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A Comprehensive Review of Fuzzy Multiple Criteria Decision-Making (MCDM) Methods: Advancements, Applications, and Future Directions

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ABSTRACT

Real-world situations can be associated with numerous conflicting criteria, imprecise information, and subjective human decisions. Traditional Multiple Criteria Decision-Making (MCDM) approaches are not able to manage such uncertainty sufficiently. MCDM methods based on fuzzy logic address these shortcomings by incorporating linguistic preferences and modelling uncertainty in expert appraisal. In this paper, fuzzy MCDM techniques are reviewed thoroughly, tracing their development from classical fuzzy extensions to more recent developments in intuitionistic, Pythagorean, and picture fuzzy models. The paper offers a systematic classification, including outranking, value-based, pairwise comparison, and hybrid decision models. Important application areas such as energy planning, healthcare, supply chain management, transportation, and intelligent systems are critically scrutinized. Challenges related to computational complexity, subjectivity, model validation, and real-time deployment are addressed. Finally, future directions are identified, including intelligent automation, data-driven decision support, standardization of uncertainty modelling, and autonomous decision-making in dynamic environments.

1. Introduction

The decisions are important in the process of solving complicated problems in the real world, where they have to consider several widely-ranging, even contradictory, criteria at once. In the case of engineering design to planning of healthcare, supply chain optimization to sustainability assessment, decision makers are often faced with the need to choose the most appropriate one among a number of viable options. In order to facilitate these kinds of analytical processes, Multiple Criteria Decision-Making (MCDM) techniques have become very popular as they are capable of organizing problems, measuring preferences and enhancing the level of transparency in the outcomes of the decision-making process [1].

Nonetheless, classical MCDM methods are very sensitive to the accuracy of numerical data and clear-cut judgments, which are not always realistic in human-based decision-making problems.

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Subjective evaluation is unavoidable in most practice fields, as the experts use language devices like good, acceptable or poor to express their preference. These qualitative information can be characterized by vagueness, ambiguity and uncertainty that cannot be well represented under the traditional MCDM models. Consequently, the judgement of the decisions might be inconsistent or less reliable when facing the unfinished or unprecise information [2]. To overcome these drawbacks, the fuzzy set theory proposed by Zadeh has become a necessary instrument of expressing uncertainties in the opinion of the experts [3]. By incorporating fuzzy logic with MCDM methods, it can be possible to transform linguistic judgments into mathematical ones, giving it a more realistic representation of human cognition. The fuzzy MCDM methods improve the level of decision making by including expert hesitation that brings in the level of membership and addressing imprecision in a systematic fashion.

With time, the ability of MCDM frameworks to model complex uncertainty has continued to develop with different extensions including intuitionistic fuzzy sets, Pythagorean fuzzy sets, and type-2 fuzzy sets [4]. This review aims to present an in-depth and systematic review of the current developments in the fuzzy MCDM techniques. The paper examines the traditional and innovative fuzzy MCDM methods, their advantages and disadvantages, and their use in various industries. A bibliometric approach is involved to trace the trends in research, determine the contribution power, and observe the field evolution. Besides, the review addresses the existing issues and new opportunities, the theme of applying fuzzy MCDM to artificial intelligence, big data analytics, and real-time decision-support systems.

The rest of this paper has been organized in the following manner: Section 2 gives the theoretical background of fuzzy logic in decision making. Section 3 is a review and classification of well-known fuzzy MCDM methods. Section 4 is about weighting strategies and measures of performance evaluation. Section 5 provides the important places of fuzzy MCDM application. Key challenges are addressed in Section 6, whereas the next research directions are presented in Section 7. Lastly, Section 8 ends the review by providing important observations and contributions.

2. Fundamentals of fuzzy logic in MCDM

2.1 Basics of fuzzy set theory

The traditional form of set theory represents elements that belong and those that do not belong to a set by binary values (0 or 1). Nonetheless, a lot of actual life situations include levels of belonging instead of definite choices. To capture this kind of uncertainty, Zadeh [3] proposed fuzzy set theory and in this approach, each element is denoted by a membership function which gives an element a value between 0 and 1, representing the extent of membership.

Membership functions: Membership functions are the conversion of linguistic terms into quantitative terms. The most popular membership functions are:

i. Triangular: This shape is simple with three parameters (low, medium, high) and the judgement is appropriate when the expert is involved.
ii. Trapezoidal: Triangular sets with a plateau area that can be extended to provide more flexibility and realism.
iii. Gaussian: Smooth and continuous functions which are usually adopted in sophisticated fuzzy modeling.

Conventional fuzzy set over the years have taken on a number of forms to ultimately model human hesitation and multi-dimensional uncertainty.

Types of fuzzy sets: The following Table shows different type of fuzzy sets that can be applied to MCDM methods.

Table 1
Types of fuzzy sets

Fuzzy Set Type	Key Concept	Mathematical Constraint	Major Advantages	Common Applications
Type-1 Fuzzy Sets [5]	Crisp membership function values representing degree of belonging	$\mu(x) \in [0,1]$	Simple, easy computation	Control systems, classical fuzzy MCDM
Type-2 Fuzzy Sets [6]	Membership grades themselves are fuzzy; captures higher-order uncertainty	FOU (Footprint of Uncertainty)	Better handling of noisy/incomplete data	Robotics, forecasting, medical decision-making
Interval Type-2 Fuzzy Sets [7]	Special case of Type-2 with interval membership uncertainty	$\mu(x) \in [l, u]$	Reduced computational load with retained uncertainty depiction	Resource allocation, prediction systems
Intuitionistic Fuzzy Sets (IFS) [8]	Membership + non-membership + hesitation degree	$\mu + \nu \leq 1$	Explicit modeling of hesitancy	MCDM, medical analysis, expert systems
Interval-Valued Fuzzy Sets (IVFS) [9]	Membership degree expressed as an interval	$\mu(x) = [l, u]$	Reflects bounded uncertainty	Risk evaluation, image processing
Hesitant Fuzzy Sets (HFS) [10]	Membership expressed as multiple possible values	$\mu(x) = \{\mu_1, \mu_2, \ldots\}$	Represents ambiguity in expert opinion	Group decision-making, recommendations
Rough Fuzzy Sets [11]	Combines rough set approximations with fuzzy membership	Lower & upper approximations	Models granularity + uncertainty	Data mining, pattern recognition
Pythagorean Fuzzy Sets (PFS) [12]	Allows larger flexibility than IFS	$\mu^2 + \nu^2 \leq 1$	Strong hesitation representation	Complex system evaluation, MCDM
Picture Fuzzy Sets [13]	Adds neutrality parameter to membership + non-membership + refusal	$\mu + \nu + \eta \leq 1$	Captures acceptance, rejection, and abstention clearly	Opinion surveys, social sciences
Type-3 Fuzzy Sets [14]	Hierarchical (uncertainty of Type-2 sets) modeling	Multi-level fuzzy uncertainty	Extremely flexible	Advanced theoretical research

2.2 Types of uncertainty and ambiguity in decision problems

The uncertainty and ambiguity in decision problems tend to be different, and come about as a result of incomplete, imprecise or conflicting information. It is important to be aware of these forms of uncertainties and the implication that they have on sound decision-making. The following is an elaborate examination of the forms of uncertainty and ambiguity that are usually faced in decision problems and their nature and applicability as observed in Table 2:

Table 2
Types of uncertainty and ambiguity in decision problems

Type of Uncertainty	Definition	Key Characteristics	Examples	Common Application Areas
Aleatory Uncertainty (Statistical/Random) [15]	Uncertainty due to inherent randomness or natural variability in a system	Irreducible; modeled using probability and statistics	Weather fluctuations, random component failures, dice roll	Weather forecasting, finance, manufacturing

Table 2
Continued

Type of Uncertainty	Definition	Key Characteristics	Examples	Common Application Areas
Epistemic Uncertainty (Knowledge-Based) [16]	Uncertainty due to lack of knowledge, incomplete or imprecise data	Reducible with more data or research; fuzzy and belief systems apply	Limited clinical trial data, geological property estimation	Engineering design, climate modeling
Ambiguity (Linguistic/Contextual)[17]	Uncertainty from vague or subjective terms and unclear definitions	Subjective; multiple interpretations possible	Terms like “high risk” or “low cost”; vague policy criteria	Group decision-making, legal and contract analysis
Fuzziness (Gradual Uncertainty) [18]	Uncertainty due to smooth or overlapping boundaries between categories	Best modeled with fuzzy sets; handles linguistic judgments	Temperature described as “warm”; income levels overlapping	Intelligent and control systems, human evaluation processes
Conflict-Based Uncertainty [19]	Arises from contradictory evidence, data, or expert opinions	Handled with Dempster–Shafer theory, probabilistic fusion	Experts disagreeing on project risks; divergent customer feedback	Policy-making, risk management, market research
System Complexity Uncertainty [20]	Originates from dynamic and highly interconnected systems	Often unpredictable; requires simulations and robust models	Environmental changes, global financial crises	Supply chain planning, ecology, traffic and network systems
Behavioral Uncertainty[21]	Unpredictability introduced by human behavior	Involves biases, emotions, bounded rationality	Consumer purchase behavior; team decision conflicts	Behavioral economics, public health, HR management
Uncertainty in Multi-Criteria Decisions [22]	Caused by trade-offs among conflicting criteria	Requires prioritization or weighting; subjective preferences	Energy system selection; job offer evaluation	Urban planning, product design, operational research

These ambiguities cannot be properly measured using classical MCDM resulting in incorrect or precise decisions. The fuzzy logic offers a sound mechanism that can be used to handle these uncertainties by allowing a degree of flexibility in preference modeling.

2.3 Why fuzzy MCDM?

Fuzzy MCDM solutions are very popular in different fields to face complex decision problems with a number of conflicting criteria. The usage of fuzzy logic on MCDM has great benefits as it has the exclusive capacity to accommodate vagueness, inaccurate data, and subjective human judgments [23-25]. Following are the main reasons why fuzzy MCDM is necessary and quite capacitive as illustrated in Table 3:

Table 3
Importance and advantages of fuzzy MCDM

Aspect	Key Points	Illustration	Applications
Dealing with Uncertainty and Vagueness	Fuzzy MCDM translates vague, subjective terms into mathematical models using membership functions (values between 0 and 1)	Supplier evaluation criteria like "timeliness" or "communication quality"	Manufacturing, project selection, risk assessment

Table 3
Continued

Aspect	Key Points	Illustration	Applications
Enhanced Decision-Making Flexibility	Supports gradual, continuous representation of preferences and multi-granular input from multiple stakeholders	Expressing criteria in precise numbers, intervals, or linguistic terms	Multi-expert decision-making, policy analysis
Aggregation of Diverse Preferences	Integrates heterogeneous inputs from group members using fuzzy linguistic scales	Doctors, patients, and administrators providing different risk assessments	Healthcare, collaborative decision-making
Improved Interpretability	Mimics human reasoning; provides interpretable relationships among criteria and alternatives	Fuzzy cognitive maps, concept lattices for visualization	Decision support systems, education, management
Sophisticated Ranking & Preference Analysis	Evaluates alternatives with complex criteria interactions and trade-offs; uses advanced fuzzy sets like Pythagorean or hesitant sets	Fuzzy pairwise comparison, fuzzy dominance matrices	Supplier ranking, project prioritization, investment decisions
Support for Multi-Attribute Decision-Making	Enables flexible criteria weighting (subjective/objective) and integration of qualitative and quantitative data	Weighting cost, time, risk, and social impact simultaneously	Engineering, urban planning, sustainability assessments
Applications Across Domains	Fuzzy MCDM is versatile and widely applicable	Engineering & Manufacturing, Environmental Management, Healthcare, Finance	Supplier selection, sustainable resource allocation, medical diagnosis, portfolio optimization
Extensions Enhancing Decision Power	Advanced fuzzy sets handle hesitation, complex membership, and additional uncertainty layers	Hesitant Fuzzy Sets, Pythagorean Fuzzy Sets, Interval Type-2 Fuzzy Sets	Complex, uncertain decision environments; high-stakes or high-ambiguity problems

Thus, Fuzzy logic has been incorporated into contemporary MCDM literature and practice, offering superior modeling facilities to the uncertain world.

3. Classification of fuzzy MCDM techniques

The Fuzzy MCDM techniques are classified according to the methodology, the tools, and the circumstances in which the particular methods are applicable. The techniques are critical in solving decision making problems in which many conflicting criteria need to be considered in uncertain and imprecise settings. The fuzzy MCDM approaches are classified in major categories as presented in Table 4 below:

Table 4
Classification of fuzzy MCDM

Category	Techniques	Key Features	Applications
Aggregation-Based Methods [26]	Fuzzy Weighted Sum Model (FWSM), Fuzzy Weighted Product Model (FWPM), Fuzzy AHP, Fuzzy TOPSIS, Fuzzy VIKOR, Fuzzy ELECTRE, Fuzzy PROMETHEE	Aggregate criteria or preferences into a single score/ranking; handle fuzzy weights and scores; consider criteria interactions	Supplier selection, project prioritization, supply chain management, strategic planning
Preference Relation-Based Methods [27]	Fuzzy Pairwise Comparison, Fuzzy Preference Degrees, Fuzzy Dominance Matrices, Fuzzy Outranking	Compare alternatives using fuzzy relational models; establish dominance relationships	Team selection, resource prioritization, multi-expert evaluations

Table 4
Continued

Category	Techniques	Key Features	Applications
Fuzzy Set Extensions in MCDM [28]	Hesitant Fuzzy MCDM, Intuitionistic Fuzzy MCDM, Pythagorean Fuzzy MCDM, Interval Type-2 Fuzzy MCDM	Incorporate membership, non-membership, hesitation; handle higher levels of uncertainty; manage decision-maker hesitation	Group decision-making, dynamic and uncertain environments, complex risk evaluation
Fuzzy Rule-Based & Cognitive Methods [29]	Fuzzy Cognitive Maps (FCM), Fuzzy Rule-Based Systems	Model causal relationships between criteria; use IF-THEN rules for reasoning	Environmental policy, social decision-making, automated decision support systems
Dynamic & Group Decision-Making Extensions [30]	Fuzzy Multi-Attribute Group Decision Making (MAGDM), Dynamic Fuzzy MCDM, Concept Lattice-Based MAGDM	Aggregate multiple decision-maker inputs; handle evolving or time-dependent problems; visualize consensus	Collaborative decision-making, portfolio analysis, heterogeneous expert groups
Fuzzy Goal Programming & Optimization-Based Methods [31]	Fuzzy Goal Programming, Fuzzy Multi-Objective Optimization	Optimize multiple fuzzy goals; consider trade-offs across criteria	Engineering design, resource allocation, sustainability planning

Fuzzy MCDM methods offer a flexible and powerful system to make decisions in the case of uncertainty. They also vary in their styles, with some of them being simple aggregative algorithms such as fuzzy AHP and TOPSIS, and others being highly complex combining hesitant and intuitionistic logic or type-2 fuzzy logic. The choice of the right method is determined by the characteristics of the decision situation, that is, the type of uncertainties, the complexity of assessing the criteria, and the participation of multiple stakeholders or the conflict of priority.

4. Performance evaluation and weighting techniques

In fuzzy models of MCDM, proper distribution of importance of criteria, and correct combination of professional assessments is a major factor in obtaining credible decisions. Basing their choices on numerous criteria, these methods [32-35] provide the means of assessing alternatives in relation to the different criteria and a weighting factor of the criterion in relation to how crucial it is, which allows the decision-makers to model complex systems and resolve conflicts. These aspects in fuzzy MCDM have been analyzed below as presented in Table 5.

Table 5
Performance evaluation and weighting techniques in fuzzy MCDM

Aspect	Key Points	Methods / Techniques	Applications
Fuzzy Decision Matrices	Construct matrices where alternatives are evaluated against criteria using fuzzy numbers or linguistic terms	Triangular, Trapezoidal, Interval-Valued Fuzzy Numbers	Product selection, supplier evaluation, risk assessment
Aggregation of Criteria Scores	Combine criteria scores to obtain overall evaluation	Arithmetic (weighted average), Geometric (weighted geometric mean), Hesitant Fuzzy, Intuitionistic, Pythagorean Fuzzy sets	Supplier selection, multi-factor evaluation
Alternative Ranking Techniques	Prioritize alternatives based on fuzzy evaluation	Fuzzy TOPSIS, Fuzzy VIKOR, Fuzzy ELECTRE, Fuzzy PROMETHEE	Supplier ranking, project prioritization, portfolio selection

Table 5
Continued

Aspect	Key Points	Methods / Techniques	Applications
Subjective Weighting	Based on expert judgment	Fuzzy AHP (pairwise fuzzy comparisons), Direct linguistic weight assignments	Project portfolio selection, hierarchical decision-making
Objective Weighting	Based on data characteristics	Entropy Method, CRITIC (considers variance & intercriteria correlation)	Sustainability assessment, industrial operations, environmental management
Hybrid Weighting	Combine subjective and objective approaches	Fuzzy Delphi Method, Integrated AHP-Entropy	Urban planning, energy resource selection, supply chain decisions
Recent Trends	Enhance flexibility, accuracy, and adaptability in weighting and evaluation	Hesitant Fuzzy Weights, Pythagorean Fuzzy Weights, Dynamic Fuzzy Weighting, Multi-Granular Fuzzy Systems, ML-based weight derivation	Time-sensitive decisions, large-scale data analysis, expert-consensus-based evaluations

By means of systematic weighting, aggregation and evaluation metrics, fuzzy MCDM guarantees superior reflection of expert appraisals and promotes the quality of decisions made in uncertain situations. Fuzzy MCDM frameworks are essential in sensitizing analysis to know the strength and dependability of decision-making results. It assesses the sensitivity of the results to changes in the input parameters, model assumptions or decision criteria [36, 37]. Through sensitivity analysis, researchers and practitioners are able to determine essential factors, which affect the decision, the consistency of rankings, and the effect of uncertainties. The varieties of sensitivity analysis that are normally used in fuzzy MCDM are explored in detail below as illustrated in Table 6:

Table 6
Sensitivity analysis in fuzzy MCDM

Type of Sensitivity Analysis	Key Points	Key Methods	Applications
Parameter Sensitivity	Examines how changes in input parameters within the fuzzy framework affect outcomes	- Membership function variation (triangular, trapezoidal, Gaussian) - Changes in criteria weights - Linguistic scale adjustments	Supplier selection, infrastructure prioritization, resource allocation
Criterion Sensitivity Analysis	Evaluates the effect of adding, removing, or modifying criteria on decision results	- Criterion addition/removal - Criterion threshold modification - Criteria correlation analysis	Portfolio selection, medical decision support, multi-criteria evaluation
Aggregation Operator Sensitivity	Assesses the influence of different aggregation operators on final rankings	- Weighted aggregation sensitivity - Operator selection (OWA, Choquet integrals, fuzzy Hamming distance) - Parameter dependency	Urban planning, manufacturing process optimization, multi-factor evaluations
Fuzzy Logic Model Sensitivity	Focuses on fuzzification, inference, and defuzzification stages	- Input value fuzzification sensitivity - Rule base perturbation - Defuzzification approach analysis (centroid, mean of maxima, weighted average)	Climate modeling, autonomous decision-making systems, automated control systems
Output Sensitivity Analysis	Evaluates how variations propagate to final output	- Ranking stability analysis - Stress testing with extreme conditions - Monte Carlo simulations	Investment risk analysis, disaster management planning, policy assessment

Table 6
Continued

Type of Sensitivity Analysis	Key Points	Key Methods	Applications
Hybrid Sensitivity Analysis	Combines multiple sensitivity approaches for interdependent factors	- Multi-layer modeling of criteria, weights, and rules - Interactive iterative assessment of input changes	System engineering design, healthcare multi-stakeholder decisions, supply chain management
Recent Advancements	Modern approaches enhance precision and adaptability	- Advanced fuzzy sets (hesitant, intuitionistic, Pythagorean, interval-valued) - Dynamic sensitivity for time-dependent systems - Integration with stochastic models (Bayesian networks, Markov chains)	Smart city planning, dynamic supplier evaluation, large-scale logistics, policy-making

Fuzzy MCDM sensitivity analysis offers an advanced way of making sure that decisions are robust in uncertain conditions. It enables decision-makers to determine the most important parameters that can affect the results, model validation, and improve collaborative decision-making. As fuzzy logic and computational tools evolve, the sensitivity analysis becomes increasingly holistic and accurate, so that it can be applied to various and complicated problem areas.

5. Trends in fuzzy MCDM

The temporal dynamics of the research productions on Fuzzy MCDM since 1977 judged by the data that were retrieved in Dimensions.ai database show clear and consistent growth pattern, which shows progressive maturing of the given research field. Publications before 1989 were few and mostly theoretical as the basic development of fuzzy set theory took place as shown in Figure 1.

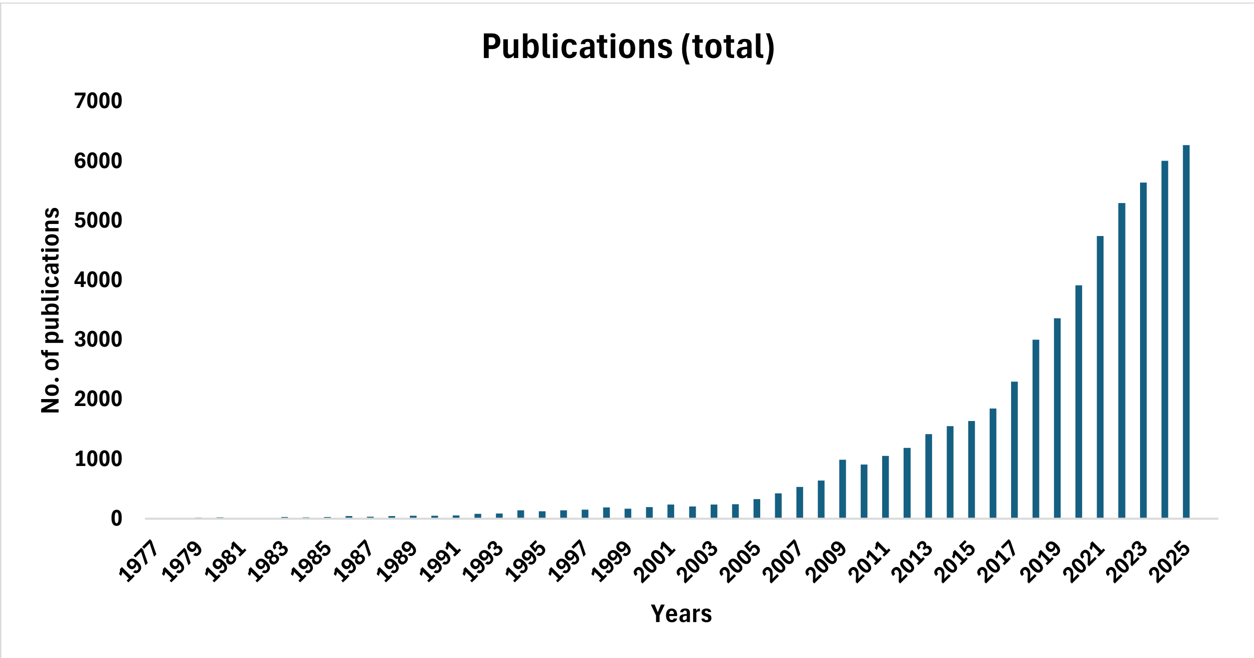

Fig. 1. Publication Trends

The development of fuzzy logic within conventional MCDM methods was a gradual process between 1990-2004. Between 2005 and 2014 development of the growth of publications was also accelerated by the increase in the areas of application and interdisciplinary use. It is characterized by high growth rates of the period 2015-2025 based on the developed fuzzy frameworks, hybrid models, and bibliometric research, and the tendencies point to the further growth of the field in the year 2026 when the necessity in decision-making under uncertainty will become even more significant.

6. Major application domains of fuzzy MCDM

The popularity of Fuzzy MCDM techniques in different fields is explained by the possibility to deal with uncertainty, imprecise data, and conflicting multiple criteria. The key areas of the application of fuzzy MCDM frameworks have been described below as indicated in Table 7:

Table 7
Major application domains of fuzzy MCDM

Domain	Applications	Methods
Engineering and Manufacturing [38]	- Supplier selection based on cost, quality, timeliness, reliability- Resource allocation of labor, material, capital- Process optimization for production efficiency	Fuzzy AHP, Fuzzy TOPSIS for ranking suppliers, design evaluation considering vague factors like “customer satisfaction”
Healthcare and Medicine [39]	- Treatment decision support considering efficacy, safety, cost- Resource allocation in medical facilities- Diagnostic ranking under imprecise symptoms	Fuzzy linguistic scales (e.g., "serious condition," "moderate risk") integrated into personalized treatment planning
Finance and Investment [40]	- Portfolio optimization under uncertain market conditions- Risk management for investment decisions- Credit scoring with imprecise financial data	Fuzzy VIKOR, Fuzzy TOPSIS to balance returns and investor preferences
Environmental Management [41]	- Resource planning (water, energy, natural resources)- Environmental impact assessment- Policy design for sustainable development	Fuzzy logic models addressing multi-dimensional sustainability metrics like “air quality improvement” or “carbon sequestration potential”
Transportation and Urban Planning [42]	- Infrastructure project prioritization- Traffic flow and transport optimization- Energy-efficient housing evaluation	Fuzzy ELECTRE, PROMETHEE for ranking infrastructure projects based on stakeholder preferences
Governance and Policy-Making [43]	- Conflict resolution in multi-stakeholder decisions- Budget allocation for public welfare projects- Disaster management prioritization	Dynamic fuzzy MCDM for adjusting public health strategies and emergency resource allocation
Education and Human Resources [44]	- Curriculum design and program evaluation- Employee selection incorporating subjective traits- Performance evaluation with linguistic scales	Fuzzy linguistic decision criteria like “excellent communication skills” applied to HR and educational assessments
Energy Systems and Sustainability [45]	- Renewable energy planning (wind, solar, hydro)- Smart grid management- Energy resource optimization under uncertainty	Fuzzy multi-attribute decision models prioritizing renewable energy installations based on cost, scalability, and environmental impact
Retail and Marketing [46]	- Product selection based on customer preferences and sales forecasts- Customer segmentation- Pricing under uncertain demand	Fuzzy QFD, hesitant fuzzy sets to align product features with market trends
Emerging Applications [47]	- Advanced fuzzy sets (hesitant, interval-valued, Pythagorean)- AI and machine learning integration- Dynamic decision models- Quantum decision frameworks- Autonomous systems decision-making	Automated fuzzy weighting, real-time disaster response modeling, intelligent robotic or vehicle decisions under high uncertainty

The Fuzzy MCDM methods have been invaluable in the solution of problems in reality which have multiplicity criteria with conflicting characteristics and uncertain parameters. Their flexibility is further improved with the development of sophisticated approaches and calculation software, which allows them to be used in virtually any sphere of decision-making.

7. Critical challenges in fuzzy MCDM

The Fuzzy MCDM systems are effective decision-making tools in the uncertainty world, but they are also known to have important challenges to overcome in order to achieve effective implementation and wider usage in various fields [48]. These challenges will be discussed in detail as illustrated in Table 8 below:

Table 8
Challenges in fuzzy MCDM Frameworks

Challenge	Issue	Implication	Proposed Solutions
Handling High Levels of Uncertainty	Extreme variability or highly conflicting criteria may exceed standard fuzzy modeling capabilities.	Disaster management scenarios with time-sensitive decisions; conflicting criteria may reduce reliability.	Use interval type-2 fuzzy sets, hesitant fuzzy sets; improve uncertainty modeling at cost of computational complexity.
Complex Computational Requirements	Advanced fuzzy models (type-2, Pythagorean, interval-valued) demand high computational resources.	Real-time autonomous navigation or energy grid control may suffer from delays.	Streamlined algorithms, heuristic methods, and AI-assisted computation for efficiency.
Aggregation Operator Dependence	Decision outcomes are sensitive to choice of aggregation operators (e.g., weighted mean, OWA, Choquet integral).	Supplier evaluation may yield contrasting rankings depending on operator choice.	Develop standardized guidelines or adaptive selection of aggregation operators.
Incorporating Dynamic Changes	Static fuzzy MCDM approaches cannot adapt to changing criteria, weights, or priorities over time.	Dynamic resource allocation during emergencies requires real-time updates.	Develop dynamic fuzzy frameworks and time-adaptive models.
Handling Subjective vs. Objective Weighting	Balancing expert judgment (subjective) and data-driven weights (objective) is challenging.	Healthcare: patient satisfaction vs. treatment cost efficiency.	Hybrid weighting approaches combining subjective and objective methods, e.g., fuzzy Delphi + entropy.
Decision Consensus	Achieving agreement among multiple stakeholders is difficult due to diverse opinions and hesitation.	Urban policy planning with conflicting priorities among engineers, officials, and residents.	Enhanced consensus methods, such as multipolar concept lattices or refined fuzzy Delphi techniques.
Transparency and Interpretability	Fuzzy systems involve abstract mathematics, making decisions hard to explain to non-experts.	Executives may require clear justification for investment or project choices.	Visualization tools, rule-based explanations, and interpretable fuzzy models.
Scalability Across Domains	Large-scale problems with many alternatives/criteria create unwieldy computations and matrices.	Supply chain optimization across multiple regions and suppliers.	Sparse matrix computation, heuristic optimization, and scalable fuzzy algorithms.
Data Availability and Quality	Limited, missing, or unreliable data affects model accuracy.	Environmental sustainability models lacking historical ecological metrics.	Robust fuzzy techniques for incomplete data, imputation methods, and adaptive fuzzy models.
Integration With Emerging Technologies	Combining fuzzy MCDM with AI, IoT, Big Data, or Blockchain presents integration challenges.	Smart city infrastructure planning with dynamic sensor data streams.	Hybrid AI-fuzzy systems, real-time data processing, and IoT-compatible fuzzy frameworks.

Table 8
Continued

Challenge	Issue	Implication	Proposed Solutions
Recent Advancements	Addressing multiple challenges via hybrid or advanced fuzzy methods.	Improved uncertainty handling, computational efficiency, and consensus-building.	Hesitant, Pythagorean, Fermatean, type-2 fuzzy sets; AI integration; scalable algorithms; multipolar consensus models.

Fuzzy MCDM have transformative advantages but have to be refined with time to overcome their critical challenges. Due to the development of hybrid modeling, computational optimization, and enhanced interpretability, the methods will broaden their field of use in the medical sphere, engineering, policy-making, and sustainability planning.

8. Future research directions

Fuzzy MCDM should aim at addressing the current shortcomings, exploiting the advances of technology, and interdisciplinary usage as depicted in Table 9.

Table 9
Future research directions in fuzzy MCDM

Research Area	Direction	Applications	Expected Outcomes
Advancing Fuzzy MCDM Techniques	Novel Extensions of Fuzzy Sets	Fermatean, Spherical, Neutrosophic fuzzy sets; Dynamic Type-3 systems	Handle higher uncertainty, multi-parameter vagueness, and indeterminacy
	AI-Driven Fuzzy Enhancements	Machine learning integration; Reinforcement learning with fuzzy logic; Explainable AI (XAI)	Self-adaptive weighting, real-time updates, improved interpretability
	Hybrid Models	Fuzzy + Probabilistic methods (Bayesian networks), Quantum-inspired decision frameworks, Multi-level hierarchical fuzzy systems	Enhanced uncertainty handling, multi-scale decision modeling
	Real-Time and Dynamic Fuzzy MCDM	Dynamic frameworks for disaster management, stock market, autonomous vehicles; Streaming data integration	Time-sensitive decisions, adaptability to real-time data
Advancements in Weighting & Aggregation	Improved Weighting Techniques	Context-aware weights, interactive weighting, multi-expert Fuzzy MAGDM	Dynamic adjustment, better group consensus, context-sensitive importance
	Adaptive Aggregation Operators	Dombi operator variants, adaptive OWA, semantic/NLP-based aggregation	Handle nonlinear, interrelated criteria, improved interpretability
Applications in Emerging Fields	Sustainability & Climate Change	Carbon budget allocation, energy resource planning, climate action assessment	Optimized, evidence-based sustainability decisions
	Healthcare Innovation	Precision medicine, resource allocation, epidemic control, treatment prioritization	Patient-specific, adaptive decision-making
	Smart Cities & IoT	Urban infrastructure, transportation planning, IoT-driven resource management	Intelligent, data-driven city planning
	Blockchain & Cryptoeconomics	Crypto evaluation, blockchain ecosystem optimization, trust modeling	Secure, multi-criteria investment and network decisions

Table 9
Continued

Research Area	Direction	Applications	Expected Outcomes
Human-Centric & Collaborative Applications	Inclusive Decision Making	Integrating marginalized or minority preferences	Fairer, socially responsible resource allocation
	Collaborative Platforms	Real-time, multi-stakeholder online decision-making	Enhanced stakeholder participation, consensus-building
Personalized Decision-Making Frameworks	Individualized Models	E-commerce recommendations, financial planning, education program design	Adaptive, behaviorally-informed decision support
Enhancing Interpretability & Transparency	Explainability in Fuzzy Systems	Visual analytics, linguistic rules, dashboards	Stakeholder trust, transparent decision reasoning
	Validation & Sensitivity Analysis	Robust weighting, linguistic adjustments, reproducibility tests	Reliable and validated decision outputs
Leveraging Technological Advancements	Big Data & Cloud Integration	Large-scale multi-criteria problems, cloud computing for scalability	Scalable, high-performance fuzzy MCDM
	Quantum Computing	Quantum-inspired fuzzy logic for high-dimensional optimization	Faster computation, handling complex, large-scale problems
Refining Methodologies & Theoretical Foundations	New Theory on Fuzzy Uncertainty	Combine advanced fuzzy sets with Dempster-Shafer, rough sets, or neural models	Stronger mathematical foundation, hybrid uncertainty modeling
	Customization for Domain-Specific Problems	Energy management, transportation, environmental policy, geopolitical decisions	Domain-optimized fuzzy MCDM methods, enhanced practical relevance

Future studies in the fuzzy MCDM focus on the potential to extend utility by computer, mathematical, and interdisciplinary developments that will eventually provide effective, clear and scalable decision processes. The next generation of decision systems will be based on increased integration with new technologies, including AI and quantum computing, and the focus on domain customization.

9. Conclusions

Fuzzy MCDM has emerged as a vital system in addressing problem related to complex decision-making which is characterized by uncertainty, vagueness and subjective human judgement. The fuzzy MCDM methodologies have developed over the last decades since rudimentary fuzzy set implementations to complex hybrid and smart decision-support systems. Fuzzy TOPSIS, fuzzy AHP/ANP, fuzzy VIKOR and other new developments like Pythagorean, Fermatean, and spherical fuzzy sets show considerable advancement in the uncertainty capture with better accuracy and versatility. The review has thoroughly categorized the fuzzy MCDM methods including their strengths, weaknesses, and recent developments in their methodology. The results of a bibliometric overview showed that the publication trends are quickly increasing due to the interest of the global research and the multidisciplinary applications. The practical applicability and flexibility of fuzzy MCDM in contemporary problem setting can be supported by major application areas, such as sustainable energy planning, healthcare decision support, supply chain management, robotics, and financial risk assessment. In spite of success, fuzzy MCDM is also challenged with the complexity of computation, the subjectivity of the performance based on expert judgment and absence of standard validation procedures. The advent of big data, AI, IoT, and Industry 4.0 technologies creates new requirements of real-time and autonomous as well as data-driven decision-making systems. As a perspective, fuzzy MCDM in the future is characterized by incorporation of intelligence based on machine learning, harmonization on uncertainties frameworks and creation of scalable and automated decision agents that can operate in dynamic situations. Solving these issues will go a long way in establishing itself in terms of its theoretical bases and massive penetration into the industrial sphere. Summing up, the field of fuzzy MCDM is a very dynamic and fast-growing research field with great potential to bring innovation in the decision analytics field, particularly in the situations where the end result is restricted and human-like reasoning is crucial.

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Conflicts of Interest
The authors declare no conflicts of interest.

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