Factor analysis methods
Correlation and Structural Analysis Phase	2000–2015	Methodological characteristics	Advanced statistical modeling incorporating intercriteria relationships and dimensional reduction
Correlation and Structural Analysis Phase	2000–2015	Primary decision philosophy	Structural information extraction
Correlation and Structural Analysis Phase	2000–2015	Key advantages	Captures criterion conflict and hidden data structures
Correlation and Structural Analysis Phase	2000–2015	Major limitations	Complex interpretation and dependency on data quality
Correlation and Structural Analysis Phase	2000–2015	Typical application domains	Financial modeling, performance evaluation, sustainability assessment

Table 1
Continued

Evolutionary phase	Approximate period	Aspects	Description
Hybrid integration phase	2010–2020	Dominant weighting	AHP–Entropy, BWM–CRITIC, SWARA–Entropy integrated hybrid models
		Methodological characteristics	Combined subjective-objective frameworks integrating expert knowledge with statistical validation
		Primary decision philosophy	Balanced expert-data fusion
		Key advantages	Improved robustness, reduced bias, enhanced decision stability
		Major limitations	Increased computational complexity and integration challenges
		Typical application domains	Supply chain management, energy planning, infrastructure evaluation
Fuzzy and Uncertainty-Aware Phase	2015–Present	Dominant weighting	Fuzzy AHP, Fuzzy BWM, Interval-valued Entropy, Fuzzy DEMATEL
		Methodological characteristics	Weighting frameworks incorporating uncertainty, vagueness, and linguistic variables
		Primary decision philosophy	Uncertainty modeling and approximate reasoning
		Key advantages	Better handling of imprecise and incomplete information
		Major limitations	Membership function sensitivity and methodological fragmentation
		Typical application domains	Healthcare, risk assessment, sustainability and policy decision-making
Advanced objective optimization phase	2018–Present	Dominant weighting	MEREC, LOPCOW, CILOS, IDOCRIW
		Methodological characteristics	Optimization-oriented and sensitivity-based weighting methods emphasizing criterion impact analysis
		Primary decision philosophy	System performance variation and optimization
		Key advantages	High analytical precision and improved ranking discrimination
		Major limitations	Limited practical validation and growing methodological complexity
		Typical application domains	Industrial optimization, smart manufacturing, engineering analytics
Ai-driven intelligent phase	2020–Present	Dominant weighting	Machine Learning-based weighting, Neural weighting, Deep Learning
		Methodological characteristics	Intelligent and adaptive weighting systems using predictive and self-learning algorithms
		Primary decision philosophy	Data-driven autonomous learning
		Key advantages	Adaptive capability, nonlinear learning, real-time processing
		Major limitations	Black-box behavior and low explainability
		Typical application domains	Smart systems, Industry 4.0, intelligent finance, autonomous systems

Table 1
Continued

Evolutionary phase	Approximate period	Aspects	Description
Explainable and dynamic AI phase	Emerging future direction	Dominant weighting	Explainable AI (XAI)-based weighting, Reinforcement learning MCDM, Real-time adaptive weighting
		Methodological characteristics	Transparent and continuously adaptive weighting mechanisms integrated with explainable intelligence
		Primary decision philosophy	Human-centric intelligent decision support
		Key advantages	Dynamic adaptation, transparency, contextual responsiveness
		Major limitations	Lack of standardized frameworks and validation protocols
		Typical application domains	Real-time analytics, cyber-physical systems, digital twins, IoT ecosystems

The evolutionary process of the criteria weighting methods in MCDM is summarized in Table 1, which shows that the criteria weighting methods originated from the more traditional expert-driven methods and developed to the intelligent, adaptive and uncertainty-aware weighting methods. At the initial development stage, subjective approaches with focus on expert cognition and preference articulation, like AHP and Delphi, dominated [10]. Later, the introduction of statistical and information-theoretic methods put emphasis on objective and data-driven weighting mechanisms, enhancing mathematical rigor and reproducibility. This development continued to hybrid integration frameworks that integrated subjective and objective paradigms to create more robust and less methodologically biased frameworks [11]. More recently, fuzzy and uncertainty-aware weighting systems have become popular because they can be used to represent imprecise and linguistic information in complex decision-making problems. The current research direction is to integrate AI, machine learning, and the use of explainable AI techniques, resulting in the creation of intelligent and adaptive weighting systems that evolve and learn in real time while providing dynamic decision support [12,13]. Overall, the path of evolution indicates a clear methodology that from static and deterministic weighting structures has moved towards intelligent, adaptive, and context-aware decision-making structures.

The development of the criteria weighting methods is illustrated in Figure 2. As shown in Figure 2, the development of criteria weighting methods in MCDM in recent decades shows an evolutionary process, especially in the last four decades [9,10]. The figure illustrates the progressive evolution from traditional expert-based weighting methods to data-driven, statistical approaches, followed by the emergence of hybrid weighting schemes and the introduction of intelligent systems using AI integration. This evolution is to become increasingly complex and uncertain environments for decision making, and the need for adaptive, uncertainty-aware, and computationally intelligent weighting mechanisms [13,14]. The evolution of methodological priorities over time also illustrates the transition from interpretability and simplicity to robustness, scalability and real time adaptability in modern decision-support systems.

The present review was conducted according to the PRISMA approach to identify relevant studies, screen them, assess their eligibility, and include them in the systematic synthesis of the literature in a way that is methodologically transparent. The overall literature selected workflow in this study is shown in Figure 3.

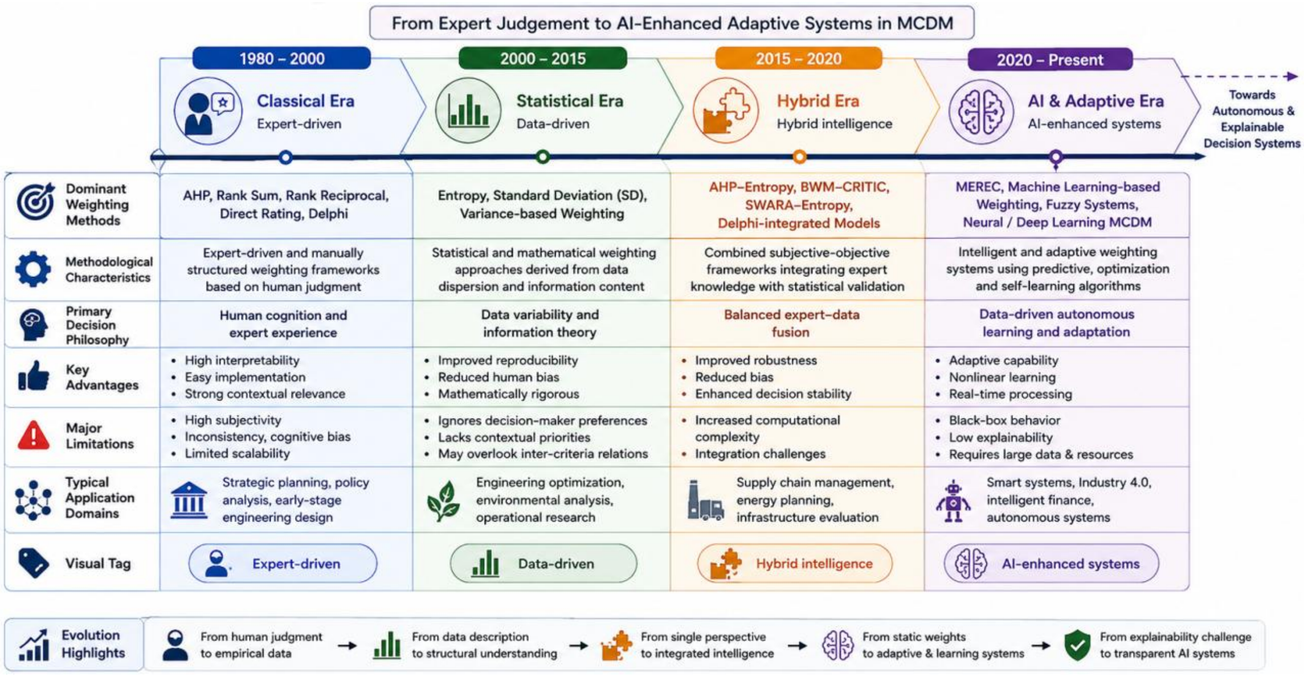

Fig. 2. Evolutionary timeline of weighting methods

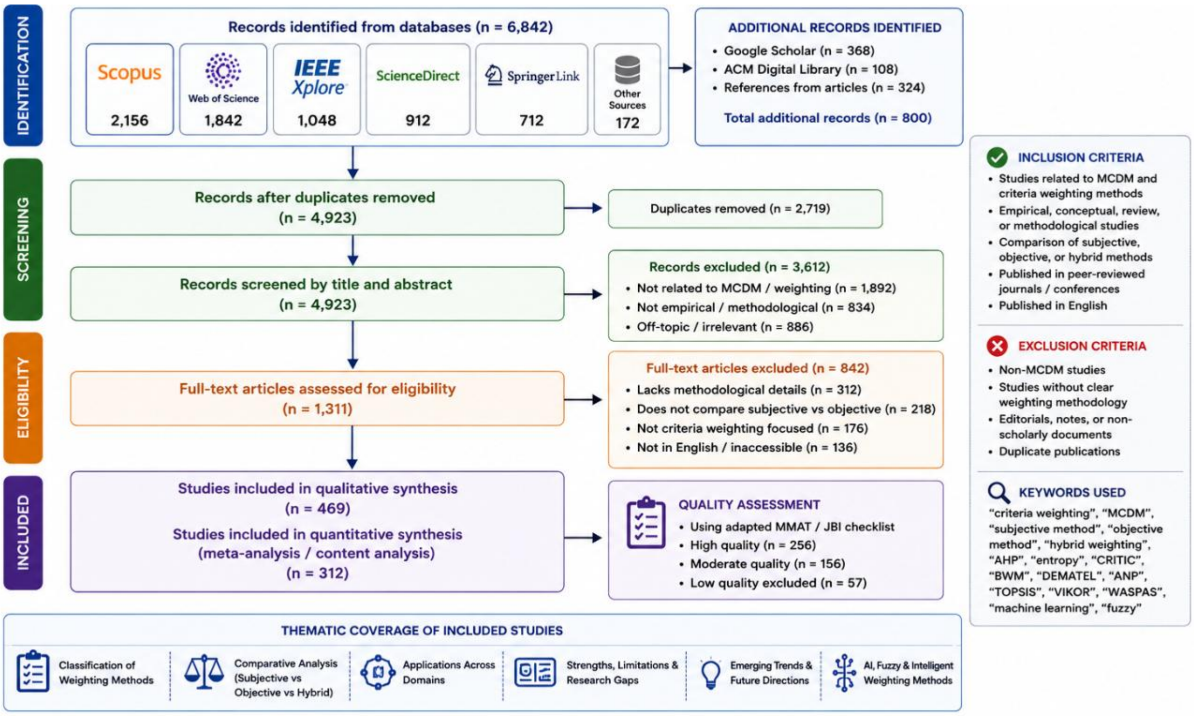

Fig. 3. Study selection process for systematic review

The systematic literature review process in this study is shown in Figure 3 following the PRISMA framework. The review process started with a thorough identification of the databases from the major scientific indexing platforms such as the Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and other scientific sources. The records retrieved after duplicate removal have been screened for relevance with the criteria weighting methods in MCDM [15] using titles and abstracts. Later, full-text eligibility was carried out based on the inclusion and exclusion criteria which were previously defined including methodological relevance, weighting paradigms, comparative analysis and application-oriented studies. The last set of studies that were selected and included was then qualitatively synthesized and categorized into the following themes: subjective, objective, hybrid, fuzzy, and AI-assisted weighting approaches [11,13]. The PRISMA framework increases the transparency and methodological robustness of the review process used in this study, as well as its reproducibility.

2. Classification of Criteria Weighting Methods

Criteria weighting is one of the basic components of MCDM because it directly affects how the evaluation models aggregate and consequently affects the ranking of the alternatives. A broad range of weighting methods has been suggested in the literature [16] that can be used for this purpose. These techniques vary greatly with respect to their theoretical bases, data dependencies, computational load, and the degree of participation of decision makers. Based on the philosophical basis and working principle, the criteria weighting methods for MCDM can be divided into three major methods which are subjective, objective, and hybrid approaches [16,17]. This classification helps develop a lens of understanding of methodological diversity and assess their applicability in various decision making situations.

2.1 Subjective Weighting Methods

Subjective weighting methods are based on human cognition, expert knowledge and preference articulation. These strategies make the assumption that decision makers have domain knowledge that can be captured in numerical weight values. They are therefore very useful when historical data is not available, incomplete or hard to quantify [18]. Despite the large number of situations in which it is possible to collect the necessary information to prioritize the criteria, in many real-world decision situations, this information can only be obtained from subjective judgment, like that of a decision maker, policy maker, or in early stages of engineering design. One of the most mature subjective techniques is the AHP developed by Saaty [19]. AHP breaks a complex decision problem down into a hierarchy and uses pairwise comparisons to compare the relative importance of criteria. This comparison matrix is then passed into eigenvector calculations to obtain consistent priority weights. It is believed that its popularity is due to its easy structure and the fact that it allows for qualitative and quantitative measures to be used in the same framework.

Beyond hierarchical structures, the Analytic Network Process (ANP) has extended the framework to a more generalized one, allowing interdependencies and feedback relationships between the criteria [20]. ANP can be used to address the more complex network structure of the example, where the criteria are not independent, unlike the AHP, but rather can affect each other, especially for systems that have networked decision factors. Another popular method is the Delphi method, a process of repeated consultation with experts. This is based on a series of structured questionnaires and controlled feedback with a goal of converging the experts opinions and reducing individual bias [19,20]. It is particularly effective when used to help reach a consensus among geographically distant or diverse groups of experts.

Besides these classical methods, some simple and improved subjective techniques have been suggested. The SWARA (Step-wise Weight Assessment Ratio Analysis) approach decreases cognitive load by asking the experts to step-wise rank the criteria and assign relative weight to each of the criteria. The Best-Worst Method (BWM), however, helps to enhance consistency by minimizing the number of pairwise comparisons, with the decision-makers being requested to rank only the best and worst criteria and then to compare them with the remaining criteria. This greatly boosts computational efficiency without compromising acceptable consistency levels [21]. Another simplified method is called Rank Order Centroid (ROC), which uses math averaging principles to convert rankings to cardinal weights. It is so easy to use that it is appealing for preliminary decision analysis or when there are few experts available.

Even though the subjective weighting methods are interpretable and easy to apply, there are several drawbacks to them. These are cognitive bias, differences in expert judgment, group dominance in consensus techniques and sensitivity to experience of decision makers. Therefore, subjective methods are extremely useful in knowledge-based systems but its usefulness could be reduced in very complex systems or in data-intensive systems.

2.2 Objective Weighting Methods

Objective weighting techniques have been developed to reduce reliance on human judgments, based on the structure and properties of the data [22]. These methods are essentially based on mathematical, statistical or information-theoretic principles and are designed to make weighting as reproducible, consistent and as unbiased as possible. The Entropy method, based on information theory, is one of the most popular objective methods. Here, entropy is a relative measure of the uncertainty or disorder for each criterion. The higher the variance and/or the information dispersion of criteria, the more weight they receive because they are thought to have more discriminating value among alternatives [23,24]. This is because in data rich environments, entropy based weighting is ideal.

Another basic method is the Standard Deviation method which gives weights according to the spread of data values throughout the alternatives. The greater the variability the more influential the criterion is in decisions because of the greater discriminatory capability [25]. The CRITIC method takes this one step further by adding contrast intensity (standard deviation) and conflict between criteria (correlation structure). The CRITIC system considers inter-criteria relationships, making it more accurate than just variance-based systems. Principal Component Analysis (PCA) based-weighting is a multivariate statistical technique of dimensionality reduction that retains maximum variance in the data. Under this concept, the weights are obtained by eigenvalues and eigenvectors of principal components, which allows the identification of dominant criteria structures [26,27]. From a decision making point of view, however, the relationship of weights computed from PCA may not be so simple.

More recently, a powerful objective weighting technique, the MEREC (Method based on the Removal Effects of Criteria), has appeared. To determine how each criterion affects the overall performance of the alternatives, MEREC evaluates how each criterion is affected by systematically removing it. Removal sensitivity, or the amount of variation due to removal, is a measure of criterion importance, and thus constitutes a solid sensitivity-based criterion weighting system. Objective methods are very beneficial in a large-scale data-driven decision making environment where reliability and reproducibility is paramount [28]. One important caveat is that they don't account for human preferences or contextual information, meaning they might give accurate mathematical answers but less significant answers in some practical uses.

2.3 Hybrid Weighting Methods

Hybrid weighting methods have evolved because of the shortcomings of purely subjective or purely objective methods. These approaches combine insights from experts with data analysis to create more balanced and robust weight estimation models that reflect context. The basic concept behind hybridization is that the quality of a decision is enhanced by merging the characteristics of the empirical data with the human expertise [29,30]. Among those hybrid frameworks, the hybrid AHP and Entropy methods are the most widely used. This method applies objective weights based on entropy to adjust or validate subjective weights, acquired from expert judgments, thus minimizing bias with keeping the weights interpretable. Likewise the BWM and CRITIC integration has come under the spotlight because of its ability to integrate both consistency-driven expert input and correlation-aware objective analysis.

Delphi-based hybrid models combine elements of expert consensus building with statistical weighting procedures, aiming to progressively improve the agreement reached by the experts by validating the data. The SWARA–Entropy integration is based on a similar concept: stepwise expert judgements are balanced with information-theoretic measures [31]. More complex hybrid models are the AHP–PCA combinations, in which hierarchical preference structures are compared with statistical variance structures [32]. Moreover, the hybrid weighting frameworks that are obtained from the DEMATEL method include causal relationships between the different criteria, which allows for the discovery of direct and indirect influence effects in complex systems [33]. This ability is further expanded by integrating DEMATEL with ANP (DANP), which brings a causal approach in network-based decision structures [34].

Other hybrid models like WASPAS and VIKOR-based weighting models are based on the combination of weighting and ranking methods that enhance the stability of the overall decisions and the quality of the compromise solution [35]. While hybrid weighting methods have methodological benefits, they also add complexity in terms of computation and there is a challenge in terms of calibration to make sure that the subjective and objective parts of the weighting are logically coherent. Furthermore, the integration itself could cause methodological uncertainty in the absence of a proper structure of the process, especially when the experts have conflicting opinions or when the datasets are heterogeneous [36,37]. However, hybrid methods are more and more being considered the most viable way of modern MCDM research, especially in a complex, uncertain and multi-stakeholder decision-making context where neither subjective nor objective methods are adequate. To generate a more rigorous and systematic synthesis, a simple comparison framework, provided in Table 2, is extended with some further methodological aspects, which are crucial to assess the weighting techniques in MCDM. They involve, among others, interpretability, adaptability, uncertainty handling, computational scalability and decision stability, terms often discussed in recent publications concerning intelligent decision systems.

Table 2
Extended comparative analysis of subjective, objective, and hybrid weighting methods

Feature	Subjective methods	Objective methods	Hybrid methods
Source of weights	Expert judgment, human cognition, and preference elicitation	Statistical properties and inherent data structure	Combination of expert judgment and data-driven computation
Theoretical foundation	Psychological and decision theory-based	Information theory, statistics, and optimization theory	Integrated multi-paradigm frameworks
Bias level	High (cognitive and behavioral bias)	Low (minimal human intervention)	Moderate (bias partially reduced through data correction)
Complexity	Medium (depends on method such as AHP or BWM)	Low to medium (algorithmic and computationally structured)	High (integration and calibration complexity)
Data requirement	Low (can operate with qualitative inputs)	High (requires complete and normalized datasets)	High (requires both expert input and structured data)
Interpretability	Very high (transparent reasoning process)	Moderate to low (mathematical abstraction)	Moderate (balanced but sometimes less intuitive)
Adaptability to context	High (captures human intuition and domain knowledge)	Low to moderate (context often ignored)	High (context incorporated via expert + data fusion)
Handling of uncertainty	Moderate (depends on expert experience; improved with fuzzy extensions)	Low to moderate (limited explicit uncertainty modeling)	High (especially with fuzzy and probabilistic integration)

Table 2
Continued

Feature	Subjective methods	Objective methods	Hybrid methods
Computational complexity	Low to medium	Low to medium	Medium to high
Scalability to large problems	Moderate (limited by expert involvement)	High (suitable for large datasets)	Moderate to high (depends on integration design)
Decision stability	Moderate (sensitive to expert inconsistency)	High (consistent under same dataset)	High (more stable due to dual validation)
Applicability domain	Early-stage design, policy-making, qualitative assessments	Data-rich environments such as engineering, finance, and analytics	Complex multi-stakeholder systems and intelligent decision environments
Typical MCDM integration	AHP, ANP, SWARA, BWM, Delphi	Entropy, CRITIC, PCA, MEREC, SD-based methods	AHP–Entropy, BWM–CRITIC, DEMATEL-based hybrids, fuzzy-integrated models
Strengths summary	High interpretability and domain relevance	Mathematical rigor and reproducibility	Balanced performance and improved robustness
Key limitations	Subjective bias, inconsistency, expert dependency	Lack of contextual and strategic insight	Higher complexity and integration challenges

Table 2 shows a broad comparison of the subjective, objective and hybrid weighting approaches in the MCDM from various methodological perspectives. The analysis goes beyond the traditional approach of just bias and data requirements and introduces other key considerations like interpretability, adaptability, uncertainty handling, computational complexity, and decision stability, creating a comprehensive framework for evaluating systems [38]. Based on the analysis, it is possible to establish that the subjective weighting approaches are characterized by high interpretability and high contextual relevance, since they are based on the knowledge and cognitive reason of the experts. They tend to be less reliable, however, in sensitive decisions on a large scale or in situations where there is human bias. In contrast, objective weighting methods show superior mathematical rigor and reproducibility, in that they do not rely on any human intervention, but are derived from data structures [39,40]. However, they lack capabilities to include contextual and strategic elements which constrain their use in knowledge-intensive decision contexts.

The hierarchy of the criteria weighting methods is shown in Figure 4. The classification tree of the criteria weighting methods in MCDM is shown in Figure 4. The figure shows that there are five main paradigms for weighting, namely subjective, objective, hybrid, fuzzy-integrated, and AI-assisted paradigms [27,31,33]. The examples in each of the branches depict representative techniques that are frequently employed in applications of decision support. The classification framework provides a clearer sense of the underlying philosophy and computational structure for different weighting approaches, providing a graphical distinction that aids in conceptual clarity [35]. Moreover, the figure shows that intelligent and adaptive weighting systems are extending the traditional MCDM systems.

Methods combining objective data-driven analysis and subjective expertise, as in hybrid weighting methods, can overcome these limitations. This means that they have a more even performance with respect to robustness, adaptability, and decision stability [28,29]. There is, however, a tradeoff for this improvement: there is greater methodological complexity and greater computational needs, especially in the case of multiple integration layers. Generally, the comparison shows that there is no predominant paradigm for each criterion of evaluation. Rather, the appropriateness of a weighting approach is tied directly to the decision situation, the data that is available and the precision of analysis desired [20, 21]. This highlights the importance of adaptable criteria weighting techniques and context-dependent weightings for current MCDM applications.

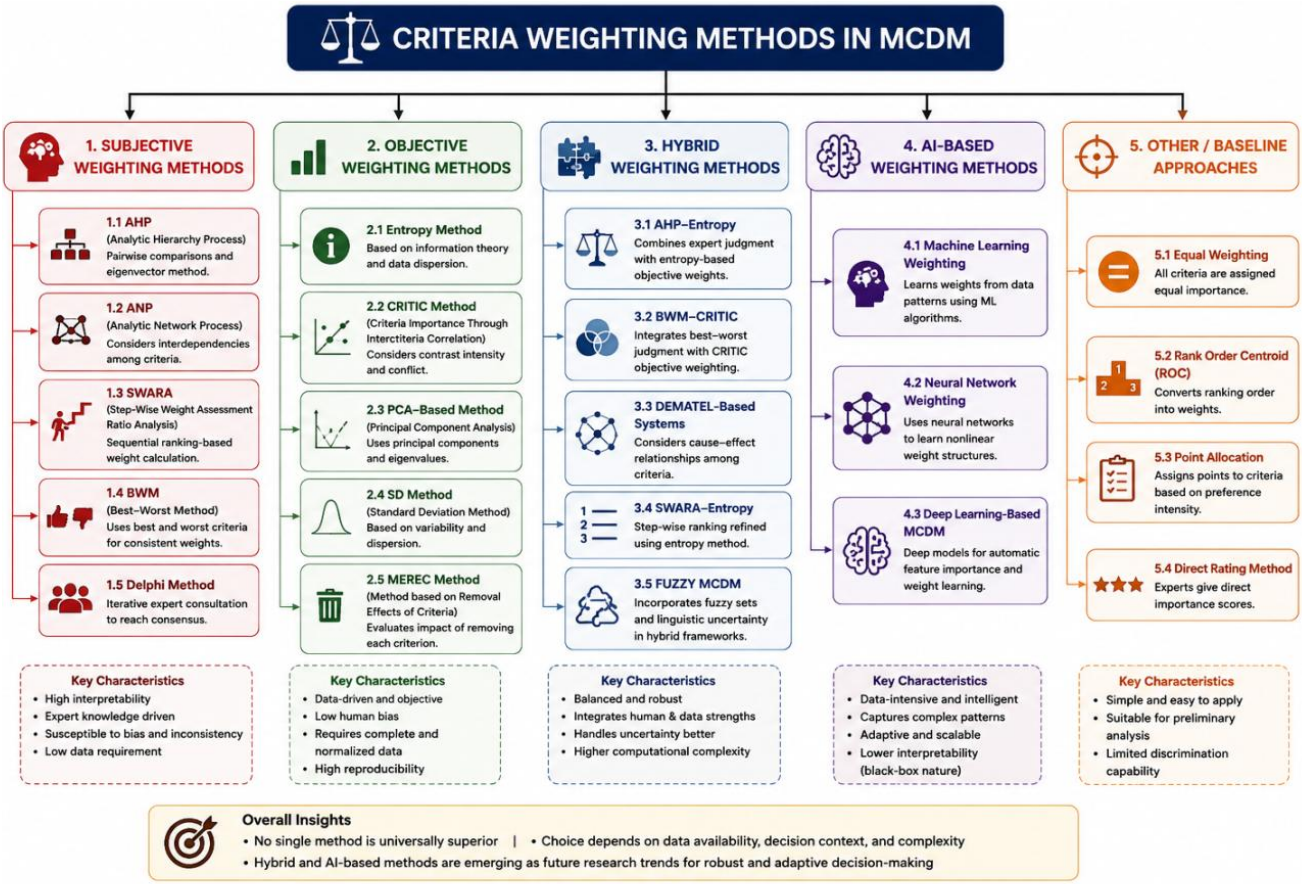

Fig. 4. Classification tree of weighting methods

3. Comparative Analysis of Weighting Methods

It is found that there are significant differences in the theoretical background, the operational logic and the applicability of each of the criteria weighting methods when used in different decision environments by a thorough comparative evaluation of the criteria weighting methods. The differences are not only methodological in nature, but rather represent different attitudes towards decision modeling, from cognitively informed reasoning to purely data oriented computation and hybrid intelligence in context [15,16]. Therefore, the choice of a suitable weighting strategy is not merely a technical one, but also a design that is dependent on the specific context and impacts the robustness, the interpretation, and the validity of decisions made with the model. Conceptually, subjective, objective and hybrid weighting methods are three different paradigms of information processing [12,13]. Subjective approaches are based on human cognition and expert perception where preferences are made explicit and then converted into numerical weights using structured elicitation mechanisms. This makes them interpretable and transparent, which enables decision makers to follow the weights' reasoning. This interpretability, however, comes with the price of being vulnerable to cognitive biases, inconsistencies in judgment and differences in expert opinion [38,39]. The stability of derived weights may be affected by factors like experience level, biased dependability, cognitive load and group dynamics and this may impact the reproducibility of results.

Objective weighting methods, on the other hand, are based on mathematical and statistical principles and rely on no direct human weighting process. These methods are based on intrinsic properties of the data, such as variability, entropy, correlation structure or contribution to overall system variance. For this reason, they are highly reproducible and mathematically rigorous and are well suited for data-rich and computationally demanding applications [40,41]. However, their basic problem is that they lack any contextual interpretation. In practical decision contexts, weights will be based solely on the data structure and thus fail to incorporate strategic priorities, stakeholder preferences or domain-specific relevance. The hybrid weighting methods try to fill this methodological gap by combining expert knowledge and data driven computation. This integration can be realized through sequential combination, multiplicative adjustment and optimization based fusion of subjective and objective weights [41]. The main benefit of hybrid models is that they are able to provide interpretability whilst maintaining a level of statistical robustness. The use of human judgment in combination with data-driven corrections improves the stability of the decisions made and mitigates the dangers of over extreme bias in stand-alone approaches. The methodological advantage, however, leads to a greater number of computational steps and to the necessity to design the model carefully so as to be logically coherent between the integrated components.

When it comes to data dependency, there is a very clear separation between the three categories. Subjective methods rely on a much smaller number of quantitative data and can be useful in situations where there is little or a lot of uncertainty. This is especially useful in situations where empirical data is not available or is not reliable for use in early-stage decision-making or in exploratory analysis or strategic planning [42]. Objective methods are more reliant on complete, consistent, and normalized data sets. Any inconsistencies or missing data can introduce a lot of error into weight estimation and can have an impact on the validity of the results obtained. Hybrid methods are the most data intensive in terms of data preparation and methodological calibration, as they rely both on high quality data sets and expert input. The appropriateness of the weighting methods depends greatly on the domain and problem structure from an application point of view [43,44]. When the information comes mainly from the expert, subjective methods are nearly always used as in the formulation of policy and strategic planning, and in early conceptual design phase.

In data-driven applications with large amounts of empirical data, such as engineering optimizations, financial modeling, or environmental assessment, the behaviour of a system can be reasonably well described statistically [42,43]. In complex, multi-stakeholder contexts, like smart systems, Industry 4.0 applications and integrated sustainability assessment, hybrid approaches are more and more preferred that combine qualitative judgment and quantitative data to hand over solid decisions. One additional important distinction is the stability and sensitivity of the method. There may be inconsistencies in expert judgments when using subjective methods, or data normalization techniques and distributional properties when using objective methods [39,40]. While the hybrid methods are usually more stable, they can generate new sensitivity mechanisms associated with the combination of the subjective and objective components, especially if the weightings in the fusion strategies are not properly designed.

Overall, the comparative analysis suggests that there is no universal optimum weighting paradigm. Rather, every category has its own unique set of strengths and weaknesses that need to be considered with respect to the context of the decision, the data available to the process, and the desired rigor of the analysis. This follows the trend of considering weighting as a context-dependent process as opposed to a method and serves as an impetus for further research to develop adaptive, intelligent and uncertainty-aware weighting frameworks for MCDM [43]. Table 3 shows the detailed classification and comparative characteristics of the weighting methods. There are 40+ criteria weighting methods and they are summarized in Table 3 under the following categories: subjective, objective, hybrid, AI-based, and baseline. It is the backbone of the review, and allows for a systematic comparison of methodological aspects, including bias, complexity, data dependency, etc.

Table 3
Taxonomy and comparative analysis of different criteria weighting methods in MCDM

Sl. No.	Method	Category	Sub-class	Principle	Data requirement	Bias level	Complexity	Key strength	Key limitation
1	AHP	Subj	Classical	Pairwise comparison	L	H	M	Interpretability	Consistency issues
2	ANP	Subj	Network	Interdependence modeling	L	H	H	Captures feedback	High complexity
3	Delphi	Subj	Consensus	Expert convergence	L	H	M	Group agreement	Time-consuming
4	SWARA	Subj	Step-wise	Sequential ranking	L	H	L	Simplicity	Expert bias
5	BWM	Subj	Optimization	Best–worst comparison	L	M	M	Fewer comparisons	Subject selection bias
6	ROC	Subj	Ranking	Rank transformation	VL	H	L	Extremely simple	No data grounding
7	FUCOM	Subj	Consistency	Full consistency model	L	M	M	High consistency	New method validation
8	LBWA	Subj	Structured ranking	Level-based weights	L	M	L	Structured logic	Limited adoption
9	Fuzzy AHP	Subj	Fuzzy extension	Uncertain pairwise comparison	M	H	H	Handles ambiguity	Interpretation difficulty
10	Fuzzy BWM	Subj	Fuzzy optimization	Fuzzy best–worst	M	M	H	Uncertainty handling	Computational load
11	Entropy	Obj	Information theory	Uncertainty measurement	H	L	M	Data-driven	Ignores preference
12	Shannon Entropy	Obj	Classical entropy	Information dispersion	H	L	M	Robust variability	Sensitive normalization
13	CRITIC	Obj	Correlation	Contrast + conflict	H	L	M	Inter-criteria structure	Data dependency
14	Standard Deviation	Obj	Dispersion	Variability measure	H	L	L	Simplicity	Weak theoretical basis
15	PCA	Obj	Dimensional reduction	Eigen vector structure	H	L	H	Extracts hidden structure	Interpretation difficulty
16	MEREC	Obj	Impact	Removal effect analysis	H	L	M	Stability-focused	Computational effort
17	CILOS	Obj	Loss	Objectivity loss score	H	L	M	Robust ranking	Limited adoption
18	EWM	Obj	Entropy variant	Weighted entropy logic	H	L	M	Improved entropy	Similar limitations
19	PSI	Obj	Preference index	Standardized scoring	H	L	L	Simplicity	Limited theory depth
20	MOORA weighting	Obj	Ratio	Normalized ratio system	H	L	L	Fast computation	Scaling sensitivity
21	MULTI MOORA	Obj	Combined system	Aggregated MOORA logic	H	L	M	Stability	Complexity
22	COPRAS weighting	Obj	Proportional system	Benefit–cost ratio	H	L	M	Interpretability	Sensitivity issues
23	ARAS	Obj	Additive ratio	Utility-based scoring	H	L	M	Structured ranking	Data sensitivity

Table 3
Continued

Sl. No.	Method	Category	Sub-class	Principle	Data requirement	Bias level	Complexity	Key strength	Key limitation
24	EDAS	Obj	Distance	Average deviation	H	L	M	Robustness	Less interpretability
25	CODAS	Obj	Distance	Euclidean/Taxicab distance	H	L	M	Strong discrimination	Parameter sensitivity
26	SPOTIS	Obj	Stability	Ideal/anti-ideal distance	H	L	M	Rank stability	New method
27	LOPCOW	Obj	Variance	Criterion impact variance	H	L	M	Novel structure	Limited validation
28	Equal weighting	Baseline	Naïve method	Uniform assignment	None	None	None	Neutral baseline	Unrealistic assumption
29	AHP–Entropy	Hybrid	Classical fusion	Expert + information theory	H	M	H	Balanced weights	Integration difficulty
30	BWM–CRITIC	Hybrid	Optimization fusion	Expert + correlation data	H	M	H	Robust weighting	Computational load
31	Delphi–Entropy	Hybrid	Consensus fusion	Expert + entropy	H	M	H	Consensus + data	Time-intensive
32	SWARA–Entropy	Hybrid	Stepwise fusion	Sequential + information	H	M	M	Balanced logic	Structural mismatch
33	AHP–PCA	Hybrid	Structural fusion	Expert + Eigen analysis	H	M	H	Structural validation	Complexity
34	DEMATEL based weighting	Hybrid	Causal modeling	Influence network analysis	M	M	H	Captures causality	Expert dependency
35	DANP	Hybrid	Network	DEMATEL + ANP	H	M	VH	Strong structure	Heavy computation
36	WASPAS weighting	Hybrid	Aggregation model	Weighted sum-product	H	L	M	Accuracy	Parameter tuning
37	VIKOR-based weighting	Hybrid	Compromise model	Utility–regret balance	M	M	M	Decision balance	Sensitivity
38	FUZZY MCDM (general)	Hybrid	Fuzzy systems	Uncertainty modeling	M	H	H	Handles vagueness	Interpretation
39	Machine learning weighting	AI-based	Data-driven learning	Predictive weighting	VH	L	VH	Adaptive learning	Black-box nature
40	Neural network weighting	AI-based	Deep learning	Nonlinear mapping	VH	L	VH	High accuracy	Interpretability issue
41	Deep learning MCDM	AI-based	Advanced AI	Feature-based weighting	VH	L	VH	Dynamic adaptation	Data requirement

VL: Very Low; L: Low; M: Medium: H: High; VH: Very High
Subj: Subjective; Obj: Objective

Table 3 is the comprehensive classification of more than forty established and emerging criteria weighting methods in MCDM in a systematical manner, which is categorized into five major groups subjective, objective, hybrid, AI-based and baseline method. A comparison of the basic design of the different methods, their data dependency, their computational complexity and their inherent bias is presented in the table. Obviously, the subjective approach focuses on the interpretability of the results, but with cognitive bias and the objective approach on mathematical rigour and lack of

Journal of Contemporary Decision Science
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interpretability. To overcome this, hybrid AI-driven approaches combine elements of both datasets and human knowledge, enhancing robustness and flexibility in complex decision-making contexts.

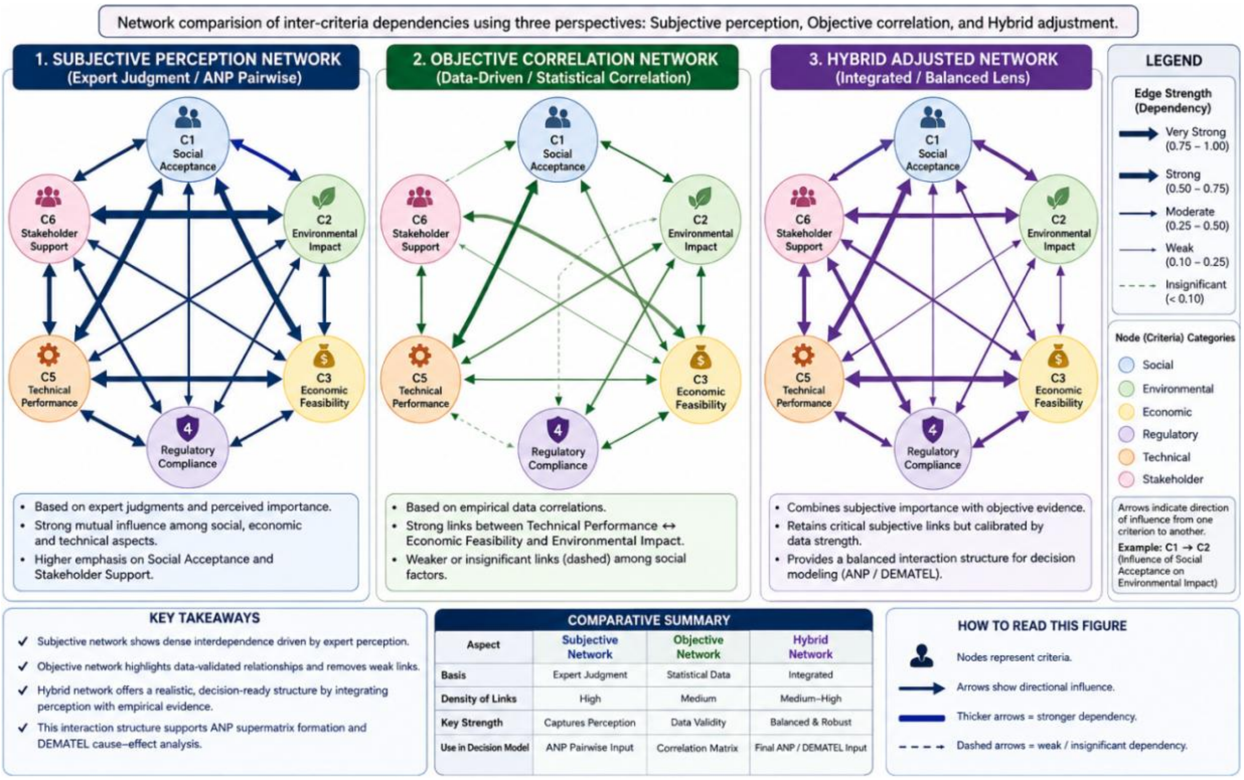

Fig. 5. Interaction between criteria (subjective vs objective vs hybrid lens)

The structural relationship between each criterion in the two different weighting paradigms is shown in Figure 5. The interactions of the criterion variables are presented graphically for the three choice criteria (subjective, objective, and hybrid weighting) in Figure 5. The figure illustrates the different types of relationships that can exist between criteria, based on either expert perceptions or statistical correlations, or a combination of the two. The subjective interaction network is based on expert-caused interpretations, while the objective network focuses on data derived correlation structures [33,34]. Furthermore, the hybrid interaction model takes these viewpoints to arrive at a more balanced view of intercriteria dependencies. This is a testament to the growing relevance of network-related weighting frameworks in complex decision systems.

Figure 6 shows the methodological approach for choosing the relevant weighting paradigms. The systematic decision flowchart for choosing the appropriate weighting method in the MCDM frameworks is shown in Figure 6. The figure starts with problem definition and the assessment of available information resources, then decision nodes for different dominant expert judgment, quantitative data, or combined information structures. The framework helps select either a subjective or an objective or a hybrid weighting paradigm depending on the characteristics of the decision environment [31,36,38]. The flowchart also illustrates how derived weights are incorporated into downstream MCDM techniques and how the sensitivity analysis is carried out. The structured flow ensures methodological transparency and aids in the selection of the weighting.

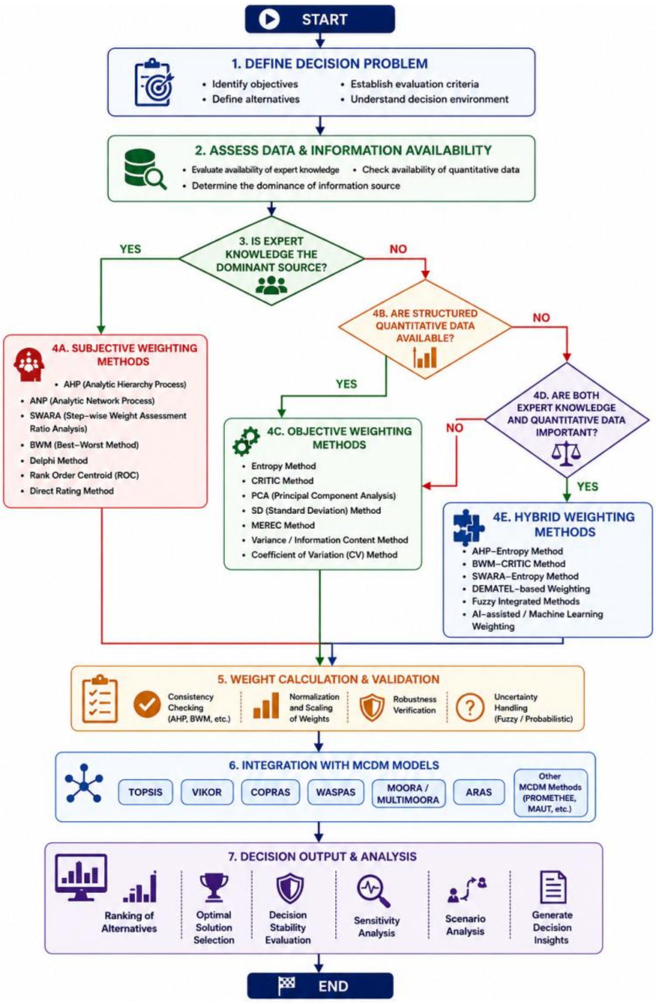

Fig. 6. Decision flowchart of weight selection process

4. Applications of Criteria Weighting in MCDM

In many practical applications, MCDM is mainly used as a decision support tool and the criteria weighting methods are the key to making MCDM more useful. Weighting has a direct impact on the relative importance of the evaluation criteria; it directly affects the final ranking results, and thus the quality and reliability of the final decisions in complex systems [45]. With the growing multi-dimensionality, uncertainty and data density of modern decision environments, the use of weighting techniques has grown considerably in engineering, energy, finance, supply chain, and urban systems, to mention a few.

In engineering design and engineering manufacturing systems, the criteria weighting is widely used to assist in optimization and multiple conflicting criteria (e.g., cost, performance, durability, manufacturability) selection problems [46]. The applications involve material selection in advanced engineering systems, optimization of machining parameters in different processes like EDM, CNC operations, and selection of manufacturing technologies under multi-objective constraints [47]. In decision-making, the subjective methods are often used when expert knowledge is the most influential in the decision context, especially at the initial design phase [48]. On the other hand, objective or hybrid weighting methods are more widely used in automated manufacturing applications where there are large amounts of objective data from sensors and simulation models, and where optimization of the process is data driven and process efficiency can be enhanced.

Weighting methods play an important role in energy systems and sustainability assessment, e.g., in assessing renewable energy options, in energy policy planning, and in environmental impact assessment. The decision problems in this area usually have competing criteria like cost efficiency, emissions to the environment, energy reliability, and technological feasibility [49]. Large-scale environmental and operational data is available which has led to the widespread use of objective methods like entropy and CRITIC. This is becoming more common in hybrid methods, such as sustainability assessment frameworks that call for expert judgment to support quantitative environmental indicators [50]. The roles played by these weighting mechanisms are important to support energy transition strategies and guide their selection of renewable energy systems, including solar, wind and hybrid energy systems.

The criteria weighting is used in supply chain and logistics management for supplier selection, logistics network optimization, inventory management strategies and risk assessment models. The complexity of today's supply chain with factors such as globalization, uncertainty, and dynamic disruptions requires strong weighting mechanisms that are able to capture quantitative performance metrics as well as qualitative risk factors [51]. This is an area where hybrid weighting methods are quite common, where one can combine expert assessments (such as supplier reliability, strategic alignment) with objective measures (such as cost, delivery time, defect rate). The weighting frameworks based on DEMATEL are also commonly used to model interdependencies between the supply chain criteria, especially in risk propagation analysis and resilience assessment [52].

The principle of criteria weighting is a fundamental one in various aspects of financial decision-making and analysis, including portfolio selection, asset distribution, credit risk analysis, financial performance assessment, etc. Weighting methods are necessary in financial environments, which are inherently uncertain and dynamic, to adjust to the varying market conditions as well as the different investment goals like minimizing risks and maximizing returns [53]. Investment preferences are captured by subjective methods like AHP and BWM and objective methods like entropy and variance-based weighting are used to model data behavior in the market [54]. Hybrid and AI-powered weighting systems are growing in prominence and are increasingly part of quantitative finance models to boost predictability and decision making strength in high-frequency and algorithmic trading contexts.

The methods of criteria weighting are also common in the assessment of sustainability indicators, infrastructure efficiency, factors of environmental quality, and socio-economic development in urban planning, infrastructure development and smart cities evaluation [55]. This is a very complex domain of decision because of the multiple stakeholders involved, conflicting policy objectives and the long time horizons in planning. Therefore, hybrid weighting methods with MCDM methods like TOPSIS, VIKOR and COPRAS are widely used to secure a balanced result in making decisions. The interdependencies between the urban development indicators, such as transportation efficiency, pollution levels, energy consumption, public services etc., can be captured by weighting methods using DEMATEL and ANP, which are useful in these cases [56,57].

In addition to their traditional application, the complexity of the contemporary decision process has made it an important role in developing new and intelligent systems, such as Industry 4.0, Artificial Intelligence (AI) supporting decision making systems, healthcare analytics and smart governance systems [58]. In these areas, combining machine learning and deep learning methods with MCDM weighting methods is facilitating the creation of adaptive and real-time decision models. AI weighting systems are especially advantageous when dealing with high-dimensional data, dynamic system responses, and environments where there's uncertainty and traditional static weighting is inadequate.

As a whole, it can be said that the use of criteria weighting in MCDM has evolved from static, expert-based to dynamic, data-driven and intelligent models. This shift is driven by the increasing demand for strong, adaptive, and context-aware weighting approaches that can handle the complexities and intricacies of contemporary decision-making systems [59,60]. Table 4 provides an overview of the mapping from application domains and suitable weighting methods. Table 4 shows the correlation of the weighting methods with the application domains of the real world (engineering, energy, finance, supply chain, smart cities).

Table 4
Domain-wise applicability and suitability of criteria weighting methods in MCDM

Application domain	Aspects	Description
Engineering design and manufacturing	Preferred weighting methods	AHP, BWM, SWARA, Hybrid AHP–Entropy
	Typical MCDM methods integrated	TOPSIS, VIKOR, WASPAS, MOORA
	Primary decision characteristics	Multi-objective optimization involving performance, cost, durability, and manufacturability
	Reason for method suitability	Expert knowledge are essential for evaluating qualitative and technical criteria
	Key challenges in the domain	Trade-off among performance, cost, sustainability, and reliability
	Emerging research trends	AI-assisted optimization, digital manufacturing, adaptive weighting systems
Energy systems and renewable energy planning	Preferred weighting methods	Entropy, CRITIC, MEREC, Fuzzy Entropy
	Typical MCDM methods integrated	TOPSIS, COPRAS, VIKOR, ARAS
	Primary decision characteristics	Data-intensive evaluation involving environmental, economic, and technical indicators
	Reason for method suitability	Large-scale operational and environmental datasets support objective weighting approaches
	Key challenges in the domain	Uncertainty in energy demand, sustainability assessment, policy variability
	Emerging research trends	Smart grid analytics, dynamic energy weighting, carbon-neutral optimization
Supply chain and logistics management	Preferred weighting methods	Hybrid methods, DEMATEL-based weighting, BWM–CRITIC
	Typical MCDM methods integrated	TOPSIS, VIKOR, ANP, PROMETHEE
	Primary decision characteristics	Multi-stakeholder and risk-sensitive decision environments with interdependent criteria
	Reason for method suitability	Combination of expert knowledge and operational data improves robustness
	Key challenges in the domain	Supplier uncertainty, disruption management, conflicting stakeholder objectives
	Emerging research trends	Resilient supply chains, AI-driven logistics analytics, real-time risk weighting
Financial decision-making and investment analysis	Preferred weighting methods	AHP, BWM, Entropy, Machine Learning-based weighting
	Typical MCDM methods integrated	TOPSIS, VIKOR, COPRAS, MOOSRA
	Primary decision characteristics	Risk-return optimization under highly dynamic and uncertain market conditions
	Reason for method suitability	Integration of investor preferences with market-driven quantitative indicators
	Key challenges in the domain	Market volatility, portfolio uncertainty, behavioral finance complexity
	Emerging research trends	Predictive AI weighting, deep learning portfolio optimization, explainable finance analytics
Urban planning and smart city evaluation	Preferred weighting methods	DEMATEL, ANP, DANP, Hybrid fuzzy methods
	Typical MCDM methods integrated	TOPSIS, VIKOR, WASPAS, COPRAS
	Primary decision characteristics	Highly interconnected socio-economic and environmental decision structures
	Reason for method suitability	Interdependency among urban indicators requires network-based weighting frameworks
	Key challenges in the domain	Complex stakeholder interactions, sustainability balancing, infrastructure uncertainty
	Emerging research trends	IoT-integrated urban analytics, digital twins, real-time smart governance systems
Sustainability and environmental assessment	Preferred weighting methods	Hybrid MCDM weighting, Fuzzy AHP, Entropy–SWARA
	Typical MCDM methods integrated	TOPSIS, VIKOR, ARAS, MULTIMOORA
	Primary decision characteristics	Multi-dimensional trade-off analysis among environmental, economic, and social criteria
	Reason for method suitability	Balanced integration of subjective sustainability priorities and objective environmental data
	Key challenges in the domain	Ambiguous sustainability indicators and uncertainty in environmental impact evaluation
	Emerging research trends	Circular economy analytics, climate-resilient decision systems, uncertainty-aware sustainability modeling

Table 4
Continued

Application domain	Aspects	Description
Healthcare and medical decision support	Preferred weighting methods	Fuzzy AHP, BWM, ML-based weighting
	Typical MCDM methods integrated	TOPSIS, VIKOR, PROMETHEE
	Primary decision characteristics	High uncertainty and risk-sensitive decisions involving clinical and operational criteria
	Reason for method suitability	Ability to incorporate expert medical judgment and uncertain patient data
	Key challenges in the domain	Diagnostic uncertainty, ethical constraints, heterogeneous healthcare datasets
	Emerging research trends	AI-assisted diagnosis, personalized healthcare analytics, explainable clinical decision support
Transportation and infrastructure systems	Preferred weighting methods	ANP, DEMATEL, CRITIC, Hybrid weighting
	Typical MCDM methods integrated	TOPSIS, COPRAS, WASPAS
	Primary decision characteristics	Infrastructure optimization involving cost, safety, efficiency, and environmental impact
	Reason for method suitability	Interdependent criteria and large-scale operational datasets require integrated weighting mechanisms
	Key challenges in the domain	Traffic uncertainty, infrastructure resilience, long-term planning complexity
	Emerging research trends	Smart transportation systems, autonomous mobility optimization, intelligent infrastructure analytics
Industrial robotics and automation	Preferred weighting methods	Objective weighting, Hybrid AI-assisted weighting
	Typical MCDM methods integrated	TOPSIS, MOORA, WASPAS
	Primary decision characteristics	Performance evaluation involving precision, efficiency, flexibility, and automation capability
	Reason for method suitability	Sensor-generated data enables objective and adaptive weighting structures
	Key challenges in the domain	Dynamic operational conditions and real-time process variability
	Emerging research trends	Industry 4.0 integration, cyber-physical systems, autonomous production optimization
Education and e-learning evaluation	Preferred weighting methods	AHP, SWARA, Entropy
	Typical MCDM methods integrated	TOPSIS, ARAS, COPRAS
	Primary decision characteristics	Mixed qualitative and quantitative evaluation of learning systems and educational quality
	Reason for method suitability	Combination of expert educational assessment and performance metrics
	Key challenges in the domain	Subjective perception variability and digital learning adaptability
	Emerging research trends	Intelligent education analytics, adaptive learning evaluation systems
Agriculture and resource management	Preferred weighting methods	Fuzzy MCDM, Entropy, Hybrid methods
	Typical MCDM methods integrated	TOPSIS, VIKOR, COPRAS
	Primary decision characteristics	Resource allocation under environmental uncertainty and sustainability constraints
	Reason for method suitability	Ability to model climatic uncertainty and multi-objective agricultural priorities
	Key challenges in the domain	Climate variability, resource scarcity, uncertain productivity patterns
	Emerging research trends	Precision agriculture, IoT-based farm analytics, climate-adaptive decision systems
Industry 4.0 and smart manufacturing	Preferred weighting methods	AI-based weighting, Dynamic hybrid methods, MEREC
	Typical MCDM methods integrated	TOPSIS, WASPAS, VIKOR
	Primary decision characteristics	Real-time intelligent decision environments driven by big data and automation
	Reason for method suitability	Adaptive weighting mechanisms are required for continuously evolving systems
	Key challenges in the domain	High-dimensional streaming data and rapid operational variability
	Emerging research trends	Self-learning MCDM systems, digital twins, explainable industrial AI

Table 4 gives an extensive mapping between major application domains and the most appropriate criteria weighting methods employed in the MCDM frameworks. The analysis shows that choice of weighting methods is strongly related to the structure of the decision environment, availability of data, level of uncertainty, and the level of interdependency between the evaluation criteria [61]. While subjective approaches like AHP and BWM are well established in expert-based fields like engineering design and policy assessment, objective approaches like entropy, CRITIC and MEREC are more appropriate in application areas in which data is abundant, such as energy systems and industrial analytics. Additionally, the table shows the increasing importance and use of hybrid and AI-supported weighting methods in situations where multiple stakeholders are involved, data streams are flowing, and uncertainty exists [62,63]. For certain sectors like smart cities, Industry 4.0, and healthcare analytics, fuzzy logic artificial intelligence (AI) and network-based modelling integrated with weighting aspects have been identified as potential solutions to improve the robustness and adaptability of decision making [64]. Overall, the comparison of the domains shows that none of the weighting methods is suitable for all problem contexts, which further justifies the need for context-aware and adaptive selection strategies for weighting methods in the current context of MCDM applications.

5. Challenges and Limitations

Although the use of criteria weighting methods has significantly progressed in the MCDM field, there are still some intrinsic drawbacks and difficulties in the application of these methods in the real world scenario [65,66]. Such restrictions are not only imposed by the mathematical formulation of the methods, but are also due to the need to rely on the quality of the data and the decisions made for data interpretation and system modeling – decisions which are related to human behavior. From a methodological point of view, subjective weighting approaches are still subject to human limitations in cognition [67]. AHP, BWM, SWARA, and Delphi are methods that give structured approaches to collect the expert preferences, but there are still subjectivity in expert's judgment, cognitive biases, and differences in decision makers' preferences. The level of expertise/experience/psychological proclivities of a person or group making the decision has a strong influence on the reliability of subjective weights [68]. Moreover, in group-based methods, problems of dominance effect, convergence bias, and absence of minority voice can lead to a distortion of the final weighting estimates and impact the integrity of the decision.

Objective weighting methods, on the other hand, are mathematically sound and repeatable, but have other limitations. The statistical structure of the data used in these methods is very crucial, and the assumption is criterion importance can be represented by statistical data variability, entropy, or correlation structure. In many real-world situations, however, there are other factors that influence contextual relevance, such as strategic priorities or preferences of stakeholders, that make this assumption untrue. Therefore, if the weighting is purely data driven, the resulting weights can be mathematically optimal, but can be misaligned from the desired practical objective. Furthermore, objective methods are very sensitive to data processing operations like normalisation and scaling that can greatly affect weight distributions at the end of the experiment [69,70]. While the idea of hybrid weighting methods aims to address the shortcomings of using pure methods, it also carries its own set of methodological complexities [71,72]. They provide a balance between subjectivity and objectivity but use complex mechanisms to implement them, which can be different across studies. The lack of a single standard for combining the subjective and objective aspects results in the methodological variety and makes it difficult to compare the results of different applications [73]. Furthermore, the hybrid approach may involve more complex algorithms, computational intensive processes, and multiple validation steps that hinder its scalability, especially in large-scale or real-time decision-making systems.

In both types of weighting methods, a key and growing problem is the volatility of weights in dynamic and uncertain environments. The traditional MCDM weighting methods are typically developed under static conditions with fixed conditions of decision criteria and their relationships that do not change over time [74]. Modern applications like smart systems, financial markets, supply chains and energy networks, however, have highly dynamic decision environments that constantly change. In this case, static weight assignments could not reflect dynamic interdependencies between criteria, which could result in less reliable decisions and changes in rankings over time. One major drawback is when uncertainty and incomplete information arise, this is the other limitation [75]. For example, many traditional weighting approaches require complete and accurate data, which is often not the case in real-world settings. In practical decision problems, the data is often imprecise, fuzzy or incomplete and the expert's judgments are linguistically or qualitatively expressed. Some fuzzy extensions of weighting methods have been constructed but they are not consistently applied and methodologically fragmented in the application of the mainstream MCDM methods.

Looking at a wider context, the situation is also characterised by a lack of standardization and unification in weighting methods. There is now a large variety of new weighting methods, and they are inconsistently used in similar problem domains [76,77]. The absence of methodological convergence makes it difficult to make comparisons to benchmarks and to identify best practices generally. As a research gap, some key research directions can be identified. First, there is clearly a need for adaptive and dynamic weighting mechanisms that can change weights when the conditions in the environment, the data stream or the behavior of the system change. On the other hand, the use of artificial intelligence and machine learning methods in weighting systems is not so well explored, especially in terms of explainability and interpretability of learned weights [78]. Third, there is a need for uncertainty-aware weighting models which can consider fuzzy, probabilistic or interval information in weight estimation procedures in a systematic manner.

Moreover, further studies are needed on the standardized hybrid frameworks to establish a set of guidelines for incorporating subjective and objective elements in a consistent and reproducible way [79]. There are no such standards now for cross-study comparability and methodological convergence in the field is slow. Last but not least, there is a growing need for effective and established frameworks for the validation and sensitivity analysis of weighting methods that can systematically assess how these methods are stable and reliable at different decision points. Overall, the difficulties and restrictions mentioned here in this section underline that although advances in the field of criteria weighting have been made, there is still a lot to be done [80]. These challenges must be tackled to further develop the theoretical foundation, practical applications and computational intelligence of future decision support systems based on the MCDM approach. Table 5 offers a comparative synthesis of weighting paradigms. A critical synthesis table, Table 5, is provided that summarizes strengths and weaknesses and best-use scenarios.

Table 5
Critical evaluation of subjective, objective and hybrid weighting paradigms in MCDM

Weighting category	Aspects	Description
Subjective weighting methods	Core strengths	High interpretability, strong incorporation of expert knowledge, context-sensitive evaluation, easy preference articulation
	Major weaknesses	Susceptible to cognitive bias, inconsistency, expert dependency, limited reproducibility
	Methodological characteristics	Human judgment-driven and preference-based weighting frameworks
	Best-suited decision environments	Expert-driven, qualitative, and early-stage decision problems
	Typical application domains	Engineering design, policy analysis, strategic planning, education evaluation
	Representative methods	AHP, ANP, SWARA, BWM, Delphi, ROC
	Computational complexity	Low to medium
	Robustness under uncertainty	Moderate (improved with fuzzy extensions)
	Future improvement potential	Integration with AI-assisted consistency evaluation and consensus optimization
Objective weighting methods	Core strengths	Strong mathematical rigor, reproducibility, reduced human bias, efficient handling of large data
	Major weaknesses	Limited contextual adaptability are sensitive to data preprocessing
	Methodological characteristics	Data-driven and statistically derived weighting systems
	Best-suited decision environments	Data-rich and quantitatively structured decision environments
	Typical application domains	Energy systems, industrial analytics, environmental assessment, finance

Table 5
Critical evaluation of subjective, objective and hybrid weighting paradigms in MCDM

Weighting category	Aspects	Description
Objective weighting methods	Representative methods	Entropy, CRITIC, PCA, Standard Deviation, MEREC, LOPCOW
	Computational complexity	Low to medium
	Robustness under uncertainty	Moderate (depending on data quality and normalization)
	Future improvement potential	Context-aware objective weighting and adaptive statistical learning
Hybrid weighting methods	Core strengths	Balanced integration of expert knowledge and data analytics, improved robustness, enhanced decision stability
	Major weaknesses	High methodological complexity, lack of standardization, computationally intensive integration
	Methodological characteristics	Fusion-based frameworks combining subjective and objective paradigms
	Best-suited decision environments	Complex multi-stakeholder and uncertainty-intensive decision systems
	Typical application domains	Supply chain management, sustainability assessment, healthcare, smart cities
	Representative methods	AHP–Entropy, BWM–CRITIC, SWARA–Entropy, DANP, Fuzzy hybrid models
	Computational complexity	Medium to high
	Robustness under uncertainty	High
	Future improvement potential	Development of standardized and self-adaptive hybrid frameworks
Fuzzy-integrated weighting methods	Core strengths	Effective handling of ambiguity, vagueness, and linguistic uncertainty, realistic representation of expert opinions
	Major weaknesses	Membership function dependency, increased computational burden, lack of unified fuzzy structures
	Methodological characteristics	Uncertainty-aware approximate reasoning systems
	Best-suited decision environments	Highly uncertain and linguistically complex environments
	Typical application domains	Risk analysis, healthcare diagnostics, sustainability evaluation, policy decision-making
	Representative methods	Fuzzy AHP, Fuzzy BWM, Intuitionistic fuzzy weighting, Type-2 fuzzy systems
	Computational complexity	Medium to high
	Robustness under uncertainty	Very high
	Future improvement potential	Integration with probabilistic and explainable AI systems
AI-assisted and intelligent weighting methods	Core strengths	Adaptive learning capability, ability to model nonlinear relationships, scalability for big data and real-time systems
	Major weaknesses	Black-box behavior, low interpretability, high data dependency, ethical transparency concerns
	Methodological characteristics	Self-learning and predictive computational intelligence frameworks
	Best-suited decision environments	Dynamic, real-time, and high-dimensional intelligent systems
	Typical application domains	Industry 4.0, smart manufacturing, autonomous systems, intelligent finance
	Representative methods	Machine learning weighting, neural weighting, deep learning-based MCDM
	Computational complexity	High
	Robustness under uncertainty	High (data-driven adaptability)
	Future improvement potential	Explainable AI (XAI)-based adaptive weighting architectures
Dynamic and real-time weighting systems	Core strengths	Continuous adaptation to changing environments, improved responsiveness, real-time decision support
	Major weaknesses	Algorithmic complexity, streaming data management challenges, validation difficulties
	Methodological characteristics	Time-dependent adaptive weighting mechanisms
	Best-suited decision environments	Cyber-physical systems, IoT-enabled analytics, digital twins
	Typical application domains	Smart grids, transportation systems, autonomous logistics, real-time analytics
	Representative methods	Reinforcement learning weighting, dynamic entropy models, adaptive hybrid frameworks
	Computational complexity	High
	Robustness under uncertainty	Very high
	Future improvement potential	Real-time explainable and autonomous decision ecosystems

A comprehensive critical evaluation of major weighting paradigms in MCDM is presented by systematically comparing their strength, weakness, computational characteristics, and handling of uncertainty and domain suitability is discussed in Table 5 [79,80]. It shows that subjective weighting approaches have the advantage of being more interpretable and relevant to the context, however they are still subject to inconsistencies and cognitive bias. The objective methods have solid mathematical foundations and their results are repeatable, thus they are very well suited for situations where there is a lot of data but they do not allow for the inclusion of contextual preferences, which restricts their applicability in practice [71,76,78]. Hybrid weighting frameworks are developed as a compromise between subjective and objective paradigms which introduces a balance and enhances the stability and robustness of decisions in complex systems. Moreover, fuzzy-integrated and AI-assisted weighting approaches are recent developments, which tackle fuzzy uncertainty and adapt learning in a changing decision context. However, these smart solutions raise fresh issues regarding the methodology, standardisation and explainability of the process [81]. The comparative synthesis results show that, in general, the effectiveness of a weighting paradigm is heavily context-dependent, uncertainty level-dependent, and data and expert knowledge-dependent, which once again emphasizes the need for context-sensitive and adaptive weighting processes in modern MCDM applications.

The conceptual connection between weight changes and ranking instability is shown in Figure 7. The sensitivity of the various rankings to different changes of the weights of the criteria in the MCDM systems is conceptually represented by Figure 7. As shown in the figure, slight changes in weight distributions can result in substantial shifts in ranking especially under highly competitive decision settings. This phenomenon underscores the need for weighting mechanisms to affect the stability and robustness of decision-making processes [79-81]. The figure highlights the need for sensitivity analysis and robustness testing in the validation of weighting frameworks particularly in multi-criterion applications, where a strong sensitivity term is encountered.

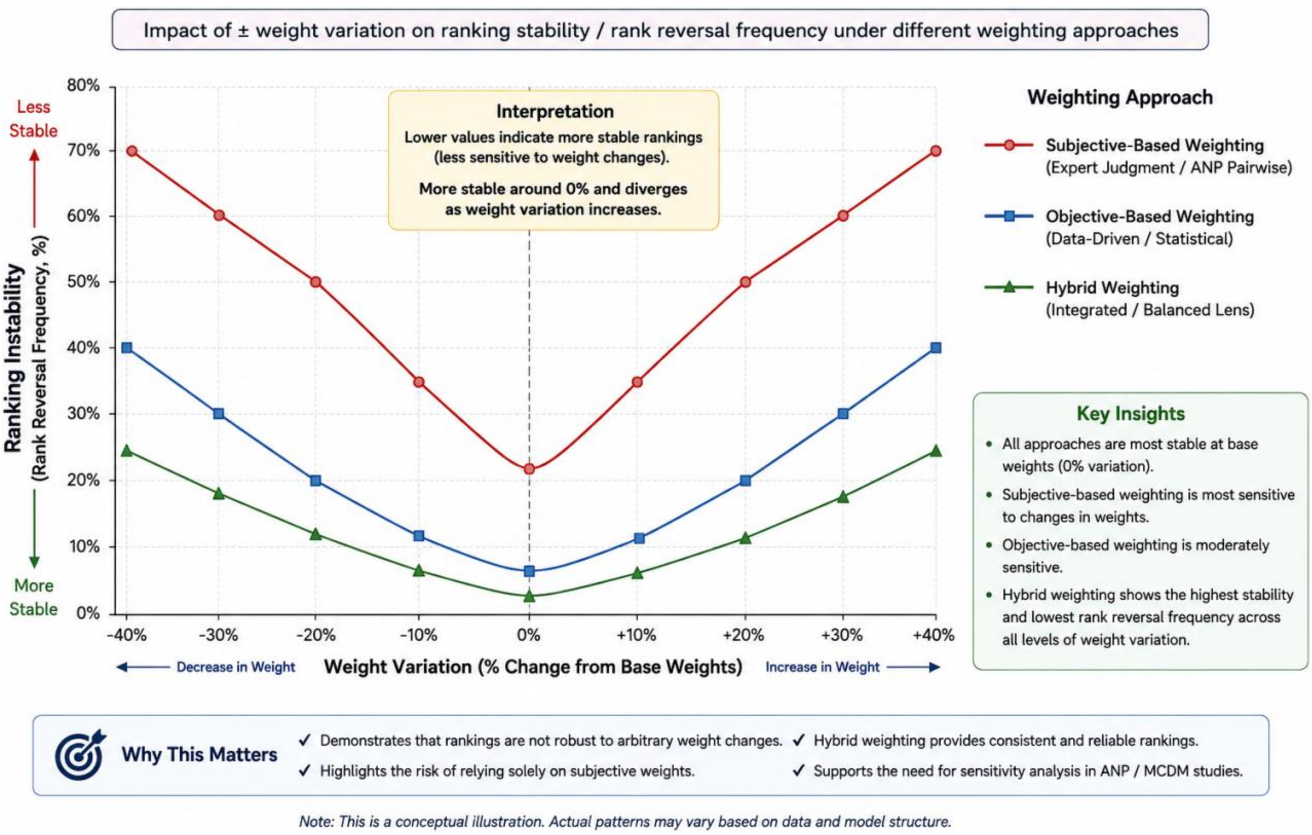

Fig. 7. Sensitivity of ranking to weight variation

6. Emerging Trends and Future Directions

From traditional rule-based weighting systems to intelligent, adaptive, and context-aware decision support systems, recent advances in MCDM have clearly shifted the paradigm. It is mainly motivated by the complexity of modern decision environments, which is related to the high dimensional data type, uncertainty, interdependent criteria structures, and real-time information flows [64,65]. Consequently, traditional weighting schemas are increasingly being supplemented or even supplanted with more sophisticated artificial intelligence applications that are able to learn, adjust and explain behavior in dynamic environments. A major achievement in this direction has been the implementation of fuzzy logic-based weighting systems to overcome the shortcomings of crisp numerical in traditional MCDM models [69, 70, 73-76]. The fuzzy set theory allows the representation of uncertainty, vagueness and linguistic ambiguities of human judgments, permitting decision makers to make their preferences in more realistic and flexible ways. In low-precision data and/or inherently subjective expert opinions, fuzzy extensions of the AHP, BWM, and entropy-based approaches have been shown to yield better results [78]. Even though the fuzzy weighting models have their benefits, they also have some problems to deal with such as membership function design, sensitivity of parameters and interpretability of the model in terms of computation.

Meanwhile, machine learning (ML) and deep learning (DL) weighting methods are starting to compete with classical deterministic methods. The goal of these data-driven structures is to learn the implicit weight structures directly from the historical datasets or behavioral patterns or from the simulation outputs [82]. In contrast to classical statistical techniques, ML-based techniques may be able to reflect non-linear relations between the criteria and adaptively change the weight distribution as the data patterns change over time. In recent years, neural network-based weighting, reinforcement learning techniques, and hybrid machine learning–MCDM (ML-MCDM) architectures have been gaining traction within the fields of financial forecasting, healthcare diagnostics, and intelligent manufacturing systems. One drawback of these methods is that they are “black-box” and lack interpretability, which can also be an issue of transparency and trust in decision-making results [69,70,79]. One of the key future areas of this is to develop adaptive and dynamic weighting mechanisms. Dynamic weighting frameworks incorporate changes in criterion importance as the environment evolves, as the system evolves, or as the preferences of stakeholders evolve, while static models have fixed criterion weights that are not modified during the decision process. This adaptability is essential in fast changing areas like smart grid, autonomous systems, supply chain network and real-time risk assessment [82,83]. Streaming Data Analytics and Learning Mechanisms based on feedback are expected to be a main part of the solution to give these adaptive capabilities.

The other field of research that is also rapidly emerging is Explainable Artificial Intelligence (XAI) based MCDM frameworks. The increasing use of AI tools for weighting has made it imperative to have transparency, interpretability, and accountability of decision models [84]. Explainable weighting systems (EWS) are designed to help close the gap between the complexity of algorithmic calculations and the comprehension of humans, offering transparent reasoning for weight assignment and decisions. This is especially crucial in high-stakes fields like public policy, healthcare, and finance, where transparency is a key part of trust and regulatory adherence. Going forward, it is hoped that explainability mechanisms will be incorporated into hybrid MCDM-AI systems without impacting the efficiency or effectiveness of the system's predictive performance [84,85]. Moreover, the combination of weighting methods and large scale optimization approaches and real-time decision systems has seen an increasing research interest. Today in Industry 4.0 and smart manufacturing ecosystems, decision making processes are increasingly becoming part of cyber-physical systems which demand ongoing monitoring, quick response and autonomous optimization. In these settings, weighting mechanisms need to work in real time, with input data that are made up of streams and changing priorities in decision making. This requires lightweight, scalable and computationally efficient weighting algorithms that can work within tight time limits.

In addition, future studies will investigate the integration of the MCDM weighting techniques with the Internet of Things (IoT), big data analytics and the digital twin technologies. These integrations will allow for more accurate representation of real-world systems; the physical and digital environments will be synchronized, allowing for continuous data and information. Such systems can evolve weighting models based on feedback loops which can be real-time, to improve the accuracy of the decisions and increase system responsiveness [82,83]. A further line of development will be a combination of fuzzy logic, stochastic modeling and Bayesian inference through the development of uncertainty aware and probabilistic weighting frameworks which will better deal with variability in data and in expert judgment. This is especially important in complex systems in which the uncertainty exists as well as is embedded in the environment of decision-making [85,86]. In conclusion, the future of criteria weighting for MCDM is looking toward an amalgamation of AI, uncertainty modeling, and real-time adaptive systems. This is an evolution from the traditional analytical models towards intelligent, context-aware and self-learning decision support architectures. Significant research progress towards this goal is crucial for solving the complexity, uncertainty, and dynamism of contemporary decision making problems. Table 6 gives a summary of the key research needs and future issues in weighting methodologies. Table 6 is a high impact narrative showing gaps, limitations and directions for future research.

Table 6
Research gap matrix in criteria weighting methods for MCDM

Research area	Current limitation	Identified research gap	Future research direction	Expected contribution
Static weighting mechanisms	Most traditional methods assume fixed criterion importance throughout the decision process	Inability to adapt to changing environments and dynamic criteria relationships	Development of adaptive and real-time dynamic weighting frameworks	Improved responsiveness and decision stability in evolving systems
Subjective bias and expert dependency	Expert judgments are prone to inconsistency, cognitive bias, and variability	Lack of robust mechanisms for reducing human-induced uncertainty	Integration of subjective and objective weighting through hybrid correction models	Enhanced reliability and reduced decision bias
Objective weighting limitations	Purely data-driven methods ignore contextual relevance and stakeholder priorities	Weak incorporation of strategic and domain-specific knowledge	Context-aware objective weighting systems with semantic integration	Better alignment between mathematical rigor and practical relevance
Ai-based weighting systems	Machine learning and deep learning models often operate as “black-box” systems	Limited transparency and interpretability of learned weights	Explainable AI (XAI)-based weighting frameworks	Improved trust, transparency, and accountability in automated decision systems
Uncertainty handling	Traditional methods inadequately address vagueness, incomplete information, and probabilistic uncertainty	Lack of unified uncertainty-aware weighting structures	Integration of fuzzy, interval-valued, and probabilistic weighting models	More realistic modeling of uncertain decision environments
Hybrid method standardization	Hybrid methods lack unified integration procedures and validation standards	Methodological inconsistency across studies	Development of standardized hybrid weighting protocols	Improved reproducibility and cross-study comparability
Interdependency among criteria	Many weighting methods assume criteria independence	Weak modeling of causal and network relationships	Advanced network-based weighting using DEMATEL, DANP, and graph-based AI systems	Better representation of complex decision structures

Table 6
Continued

Research area	Current limitation	Identified research gap	Future research direction	Expected contribution
Scalability in big data environments	Conventional methods struggle with high-dimensional and streaming datasets	Limited scalability for real-time analytics and Industry 4.0 systems	Lightweight and scalable AI-assisted weighting algorithms	Enhanced applicability in large-scale intelligent systems
Sensitivity and rank stability	Minor changes in weights may cause rank reversal and unstable outcomes	Lack of robust sensitivity evaluation frameworks	Advanced sensitivity and robustness analysis models	Increased confidence and stability in MCDM outcomes
Integration with intelligent systems	Existing methods are weakly integrated with IoT, digital twins, and cyber-physical systems	Limited real-time autonomous decision capability	Integration of weighting systems with IoT and digital twin architectures	Intelligent and self-adaptive decision ecosystems
Multi-stakeholder decision environments	Difficulty in balancing conflicting stakeholder preferences	Lack of collaborative and consensus-aware weighting models	Group decision-support frameworks using consensus optimization	Improved inclusiveness and stakeholder satisfaction
Explainability and ethical decision support	AI-assisted decision systems may lack ethical transparency	Limited focus on fairness and responsible AI integration	Ethical and explainable MCDM weighting frameworks	Responsible and human-centric intelligent decision-making

Table 6 contains a thorough matrix of research gaps that highlights the key gaps in current criteria weighting research techniques and identifies novel methodological challenges and research opportunities. Analysis shows that traditional weighting methods are still confined to static assumptions, lack uncertainty management capabilities, and do not provide a good integration with intelligent computational systems. Of particular concern, subjective methods are still plagued with issues of cognitive bias and inconsistent results, while objective methods frequently miss out on contextual relevance and stakeholder intent. Table 6 also illustrates the increasing relevance of adaptive, explainable and uncertainty aware weighting methods that are able to work in dynamic, data-rich environments. Recent research trends show that AI, fuzzy logic, probabilistic modeling, and real-time analytics are becoming more prominent in MCDM weighting systems [87]. Moreover, it is pointed out that the need for methodological standardization, robustness against sensitivity and scalable architecture for calculations are also highlighted as critical needs for developing next generation intelligent decision support systems.

The conceptual structure of the AI-aided adaptive weighting model is shown in Figure 8. Figure 8 shows an intelligent weighting framework with an AI model for next generation MCDM systems. The framework combines machine learning, fuzzy logic, big data analytics, explainable AI and adaptive weighting mechanisms into a single decision-support framework. The Figure 8 depicts a dynamic approach of updating the weights of the criterion based on the evolution of decision conditions which is enabled by streaming data, real-time environmental feedback, and intelligent learning algorithms. Moreover, the inclusion of explainability modules enhances explainability and trust in automated weighting systems [88]. This framework is the future direction of intelligent and adaptive MCDM methodologies for Industry 4.0 and smart analytics.

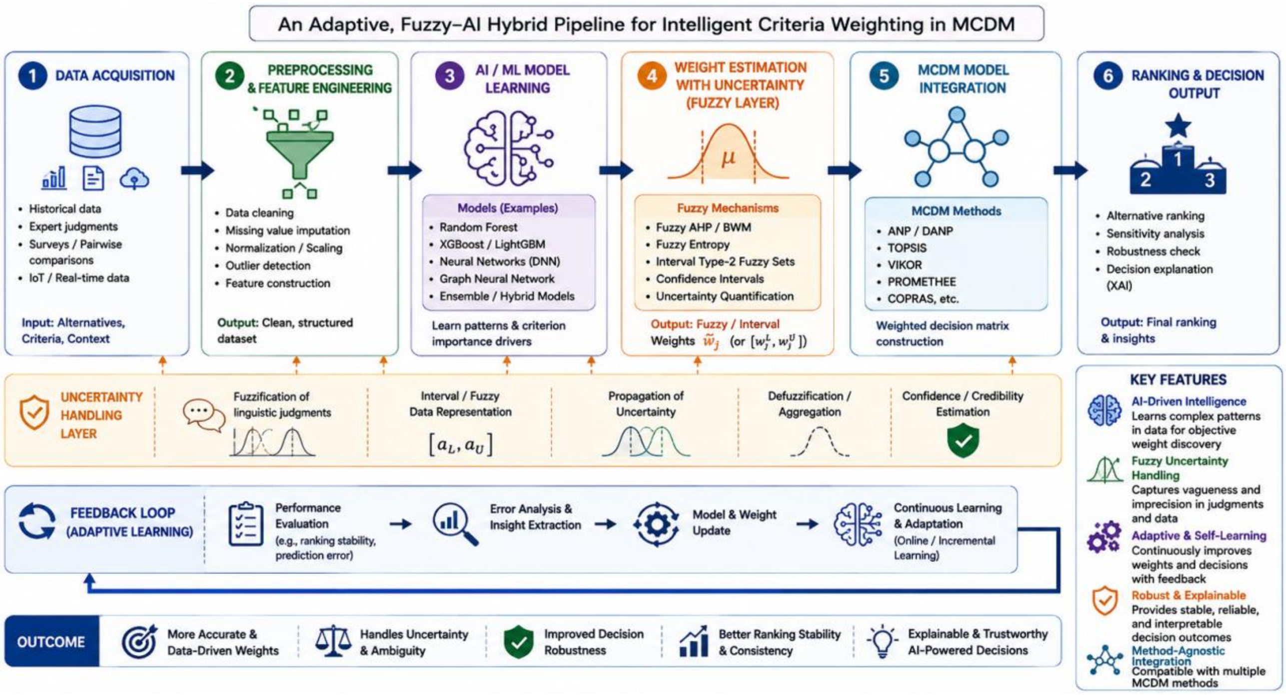

Fig. 8. AI-enhanced weighting framework

7. Conclusion

Criteria weighting is one of the most important and influential aspects of MCDM because it is directly related to the aggregation behaviour of the evaluation models and also determines stability, consistency and credibility of the final decision results. The choice and design of the weighing mechanisms are important and relevant to the overall performance of MCDM frameworks in the various application areas. This review was a systematic examination of how the criteria weighting approaches have evolved over time, classified, and characterized in terms of methodology, with a particular emphasis on the subjective and objective paradigms and hybrid. The results show that AHP, ANP, SWARA, and BWM are still of great value in the context of expert systems because of their interpretability, intuitive structure and capability of integrating knowledge from the field. But they are also subject to the inherent human judgment that can bring inconsistencies, biases and variations among decision makers.

Objective weighting methods (entropy, CRITIC, PCA, MEREC) have been developed, which offer a strong mathematical basis and reproducibility as they are based on data structures. However, their drawback is that they do not include contextual and strategic decision-maker preferences, which may decrease their practical interpretability in some real-world scenarios. Hybrid weighting schemes have appeared as a possible compromise of the subjective and objective schemes. These methods are an amalgamation of expertise and data analysis, making them more robust, less biased, and ensuring greater reliability in decisions. Nevertheless, the hybrid approach can bring in its own methodological complexity and force the need to carefully calibrate the various components to guarantee consistency. This review highlights the fact that there are no clear universal best practices for weighting in relation to any specific method of weighting. The performance and suitability of any weighting technique is very context specific, depending on data availability, complexity of problems, levels of uncertainty, and dynamics of the decision environment. This affects the basic idea that the weightings of the criteria are to be treated as an adaptive and context-sensitive part of the MCDM process, rather than as a predetermined step.

This research adds to the literature in several ways. First, it offers a structured classification of the criteria weighting methods, which helps to understand their differences and the evolution of the methods. Second, it provides a comparative synthesis of the subjective, objective, and hybrid methods and highlights the advantages and disadvantages of each and their suitability to use. Third, it pinpoints the need for critical research gaps, especially on issues of uncertainty handling, dynamic weighting and methodological standardization. Lastly, the researchers' work identifies new areas in which AI, machine learning and fuzzy logic are likely to have a transformative effect on the evolution of future weighing systems. Moving forward, the area of criteria weighting will become more adaptive, intelligent and uncertainty aware with regard to decision frameworks. The use of AI methods, live data analysis, and understandable decision models will probably change the concept of weighting as we know it. The ability to adapt to changing environments through dynamic weighting systems and the use of explainable AI-based MCDM will be crucial for maintaining transparency, robustness, and applicability in complex decision-making scenarios. In conclusion, this review offers a thorough overview of the current weighting approaches and sets the groundwork for future studies exploring the potential for increased resilience, adaptability, and intelligence in decision-support systems for the MCDM framework.

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Conflicts of Interest
The authors declare no conflicts of interest.

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