Journal of Contemporary Decision Science

Journal homepage: www.cds-journal.org/
ISSN: 3104-3380

Three Decades of Multiple Criteria Decision-Making (MCDM) Methods (1996–2026): A Comprehensive Review of Advancements, Applications, and Future Directions

Sushil Kumar Sahoo[1,2,*], Bibhuti Bhusan Choudhury[1,2], Prasant Ranjan Dhal[1,2], Sudhakar Majhi[1,2], Ipsita Dhar[1,2], Supriya Sahu[1,2]

[1] Department of Mechanical Engineering, Indira Gandhi Institute of Technology, Sarang, Odisha, India
[2] Biju Patnaik University of Technology, Rourkela, Odisha, India

ARTICLE INFO

Article history:
Received 21 February 2026
Received in revised form 28 April 2026
Accepted 8 June 2026
Available online 13 June 2026

Keywords:
Multiple Criteria Decision-Making; Multi-Attribute Decision-Making; Fuzzy MCDM; Hybrid Decision Models; Artificial Intelligence; Machine Learning; Bibliometric Analysis; Decision Support Systems.

ABSTRACT

Multiple Criteria Decision-Making (MCDM) techniques have proven to be indispensable tools for addressing decision problems involving multiple conflicting criteria across a wide range of applications. This review paper comprehensively examines the evolution, applications, and future directions of MCDM methods from 1996 to 2026. A systematic literature review was conducted using publications retrieved from multiple scientific databases, and the collected studies were analyzed through bibliometric and thematic approaches. The review highlights the growing importance of widely adopted methods such as AHP, TOPSIS, VIKOR, DEMATEL, ELECTRE, PROMETHEE, MOORA, COPRAS, MARCOS, and CoCoSo across diverse domains, including engineering, healthcare, robotics, renewable energy, transportation, and sustainability. Furthermore, hybrid frameworks integrating fuzzy logic, grey theory, machine learning, deep learning, and artificial intelligence have significantly enhanced decision-support capabilities under uncertainty. The study also identifies key research gaps and future directions related to computational complexity, scalability, interpretability, and real-time intelligent decision-making systems.

1. Introduction

Multiple Criteria Decision-Making (MCDM) techniques have been one of the most influential analytical solutions for the multiple criteria decision problems. Over the past 30 years, MCDM has undergone significant development, thanks to the rapid advances in computational intelligence, artificial intelligence and optimization methods. They are widely applied in multiple fields such as engineering, healthcare, management, sustainability, robotics, energy systems, transportation and other areas where decision makers need to assess and compare multiple options that are evaluated based on multiple criteria [1].

[*] *Corresponding author.*
E-mail address: sushilkumar00026@gmail.com

1.1 Background of MCDM

MCDM is an iterative decision-making support method applied to assess, compare, rank and select among alternatives that are evaluated using multiple and often conflicting parameters. In practical situations, there are often multiple factors, quantitative and qualitative, that decision-makers need to take into account at the same time. The aim of the MCDM techniques is to help to reduce the complexity of such problems by giving them a structured analytical framework for making effective and rational decisions. The use of these methods has become increasingly crucial in various engineering, healthcare, management, manufacturing, sustainability, transportation and other fields, as they contribute to the enhancement of the quality of the decisions, reduction of uncertainty and optimization of the use of resources [2]. Table 1 below summarizes the major importance and benefits of MCDM.

Table 1
Definition and Importance of MCDM

Importance Aspect	Description	Key Benefit	Example Application
Complex Decision Support	Assists in solving problems involving multiple criteria	Improves decision quality	Engineering design selection
Handling Conflicting Criteria	Balances trade-offs among competing objectives	Achieves optimal decisions	Cost vs performance analysis
Decision Accuracy	Provides systematic evaluation frameworks	Reduces human bias	Supplier evaluation
Transparency and Consistency	Offers clear and traceable decision procedures	Enhances reliability	Policy and strategic planning
Uncertainty Management	Handles vague and uncertain information effectively	Better risk management	Healthcare diagnosis
Resource Optimization	Supports efficient allocation of resources	Improves productivity	Manufacturing optimization
Strategic Planning	Assists long-term planning and policy formulation	Better organizational performance	Energy planning
Multi-disciplinary Applications	Applicable across diverse sectors and domains	Wide adaptability	Transportation and logistics
Intelligent Decision Support	Integrates AI, fuzzy logic, and optimization methods	Smart automated decisions	Smart city systems
Sustainability Assessment	Supports environmental and sustainable decision-making	Sustainable development	Renewable energy selection

Over the past few decades, the development of the MCDM techniques has made a great leap, from a simple mathematical optimization model to a more sophisticated intelligent and hybrid decision support system. Traditional theories and methods of decision making were primarily based on single-objective optimization and utility-based theories. As problems in the real-world involving uncertainty, multiple criteria, and huge amounts of data became more complex, however, there is a proliferation of sophisticated MCDM methodologies [3] that were developed. A brief history of the MCDM techniques starting from traditional models to modern AI based models is summarized in Table 2.

Table 2
Historical Evolution of MCDM Techniques

Period	Major Development	Representative Methods	Key Characteristics	Major Advantages	Limitations
Before 1990	Traditional decision models	Utility Theory, Linear Programming	Single-objective optimization and mathematical modelling	Simple and mathematically rigorous	Limited handling of multiple conflicting criteria
1990–2000	Classical MCDM growth	AHP, TOPSIS, ELECTRE	Structured multi-criteria evaluation methods	Easy implementation and ranking capability	Subjectivity in weighting
2001–2010	Fuzzy and hybrid approaches	Fuzzy AHP, Fuzzy TOPSIS, DEMATEL	Handling uncertainty and vagueness using fuzzy logic	Improved decision accuracy under uncertainty	Increased computational complexity
2011–2023	Intelligent optimization integration	ANP, VIKOR, MOORA, COPRAS	Integration with optimization and network analysis	Better handling of interdependent criteria	Complexity in large-scale systems
2023–2026	AI-driven and explainable systems	AI-MCDM, ML-integrated MCDM, Explainable AI	Intelligent, adaptive, and real-time decision-making	High prediction capability and automation	Interpretability and transparency issues

The MCDM methods are useful to handle multiple conflicting criteria in various decision domains, and are used in solving complex decision problems. The major application areas, common applications, widely used methods and key decision criteria for the MCDM are summarized in Table 3 below.

Table 3
Role of MCDM in Various Domains

Domain	Major Applications	Commonly Used MCDM Methods	Key Decision Criteria
Engineering	Material selection, design optimization	AHP, TOPSIS, VIKOR	Cost, strength, durability, efficiency
Manufacturing	Supplier selection, process optimization	DEMATEL, MOORA, COPRAS	Quality, productivity, lead time
Robotics	Path planning, component selection	TOPSIS, ANP, CoCoSo	Accuracy, energy consumption, speed
Healthcare	Disease diagnosis, treatment planning	Fuzzy AHP, VIKOR	Risk, effectiveness, patient safety
Energy	Renewable energy evaluation	AHP, PROMETHEE, MARCOS	Sustainability, cost, efficiency
Transportation	Traffic management, route optimization	TOPSIS, ELECTRE	Time, fuel consumption, safety
Sustainability	Environmental impact assessment	Fuzzy TOPSIS, COPRAS	Pollution, resource utilization
Disaster Management	Risk analysis and emergency planning	DEMATEL, ANP	Vulnerability, response time
Finance	Investment and portfolio selection	AHP, VIKOR, MOORA	Profitability, risk, return
Supply Chain	Logistics and vendor evaluation	TOPSIS, WASPAS	Reliability, cost, delivery time

Table 3
Continued

Domain	Major Applications	Commonly Used MCDM Methods	Key Decision Criteria
Agriculture	Crop selection, irrigation planning	AHP, Fuzzy MCDM	Yield, water usage, soil quality
Education	Faculty evaluation, course selection	AHP, TOPSIS	Performance, quality, satisfaction
Construction	Contractor and site selection	PROMETHEE, ELECTRE	Cost, safety, project duration
Information Technology	Software selection, cybersecurity evaluation	TOPSIS, DEMATEL	Security, scalability, performance
Smart Cities	Urban planning, smart infrastructure evaluation	VIKOR, CoCoSo	Sustainability, connectivity, efficiency
Environmental Management	Waste management, pollution control	Fuzzy TOPSIS, MARCOS	Environmental impact, cost
Aerospace	Aircraft component selection	AHP, ANP	Weight, reliability, fuel efficiency
Water Resource Management	Reservoir and water allocation planning	ELECTRE, VIKOR	Water quality, availability, sustainability
Telecommunications	Network selection and optimization	TOPSIS, WASPAS	Signal quality, bandwidth, latency
Military and Defense	Weapon system evaluation, strategic planning	AHP, DEMATEL	Reliability, operational efficiency, security

1.2 Motivation for the Study

The rapid emergence of increasingly complex real-world decision-making problems has significantly stimulated the development of advanced Multiple Criteria Decision-Making (MCDM) approaches. Over the past three decades, a wide range of classical, fuzzy, hybrid, and artificial intelligence-based MCDM methods have been proposed and applied across diverse disciplines. This period has witnessed a substantial growth in MCDM-related publications, reflecting the expanding interdisciplinary adoption of these methods in engineering, healthcare, energy, transportation, sustainability, and other domains. Simultaneously, the integration of artificial intelligence, machine learning, and optimization techniques has enhanced the capability of MCDM models to address uncertainty and complexity. The emergence of fuzzy, grey, and neutrosophic environments has further expanded the methodological foundations of decision analysis, while the growing demand for intelligent decision-support systems has accelerated research and practical implementations. Despite these advancements, there remains a lack of comprehensive comparative studies covering the developments of the last three decades, highlighting the need for a unified and up-to-date review of the MCDM field.

1.3 Research Objectives

This review paper is guided by three primary objectives. First, it aims to provide a comprehensive bibliometric analysis of the MCDM literature by examining publication trends, research keywords, influential journals, leading authors, and prominent research institutions. Second, the study seeks to critically evaluate the strengths and limitations of existing MCDM methods, highlighting their applicability across different decision-making contexts. Third, it explores emerging research opportunities and identifies key challenges that are expected to shape the future development of MCDM methodologies, particularly in the context of intelligent, data-driven, and uncertainty-aware decision-support systems.

1.4 Research Questions

In order to answer several important research questions regarding MCDM advancements and applications, this review tries to answer those questions as stated in Table 4.

Table 4
Research Questions of the Study

Research Question ID	Research Question
RQ1	Which MCDM methods are most widely used during 1996–2026?
RQ2	What are the major advancements in MCDM methodologies?
RQ3	Which application domains dominate MCDM research?
RQ4	What are the limitations and research gaps in current MCDM methods?
RQ5	What future directions can improve intelligent decision-making systems?

This is a review paper that is divided into 13 sections. Section 1 introduces and sets background to the research and Section 2 outlines the research methodology and review framework. In Section 5 bibliometric and the fundamentals and classification of MCDM methods are discussed, respectively, followed by the evolution of MCDM techniques from 1996–2026 in Section 6. The major methods of MCDM are reviewed in detail in Section 6 and the various weighting techniques are explained in Section 7. Section 8 presents the hybrid and AI-based MCDM approaches, while Section 9 outlines predominant application fields. A comparative analysis of MCDM methods discussed in Section 10. Section 11 presents the research challenges and gaps; Section 12 presents future research directions and Section 13 concludes with final remarks.

2. Research Methodology

This research is conducted using a systematic and structured research methodology and gathers the knowledge on the development, application and development trends of the MCDM methods from 1996 to 2026. The Systematic Literature Review (SLR) approach was used to guarantee transparency, reliability, and reproducibly of the review process. The review framework is based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology, which offers a systematic approach to the identification, screening, eligibility assessment and selection of relevant literature.

The literature data for this study have been obtained only from Scopus database for its wide coverage of high-quality peer-reviewed journals, conference proceedings and multidisciplinary research publications. The Scopus database was selected due to its well-known reliability, capability of citation indexing and the fact that it has a comprehensive body of academic data, suitable for bibliometric and scientometric analyses.

A comprehensive search strategy was developed with the help of appropriate key words related to MCDM techniques and applications. The main keywords used in the search were: Multiple Criteria Decision-Making, MCDM, Multi-Attribute Decision-Making, MADM, AHP, TOPSIS, VIKOR, DEMATEL, Fuzzy MCDM, Hybrid MCDM, AI-based decision-making, PROMETHEE, ELECTRE, ANP, MOORA, COPRAS, WASPAS, MARCOS, and CoCoSo. The inclusion criteria included only studies published between 1996 and 2026, published only in peer-reviewed journals, and in English and relevant to MCDM methodologies and applications. Then, duplicate records, non-English publications, incomplete articles and studies not methodologically relevant were excluded.

The data collection and screening were done following the PRISMA framework as depicted in Figure 1. Firstly, relevant publications were searched in the Scopus and then related and duplicate publications were excluded. The screening stage comprised titles, abstracts and keywords screening for relevance. Then, full-text articles were reviewed in the eligibility stage to assess their methodological suitability and quality of research. The selected publications were finally reviewed and analyzed in detail.

To thoroughly analyze the gathered materials the following analytical techniques have been used. The publication productivity, influential authors, influential journals and research trends were studied through bibliometric analysis. The yearly evolution and growth of MCDM research were identified by using trend analysis. Citation analysis was carried out to identify the most highly cited publications and the greatest research contributions in the area. In addition, thematic classification was also applied to classify MCDM methods, application domains, hybrid approaches, and emerging research directions, in order to gain a broad knowledge of the evolution and future potential of MCDM methodologies.

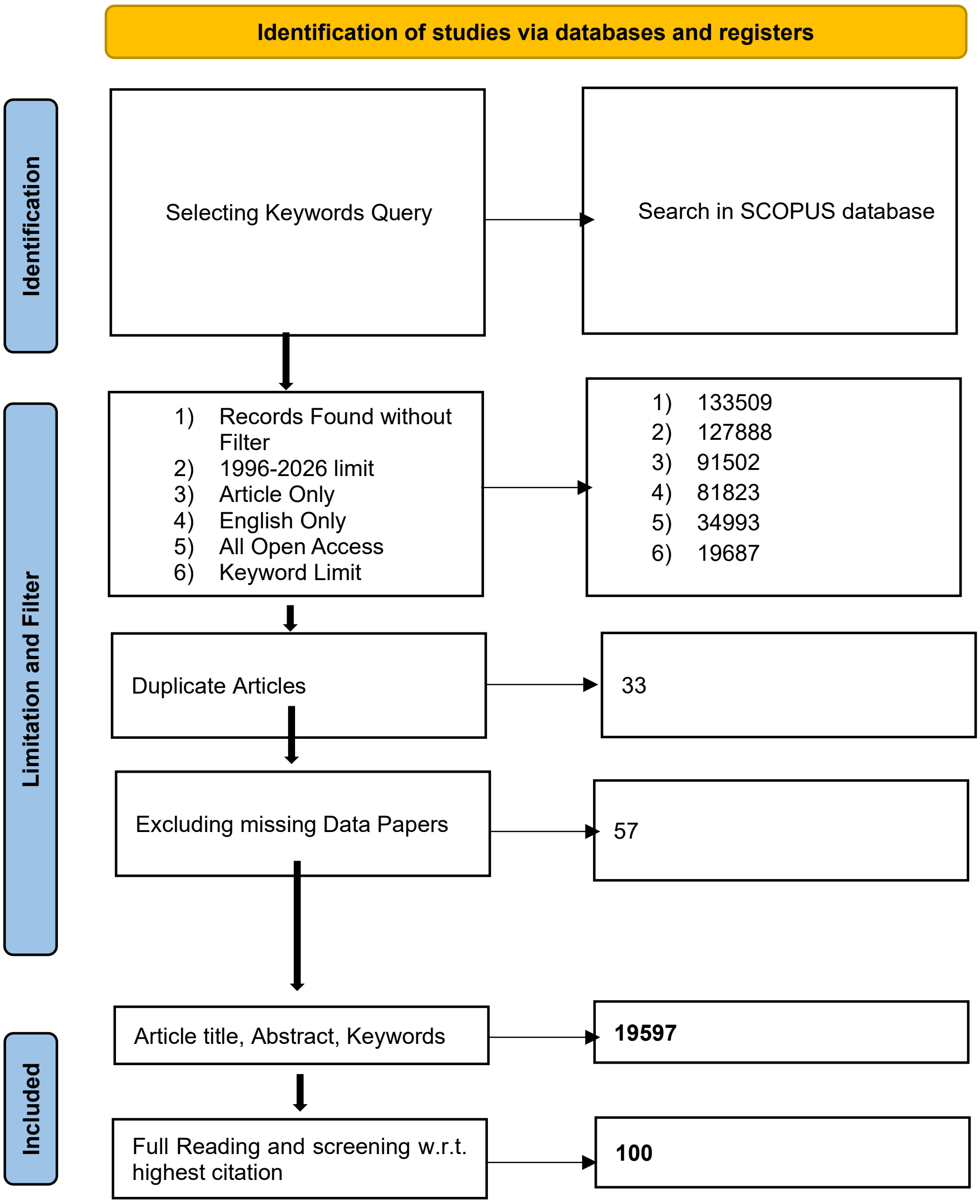

Fig. 1. PRISMA 2020 flow diagram for new systematic reviews

3. Bibliometric Analysis

Bibliometric analysis is a quantitative evaluation that can be used to investigate the research landscape of the MCDM methods, such as publications and citations, influential contributors, and emerging research themes. It assists in tracing the history of MCDM, can identify the top journals, authors, institutions, and countries, and can unveil the intellectual landscape of MCDM [4]. Bibliometric techniques provide valuable information on the evolution, hot research areas, and future trends of MCDM studies through trends in publications, citations performance, and keyword occurrences. The results of MCDM studies from 1996 to 2026, including the number of publications and citations per year, the most productive journals, the leading authors, the top contributing institutions and countries and the thematic analysis through keywords are presented in the following subsections.

3.1 Annual Publication, Citation Trends

Between 1996 and 2026 a tremendous development and increasing interest in Multiple Criteria Decision Making (MCDM) study is illustrated by its annual publications. In the first phase (1996-2005) the volume of publications was low, corresponding to the initial introduction of classical MCDM methods. The fuzzy, grey and hybrid MCDM approaches made an impact from 2006 to 2017, and a steady growth phase was observed. The number of publications in the field kept growing exponentially after 2018, reaching 3,459 in 2025, as indicated in Figure 2. This fast growth underscores the growing convergence of MCDM and artificial intelligence, machine learning, sustainability, and Industry 4.0 applications, showing high research potential and academic interest in MCDM around the world.

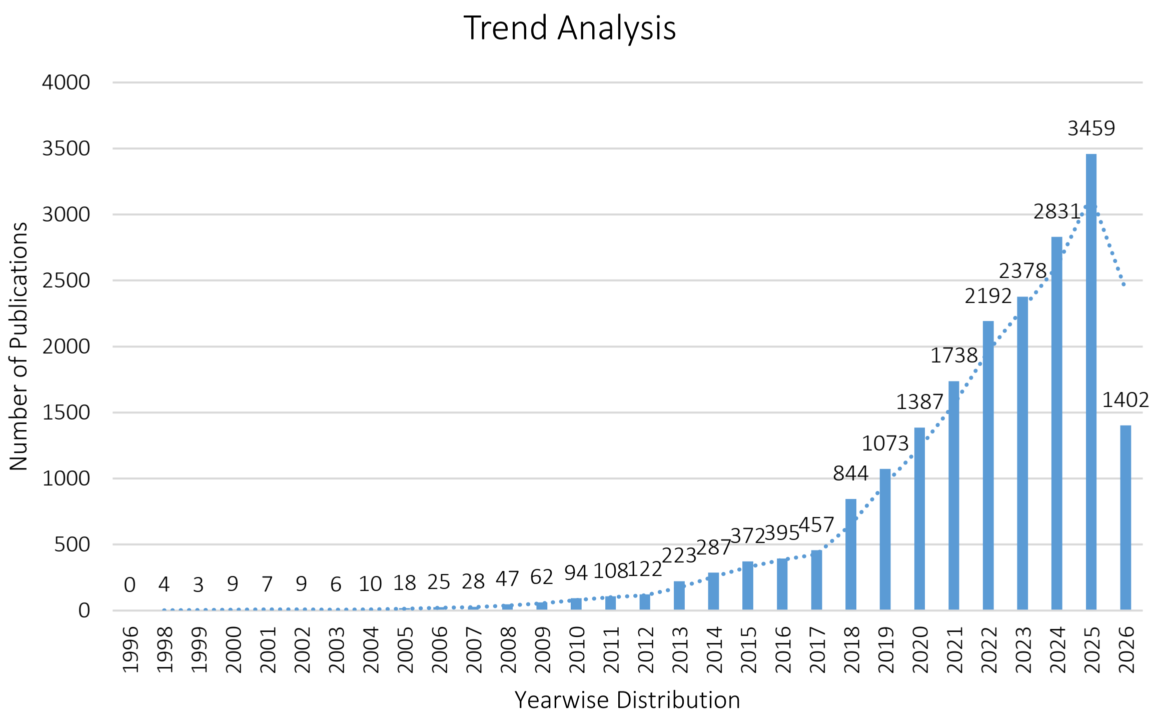

Fig. 2. Publication year wise distribution

The graph of citations per year for MCDM research shows that in the 30 years since 1996, the field has had growing academic influence and global recognition. Citation numbers were relatively low during the first years (1996-2005), indicating the initial stage of the research in MCDM, and the small number of studies published during this period. The number of citations has been found to be gradually growing from 2006 to 2015, related to the wide use of the methods like AHP, TOPSIS, VIKOR, DEMATEL, fuzzy MCDM in a large number of fields. The increase started to become strong in 2016, particularly after the number of citations went up to over 51,000 in 2020 from about 14,000 citations in 2015. The levels of citations did not change much between 2021-2023, showing the maturity and use of MCDM methodologies. The drop after 2023, especially after 2025–2026, is likely due to the citation lag and incomplete indexing of more recently published documents, which is more apparent in citation analysis, as seen in Figure 3, than to a decrease in research impact. The general pattern in the citation trend indicates that the MCDM methods continued to play a significant role in the scientific world, especially in tackling complex decision-making issues globally across various fields and disciplines.

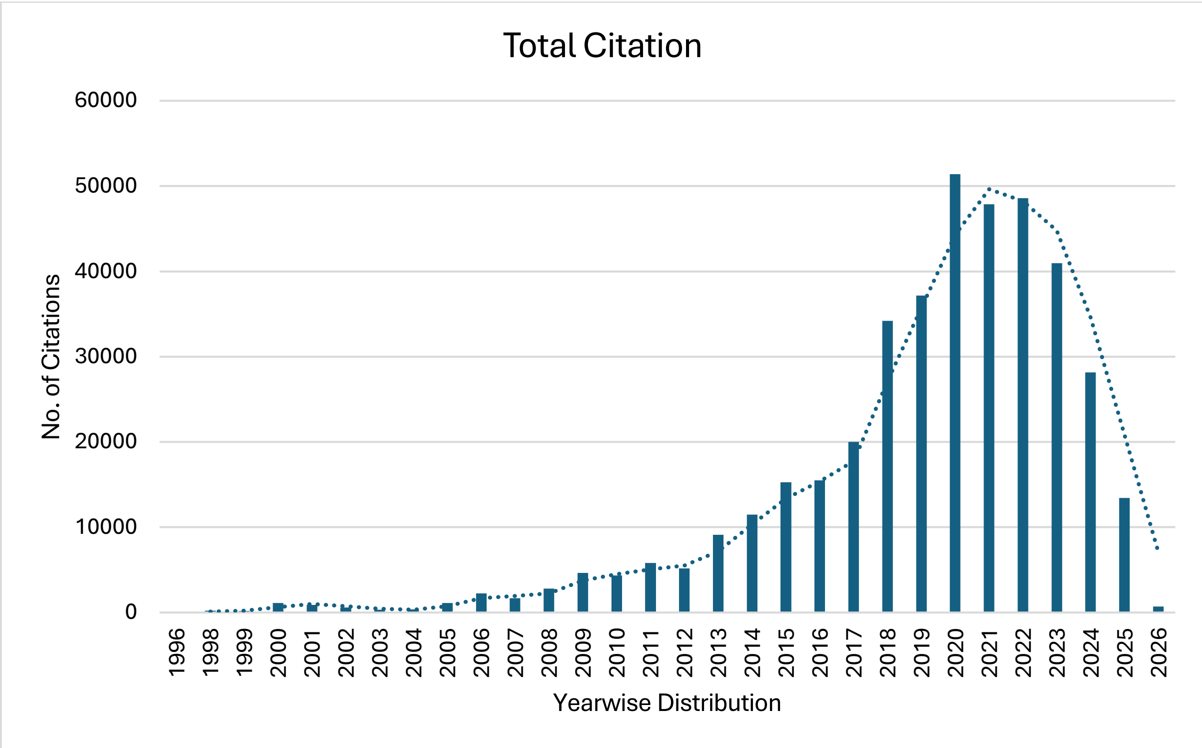

Fig. 3. Citation year wise distribution

3.2 Most Productive Journals

The analysis of the most productive journals reveals that MCDM research has been published across a wide range of multidisciplinary journals, reflecting the broad applicability of decision-making methodologies in engineering, sustainability, management, environmental sciences, and computational intelligence. Among all sources, Sustainability emerged as the most productive journal with 2,023 publications and 40,449 citations, indicating its dominant role in disseminating MCDM-related research, particularly in sustainability assessment, renewable energy, and environmental management. IEEE Access ranked second with 639 publications and 13,696 citations, highlighting the growing integration of MCDM with artificial intelligence, smart systems, and engineering applications. Other influential journals include Scientific Reports (528 publications), Energies (464 publications), Water (351 publications), Mathematics (325 publications), PLOS One (321 publications), Applied Sciences (315 publications), and Buildings (267 publications). The VOSviewer source network further confirms that Sustainability, Scientific Reports, Mathematical Problems in Engineering, Buildings, and the International Journal of Environmental Research and Public Health serve as major publication hubs within the MCDM research landscape. These findings demonstrate the interdisciplinary nature of MCDM research and its increasing importance in addressing complex decision-making challenges across diverse scientific and industrial domains as shown in network analysis in Figure 4.

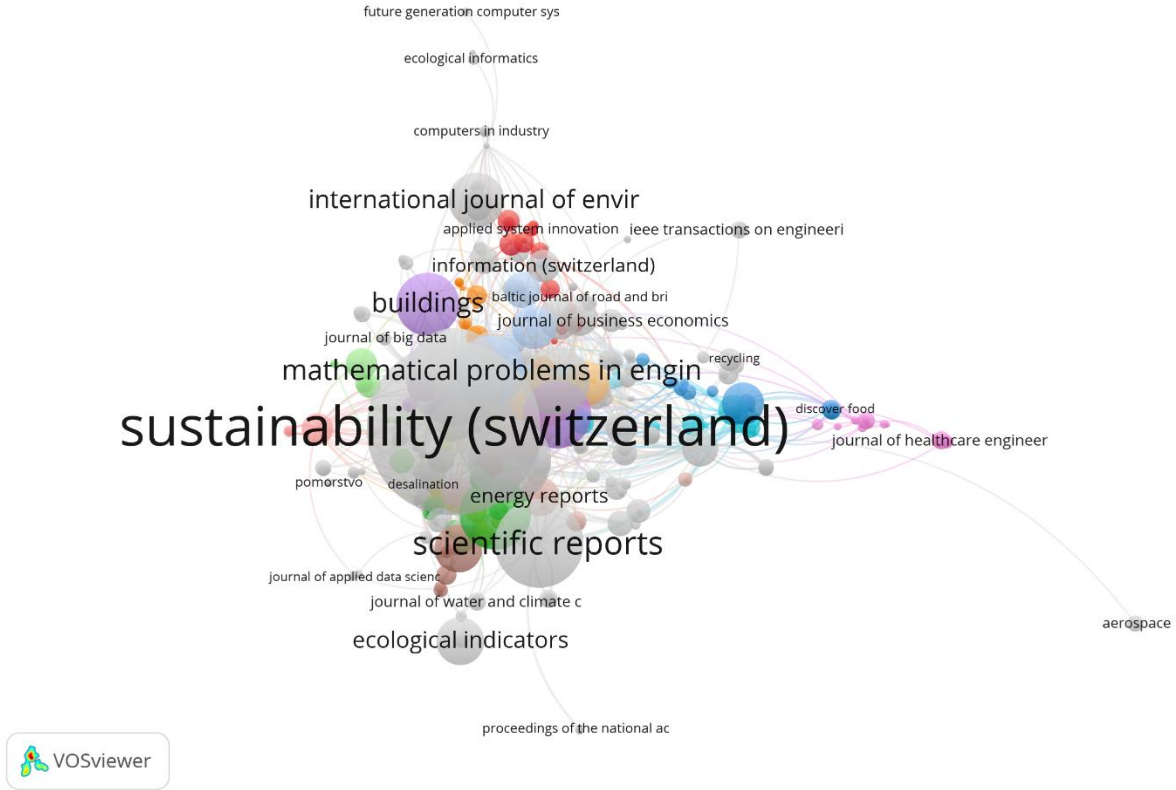

Fig. 4. Network analysis of most productive journal

3.3 Leading Authors

Based on the analysis of leading authors, it is found that during 1996-2026, there is a relatively small number of researchers who have been able to make a significant contribution to the development and advancement of MCDM methodologies. Edmundas Kazimieras Zavadskas was the most productive author among all contributors and has published 169 papers, with 15,508 citations, showing the great influence this author has had on the field, especially on the development and use of modern techniques of MCDM. Dragan Pamučar had second position with 145 publications and 4,889 citations, which have been important for his contributions in hybrid, fuzzy and intelligent MCDM models. Other important contributors include Muhammet Deveci (90 publications), Zeeshan Ali Turkis (76 publications), Harish Garg (52 publications), who have actively contributed to the development of uncertainty-based and intelligent decision-making approaches.

The VOSviewer co-authorship network shows high level of collaboration among leading researchers, with the central and most influential cluster of collaborators being Zavadskas, Pamučar and Deveci as indicated in Figure 5. There are several groups of authors that are interconnected, suggesting the existence of active knowledge sharing and cooperation in MCDM research across different countries. The network also identifies new collaborative clusters that are developing on fuzzy logic, artificial intelligence, optimization, sustainable assessment and applications in engineering. The overall results show that MCDM research is very collaborative worldwide, with highly influential authors still influencing the methodological development and interdisciplinary use of decision-making techniques.

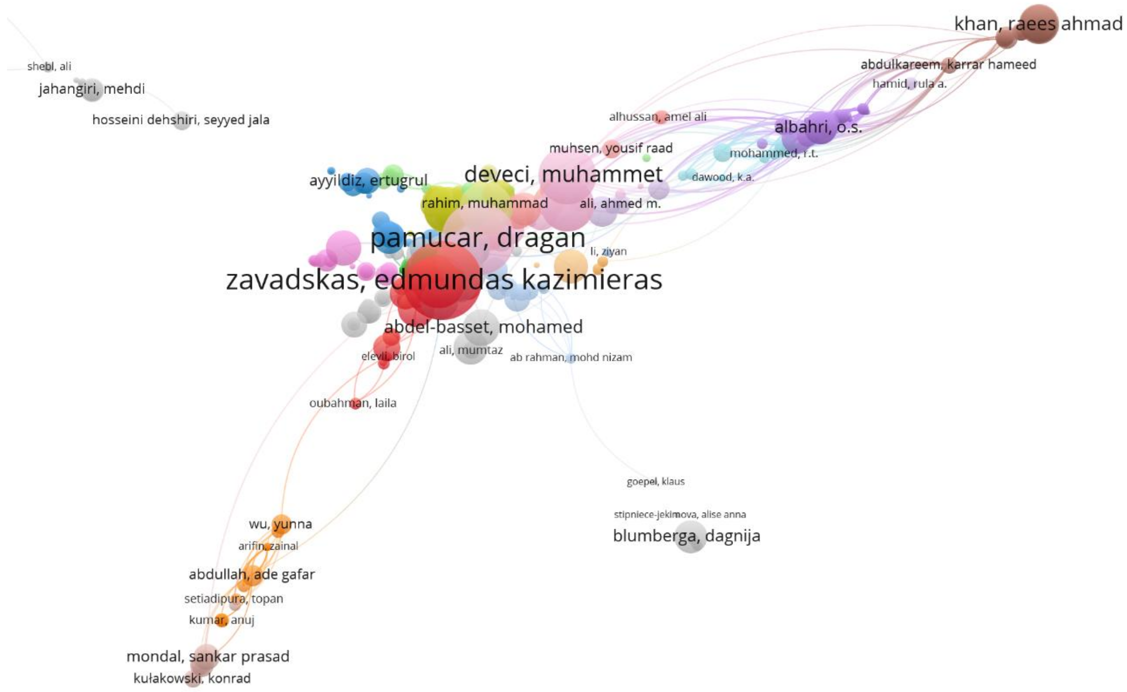

Fig. 5. Network analysis of Leading Authors

3.4 Top Institutions

The institutional analysis reveals that universities and research institutions play an important role in pushing forward MCDM research in the period of 1996-2026. Among the top institutions, North China Electric Power University led with 57 publications and 1,622 citations, reflecting its high level of research in decision-making on energy systems and sustainability. Imperial College London was next with 32 publications and 1,225 citations and Lebanese American University with 31 publications and 1,014 citations. There are also other known institutions that have contributed significantly to the development of MCDM methodology and applications, such as Wuhan University, Sichuan Normal University, and Royal School of Mines (Imperial College London).

The VOSviewer institutional collaboration network shows that the research structure is very interconnected and clusters are clearly visible, dominated by schools of economics, operations research, engineering departments and applied science research centres. Schools and departments like the School of Economics and Management, Department of Operations Research, Applied Science Research Centre, and Royal School of Mines are important collaboration hubs that connect interdisciplinary researchers as illustrated in Figure 6. Additionally, the network shows a high level of cooperation between institutions from China, UK, Lebanon, Turkey and other countries. The overall results show that the institutional structure of MCDM research is quite diverse and connected; it has been an important factor in the advancement of methodological innovations and in the spread of MCDM techniques throughout engineering, management, sustainability, health care, and intelligent systems fields.

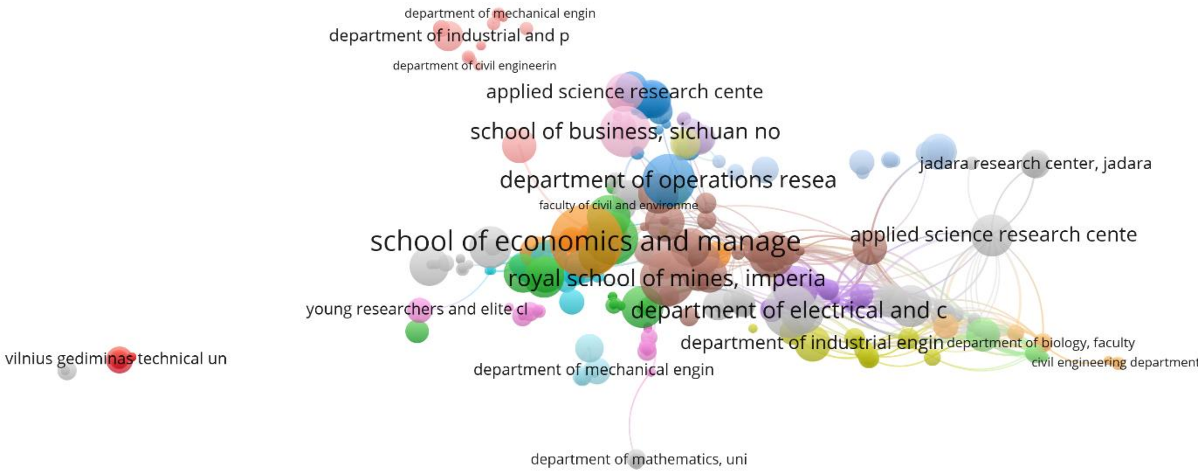

Fig. 6. Network analysis of Top Institutions

3.5 Top Country-wise Research Contribution

The results of country-wise analysis indicate the cross-pollination and global expansion in the MCDM research literature (1996-2026). Among all countries, China became the largest contributor with 5,749 publications and 99,122 citations, which indicates its leading position in the development of MCDM applications in the fields of engineering, energy system, sustainability, and intelligent technologies. India was second with 2,247 publications and 56,562 citations, followed by Turkey (1,591 publications and 35,777 citations). Other significant contributors are from Iran, United Kingdom, Saudi Arabia, United States, Taiwan, Pakistan and Spain, reflecting the interest in MCDM methodologies in various countries around the world. The collaboration network of the VOSviewer also highlights good international research cooperation among countries, with China, India, Turkey, Iran, Saudi Arabia and the United Kingdom representing important collaboration hubs in Figure 7. China is the hub of the network, suggesting that it has many countries involved in collaborative linkages. Turkey and Iran also show strong connectivity with each other, in line with their active participation in international MCDM research projects. In general, it can be concluded that MCDM has become a well-established research field that enjoys extensive international cooperation, and it is still a field of research that is evolving with developments in practical applications in engineering, management, sustainability, healthcare and intelligent decision-support systems.

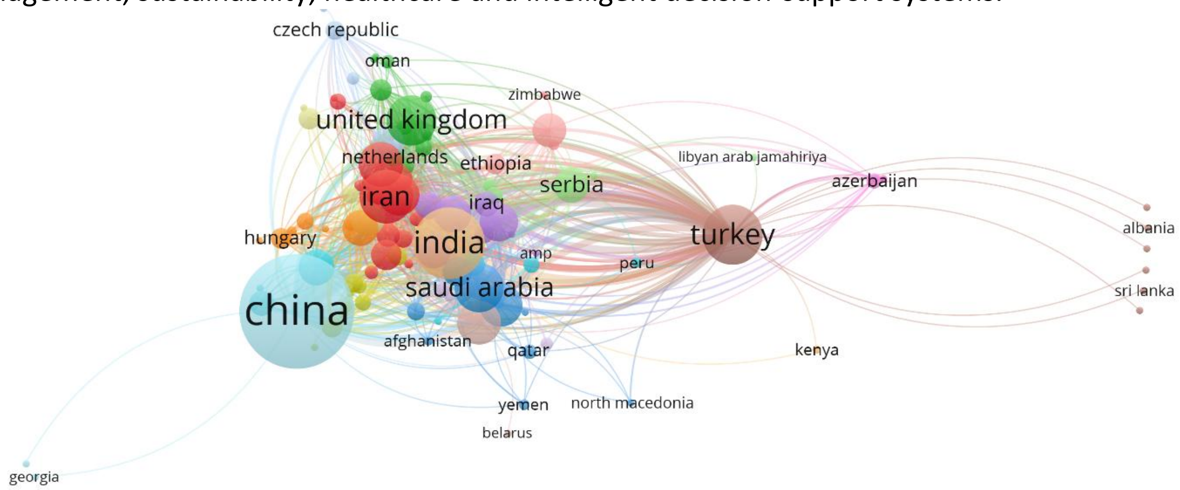

Fig. 7. Network analysis of Top Country-wise Research Contribution

3.6 Keyword Analysis

The keyword analysis helps to identify the key research themes, methodological advances and new applications areas in the MCDM during 1996–2026. TOPSIS was the most frequently occurring keyword with 2,331 occurrences and 4,865 links as it is being widely used across various decision-making applications. Among the classical methods of MCDM, MCDM was the most preferred with 1715 occurrences followed by AHP (1663 occurrences) and Analytic Hierarchy Process (830 occurrences). The other important words are Sustainability (717 occurrences), GIS (559 occurrences), and Fuzzy AHP (527 occurrences) indicating the increasing application of MCDM techniques for sustainability assessment, spatial decision-making and uncertainty modelling as seen in Figure 8. The VOSviewer keyword co-occurrence network shows a number of thematic clusters around decision-making methodologies, sustainability, renewable energy, supplier selection, a circular economy, GIS applications, multi-objective optimization, and fuzzy decision systems. New terms like blockchain, circular economy, renewable energy, entropy weight method, and multi-objective optimization reflect a new paradigm of intelligent, sustainable, and data-driven decision-support frameworks. Overall, the keyword analysis shows that the research of MCDM has been progressed from conventional ranking methods to sophisticated hybrid and interdisciplinary decision-making methods to solve complex real-world problems.

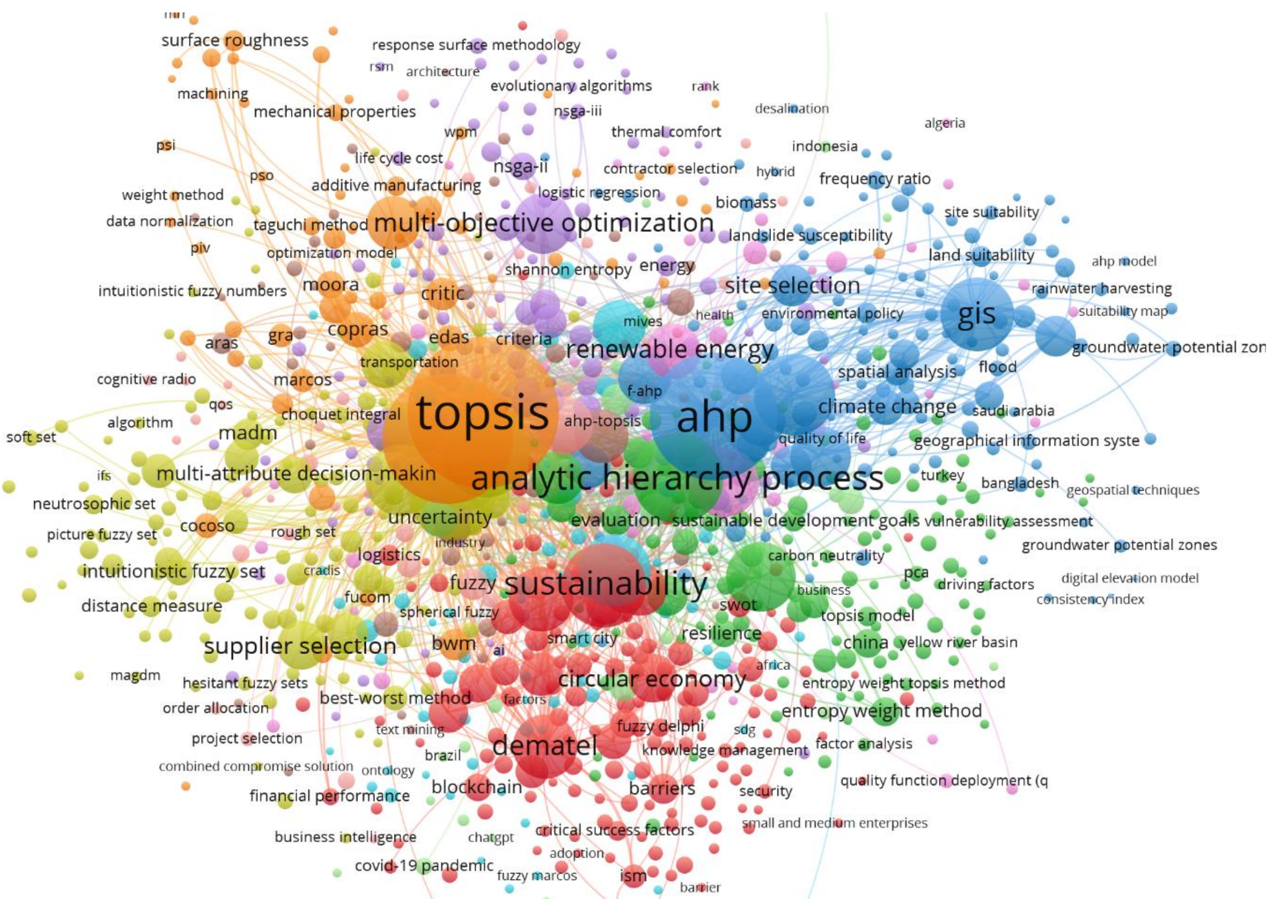

Fig. 8. Network analysis of Keywords

4. Fundamentals of MCDM

MCDM is an elaborately designed decision support approach for addressing complex decision-making problem with multiple and conflicting criteria. In the current engineering, management, healthcare, sustainability and industrial systems, decision-makers often find themselves in the situation where they need to consider multiple alternatives for a given problem or situation simultaneously, accounting for quantitative and qualitative considerations. The systematic mathematical and analytical tools such as MCDM methods can enhance the quality of the decision-making process, maximize resources utilization and minimize uncertainty [5]. The following subsections discuss the following key concepts, classifications, procedural steps, benefits and challenges of MCDM.

4.1 Concept of Decision-Making

Decision making is the process of choosing the best alternative out of the various alternatives available, based on the predetermined objectives and criteria. Traditional methods of decision making tend to have a single criterion like cost or profit, while in the real world, a problem may present several conflicting criteria as for example cost, quality, risk, sustainability, efficiency and performance [6]. Based on the number of the evaluation criteria, decision making can be divided into single-criteria decision making and multi-criteria decision making, as discussed in Table 5.

Table 5
Single-Criteria vs Multi-Criteria Decision-Making

Aspect	Single-Criteria Decision-Making	Multi-Criteria Decision-Making
Number of Criteria	One criterion	Multiple criteria
Complexity	Simple	Complex
Decision Focus	Single objective optimization	Simultaneous evaluation of conflicting objectives
Flexibility	Limited	Highly flexible
Real-World Applicability	Low for complex systems	High for practical decision problems
Examples	Cost minimization	Supplier selection, energy planning

4.2 Classification of MCDM Methods

The MCDM techniques can be divided into two main categories: Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM). The main criteria are the nature of the decision problem, the kind of alternatives acting upon the decision maker, and the mathematical structure of the optimization process. Multi-Attribute Decision Making (MADM) techniques are used to address problems having a finite number of alternative solutions that are assessed under multiple criteria or attributes [7]. They are mostly applied to ranking, selection and evaluation problems, where decision makers need to select one optimal alternative from a finite number of alternatives. The widely used AHP, TOPSIS, VIKOR, ELECTRE, PROMETHEE, COPRAS and MOORA are a number of common multiple criteria decision-making methods that are broadly used in supplier selection, material selection, healthcare, transportation, and sustainability assessment. For optimization problems with continuous decision variables and multiple objective functions, on the other hand, there are a class of methods called Multi-Objective Decision Making (MODM). These methods seek to find "best" or "best possible" solutions when there are conflicting objectives and/or constraints. The MODM methods have been widely used in engineering optimization, resource allocation, scheduling, and in the design of industrial systems. Most commonly used MODM methods are Goal Programming, Multi-Objective Linear Programming, Evolutionary Optimization, Genetic Algorithms, and Particle Swarm Optimization. Comparing these two approaches, overall, MADM is more concerned with selection and ranking problems while MODM is more concerned with optimization and solution generation in complex decision environments as can be seen in Table 6.

Table 6
Classification of MCDM Methods

Classification	Characteristics	Nature of Alternatives	Representative Methods	Major Applications
MADM	Selection and ranking problems	Finite alternatives	AHP, TOPSIS, VIKOR	Supplier selection, material selection
MODM	Optimization problems	Infinite or continuous alternatives	Goal Programming, GA, PSO	Design optimization, scheduling

4.3 General Steps in MCDM

The general decision-making process is similar for different MCDM methods, although they differ in computational procedures [8]. In general, the MCDM framework involves five steps: problem identification, criteria selection, weight determination, evaluation of alternatives, and ranking or selection, which are illustrated in Table 7.

Table 7
General Steps in MCDM Process

Step	Description	Purpose
Problem Identification	Define objectives and decision problem	Establish decision framework
Criteria Selection	Select evaluation criteria	Ensure comprehensive assessment
Weight Determination	Assign criteria importance	Reflect decision-maker preferences
Alternative Evaluation	Analyse alternatives	Compare performance
Ranking and Selection	Rank and choose best alternative	Final decision-making

4.4 Benefits and Challenges of MCDM

In numerous engineering, medical, manufacturing, sustainability, transportation, and finance applications, multiple conflicting decision criteria are encountered in complex decision problems and the use of MCDM methods is proven to be highly effective in solving such problems [9]. These techniques give analytical frameworks that enhance the decision accuracy, transparency, consistency, and optimization ability. MCDM approaches are also suitable to tackle qualitative and quantitative criteria at the same time, thus they are well appropriate when it comes to real-world decision contexts. Although MCDM methods have many benefits, they have also encountered some shortcomings and research challenges, especially in situations of uncertainty, big data, dynamic systems and intelligent environment with AI integration. Some problems such as subjective weighting, computational complexity, sensitivity to input data, interpretability, absence of standard evaluation frameworks are still considered significant concerns in contemporary MCDM research. Table 8 shows the main advantages and drawbacks of using MCDM methods.

Table 8
Benefits and Challenges of MCDM

Benefits	Description	Challenges	Impact of Challenge	Possible Improvement
Improves decision quality	Provides systematic and logical evaluation	Subjective weighting issues	Biased decision outcomes	Use hybrid or objective weighting methods
Handles multiple criteria	Simultaneous evaluation of conflicting factors	Computational complexity	Increased processing time	Develop efficient algorithms
Enhances transparency	Clear ranking and evaluation procedures	Sensitivity to data variations	Unstable ranking results	Robust sensitivity analysis

Table 8
Benefits and Challenges of MCDM

Benefits	Description	Challenges	Impact of Challenge	Possible Improvement
Supports optimization	Helps identify optimal alternatives	Difficulty in uncertainty modelling	Reduced reliability in vague environments	Advanced fuzzy and probabilistic models
Applicable in diverse domains	Flexible across multiple sectors	Lack of standardized frameworks	Difficulty in method comparison	Develop universal evaluation standards
Facilitates strategic planning	Supports long-term decision-making	Interpretability limitations in AI models	Reduced trust in intelligent systems	Explainable AI-based MCDM
Integrates qualitative and quantitative data	Improves comprehensive evaluation	Large dataset handling issues	Scalability problems	Big data compatible frameworks
Reduces human error	Structured mathematical procedures	High dependency on expert judgment	Inconsistency in evaluations	Automated intelligent decision systems
Supports intelligent decision-making	Integration with AI and optimization	Real-time processing limitations	Delayed decision response	Real-time adaptive MCDM models
Enhances resource allocation efficiency	Better utilization of available resources	Complex implementation procedures	Difficulty in practical adoption	User-friendly decision-support tools

5. Evolution of MCDM Methods (1996–2026)

It is interesting to note that MCDM methods have continued to evolve from 1996 to the present, and will continue to evolve until 2026 and beyond, at the same time reflecting the ongoing development of decision-support systems to address the growing complexity of the real world problems. In this era, the MCDM methods were developed from the classical ranking and evaluation methods into intelligent hybrid methods, which are combined with methods from artificial intelligence, machine learning, fuzzy logic, optimization methods and explainable decision models. The growth of computational technologies, big data analytics, Industry 4.0/5.0, Internet of Things (IoT) and autonomous systems propelled advanced MCDM methodologies to a fast development pace. MCDM methods can be divided into three large stages: Early Development Phase (1996–2005); Expansion Phase (2006–2015); Intelligent and Hybrid Phase (2016–2026).

5.1 Early Development Phase (1996–2005)

Between 1996 and 2005, the current "embryonic" period of the modern MCDM methodologies is a time of basic development. In this period, the attention of the researchers was directed toward structuring mathematical methodologies that are able to systematically assess several conflicting criteria. The classical MCDM methods were found to have gained wider acceptance due to their simplicity, the efficiency of computation, and the fact that they are applicable to real-world engineering, management and operational research issues. With the ability to highlight the advantages of the pairwise comparison method and the hierarchical decision structure, the Analytic Hierarchy Process (AHP) emerged as one of the most popular approaches. The idea of ideal and negative-ideal solutions led to the development of TOPSIS as an effective ranking method, and ELECTRE and PROMETHEE were new outranking methods that addressed the complexity of preferences. As can be seen in Table 9, the Simple Additive Weighting (SAW) method was also well used for simple multi-criteria evaluation problems.

Table 9
Major MCDM Methods in the Early Development Phase (1996–2005)

Method	Key Principle	Major Advantage	Limitation	Common Applications
AHP	Pairwise comparison hierarchy	Simple and intuitive	Subjective weighting	Supplier and material selection
TOPSIS	Distance from ideal solution	Easy ranking process	Sensitive to normalization	Engineering optimization
ELECTRE	Outranking relations	Handles conflicting criteria	Complex calculations	Policy and strategic planning
PROMETHEE	Preference ranking	Flexible preference modeling	Parameter sensitivity	Environmental assessment
SAW	Weighted summation	Simple implementation	Limited uncertainty handling	Basic evaluation problems

5.2 Expansion Phase

In 2006–2015, the research of MCDM was greatly developed by the introduction of fuzzy logic, grey theory, network analysis and optimization techniques. Classical approaches were identified as having a number of limitations in the processing of uncertain, incomplete, and vague information, and thus a hybrid and uncertainty-based decision-making framework has been developed. It was proposed a compromise ranking method which is based on closeness to ideal solutions under conflicting criteria (VIKOR). Interdependencies between elements of the decision-making process were introduced in the Analytic Network Process (ANP), which is an extension of the AHP, and DEMATEL became important for analyzing cause-and-effect relationships between criteria. In the fuzzy MCDM methods and Grey Theory based approach, it was found that these methods are powerful tools to deal with ambiguity and incomplete information as discussed in Table 10.

Table 10
Major MCDM Methods in the Expansion Phase (2006–2015)

Method	Key Principle	Major Advantage	Limitation	Common Applications
VIKOR	Compromise ranking solution	Balances group utility and regret	Sensitive to parameter selection	Sustainability assessment
DEMATEL	Cause-effect relationship analysis	Identifies interdependencies	Complex interpretation	Risk management
ANP	Network-based decision structure	Handles criteria interdependence	High computational complexity	Strategic planning
Grey Theory	Incomplete information modeling	Effective under uncertainty	Limited predictive capability	Manufacturing systems
MABAC MCDM	Border approximation area-based alternative evaluation	Stable and reliable ranking results	Sensitive to weighting methods	Engineering design, supplier selection, sustainability assessment
MAIRCA MCDM	Comparison between theoretical and actual alternative performance	Reduced ranking ambiguity	Dependence on preference structure	Resource allocation, risk assessment, manufacturing systems
Fuzzy MCDM	Fuzzy logic integration	Handles vagueness effectively	Increased computational burden	Healthcare and environmental analysis

5.3 Intelligent and Hybrid Phase (2016–2026)

RAFSI uses a new interval-mapping normalization method that increases the uniformity of alternative rankings, and ARTASI offers adaptive interval standardization and mitigates rank reversal problems. These methods, along with the progress made in artificial intelligence, machine learning, deep learning, blockchain technology and systems that can be connected to IoT, have helped to create more intelligent, adaptive, resilient, and real-time decision-support frameworks to tackle the increasingly complex and dynamic decision environment as discussed in Table 11.

Table 11
Major MCDM Developments in the Intelligent and Hybrid Phase (2016–2026)

Technology/Approach	Key Contribution	Major Benefit	Limitation	Application Areas
ARTASI MCDM	Adaptive standardized interval-based ranking with rank reversal elimination	Improved ranking stability and flexible standardization	Computational complexity and parameter selection	Engineering optimization, performance evaluation, strategic planning
RAFSI MCDM	Functional mapping of criterion sub-intervals into a unified interval	Robust normalization and ranking consistency	Sensitivity to interval definition	Supplier selection, energy planning, logistics management
AI-integrated MCDM	Intelligent automated decisions	High prediction capability	Interpretability challenges	Smart systems
Machine Learning-assisted MCDM	Data-driven decision support	Improved learning accuracy	Large data requirements	Healthcare analytics
Deep Learning Integration	Complex pattern recognition	Enhanced predictive analysis	High computational cost	Autonomous systems
Blockchain-based MCDM	Secure decentralized decisions	Improved transparency	Scalability issues	Supply chain management
IoT-integrated MCDM	Real-time data processing	Faster decision-making	Data security concerns	Smart cities

6. Review of Major MCDM Methods

MCDM methods have undergone a lot of development to solve complex decision problems with multiple conflicting criteria. Each of the MCDM techniques has a different mathematical form and a different decision evaluation process and is applicable to a variety of problems. Some of the approaches are focused on ranking alternatives, some on compromise solutions, some on interdependency analysis, and some on uncertainty handling, as discussed in Table 12. This section provides an in-depth survey of some of the prominent and common MCDM methods that are utilized in engineering, management, health care, sustainability, robotics, and industry applications. The following is a brief summary of the concept, mathematical procedures, advantages, disadvantages and significant applications of each method.

Table 12
Comparative Review of Major MCDM Methods

Method	Basic Concept	Mathematical Procedure	Advantages	Limitations	Major Applications
AHP [10]	Hierarchical pairwise comparison of criteria and alternatives	Pairwise comparison matrix, eigenvector calculation, consistency ratio	Simple, intuitive, handles qualitative criteria	Subjective judgments, consistency issues	Supplier selection, material selection, project management
TOPSIS [11]	Selection based on closeness to ideal and negative-ideal solutions	Normalization, weighted matrix, distance calculation	Easy implementation, logical ranking	Sensitive to normalization method	Engineering optimization, healthcare evaluation

Table 12
Continued

Method	Basic Concept	Mathematical Procedure	Advantages	Limitations	Major Applications
VIKOR [12]	Compromise ranking based on group utility and regret measures	Utility measure, regret measure, compromise ranking index	Effective for conflicting criteria	Parameter sensitivity	Sustainability assessment, energy planning
ELECTRE [13]	Outranking method based on concordance and discordance relations	Concordance-discordance analysis	Handles conflicting criteria effectively	Complex calculations	Strategic decision-making, policy analysis
PROMETHEE [14]	Preference ranking using pairwise comparison flows	Preference functions and net outranking flow	Flexible preference modeling	Requires parameter tuning	Environmental management, logistics
DEMATEL [15]	Cause-effect relationship analysis among criteria	Direct relation matrix and total relation matrix	Identifies interdependencies	Difficult interpretation in large systems	Risk analysis, system evaluation
ANP [16]	Network-based extension of AHP considering interdependencies	Supermatrix and weighted supermatrix calculations	Handles feedback and dependency	High computational complexity	Strategic management, engineering systems
MOORA [17]	Ratio analysis for evaluating alternatives	Normalization and ratio system	Simple and computationally efficient	Limited uncertainty handling	Manufacturing and industrial evaluation
COPRAS [18]	Complex proportional assessment of alternatives	Weighted normalized decision matrix	Simultaneous benefit-cost analysis	Sensitive to weight assignment	Construction management, supplier evaluation
WASPAS [19]	Combination of weighted sum and weighted product models	Additive and multiplicative aggregation	Improved ranking accuracy	Computational sensitivity	Material selection, energy systems
TODIM [20]	Prospect theory-based ranking method	Dominance function and gain-loss evaluation	Considers psychological behavior	Complex computation	Behavioral decision-making, economics
EDAS [21]	Evaluation based on distance from average solution	Positive and negative distance measures	Stable and reliable ranking	Dependence on average solution	Performance evaluation, risk assessment
MARCOS [22]	Utility-based ranking relative to ideal and anti-ideal solutions	Utility degree function and normalization	Accurate ranking performance	New method with limited validation	Sustainability and engineering decisions
CoCoSo [23]	Combined compromise solution approach	Aggregation of weighted comparability sequences	High ranking stability	Complex mathematical formulation	Renewable energy, manufacturing
MEREC [24]	Objective weighting based on removal effects of criteria	Criterion removal impact calculation	Reduces subjectivity	Sensitive to dataset structure	Weight determination problems

Table 12
Continued

Method	Basic Concept	Mathematical Procedure	Advantages	Limitations	Major Applications
Entropy [25]	Objective weighting using information entropy	Entropy calculation and weight assignment	Objective and data-driven	Ignores expert judgment	Decision-support systems, optimization
MABAC [26]	Border approximation area-based ranking	Normalize, Weight, Calculate BAA, Rank	Stable ranking, simple	Weight sensitive	Supplier selection, engineering design
MAIRCA [27]	Compares theoretical and actual evaluations	Preference matrix, Deviation matrix, Rank	Easy interpretation, reduced ambiguity	Depends on preference assumptions	Manufacturing, logistics, project evaluation
ARTASI [28]	Adaptive interval-based ranking method	Standardize, Utility calculation, Rank	Eliminates rank reversal, flexible normalization	Computational complexity	Performance evaluation, sustainability assessment
RAFSI [29]	Maps criteria into a unified interval	Standardize, Calculate utility scores, Rank	Robust normalization, ranking consistency	Sensitive to interval selection	Energy planning, supplier selection, transportation

7. Weighting Techniques in MCDM

Weight determination is one of most important stages in MCDM since the final ranking of alternatives is highly sensitive to the weights assigned to the evaluation criteria. Weighting techniques are used to measure the relative importance of the criteria in the decision making problem. Such techniques can be broadly divided into subjective weighting techniques, objective weighting techniques and hybrid weighting techniques [30]. The subjective approaches are based on expert judgments and preference of decision makers, while the objective approaches are based on mathematical and statistical properties of the data and the resulting weights. Hybrid methods are a combination of subjective and objective methods to increase reliability and decrease bias. This section introduces the important weighting methods commonly used in MCDM and their features, benefits, shortcomings and uses.

7.1 Subjective Weighting Methods

The criteria importance is determined by subjective weighting methods, which depends on the human judgement, experience and expert opinion. These are the common methods used when the decision makers have knowledge of the domain and qualitative evaluations are significant [31].

7.1.1 AHP (Analytic Hierarchy Process)

Thomas L. Saaty developed the Analytic Hierarchy Process (AHP) in 1980, which is one of the most popular subjective weighting techniques in MCDM. Pairwise comparisons within a hierarchical structure of the goal, criteria, sub-criteria, and alternatives are used for determining criteria weights in AHP [32]. Decision-makers compare the importance of the criteria on the fundamental scale of Saaty and eigenvector calculations are then used to calculate priority weights. The structured approach, and the fact that it is possible to include qualitative and quantitative elements, has led to a wide variety of applications of AHP in engineering, the health care sector, supplier selection and sustainability assessment, and strategic management [33].

AHP's advantages are the simplicity and intuitiveness of the model which allow decision makers to break down complex problems in a systematic manner into a hierarchical structure. The approach is applicable to qualitative criteria and allows to incorporate expert opinions into the decision-making. Moreover, a consistency ratio mechanism is presented in AHP to determine the reliability of the pairwise comparisons, which further validates the accuracy of the weights derived. Ishizaka and Labib [34] reported that simplicity, flexibility and the ability to systematically solve complex decision problems are a few reasons why AHP is still one of the most popular weighting methods in MCDM. Although popular, AHP has some drawbacks. The method is subjective and is bound to bring in some bias in the decision-making process. When decision makers carry out many comparisons, especially for a large and complex problem with many criteria, there may be inconsistencies. Furthermore, the larger the number of criteria, the more comparisons that need to be made, so the method is not very practical to use in large-scale applications. Emrouznejad and Marra [35] reported that the traditional AHP has been facing certain limitations, which have led to the development of fuzzy, hybrid and AI-integrated approaches to enhance its effectiveness in complex and uncertain decision-making situations.

7.1.2 SWARA (Step-wise Weight Assessment Ratio Analysis)

Zavadskas et al. [36] introduced the Step-wise Weight Assessment Ratio Analysis (SWARA) method as a subjective weighting method to assess the importance of the criteria by expert judgments. The first step in SWARA is to rank the criteria based on their perceived importance by experts. Next, the significance coefficient of each criterion compared to the preceding criterion is determined and then the criterion weights are computed step by step. The approach has received a lot of attention in the MCDM research because of its simplicity and effectiveness in integrating the expert knowledge in the weighting process.

It is one of the best features of SWARA that it is a very simple computational process and fewer pairwise comparisons are required than in AHP. This minimizes the burden on experts, and makes the process of weighing easier. In addition, SWARA is very appropriate for an expert-based evaluation when the decision makers have a considerable amount of domain knowledge and can properly prioritize criteria based on their level of importance. The drawbacks of SWARA were discussed by Stanujkic et al. [37] which states that the SWARA method is highly dependent on the expert's judgment and on the order of the initial criterion.

The drawbacks have stimulated the research for the development of fuzzy, rough and hybrid SWARA to enhance robustness and uncertainty handling in complex decision-making environment. Although SWARA has benefits, there are certain drawbacks. The method is very much dependent on the individual opinions of experts and therefore is open to the possibility of subjective bias and differences in expert opinion. Also, it is important to note that the final weights are also dependent on the ranking sequence of the criteria; the ranking sequence may have a significant impact on the weights and decision results. To overcome these drawbacks, some researchers have introduced fuzzy SWARA, rough SWARA and hybrid SWARA-based approaches which are aimed to overcome the weakness of handling uncertainty and increase the robustness of SWARA in the complex decision problem.

7.1.3 BWM (Best Worst Method)

Rezaei [38] proposed an efficient subjective weighting method for weighting criteria in MCDM problems, which is called the Best Worst Method (BWM). The general steps in BWM are to determine the most important (best) and the least important (worst) criteria in order to make pairwise comparisons among all criteria and the most important and least important criteria. A model in optimization is then used to obtain the optimal weights with a minimum level of inconsistency. The method has become quite popular because it can be used to obtain reliable weights with fewer comparisons than the commonly used traditional methods like AHP. The benefits of BWM were pointed out by Rezaei [39] due to the absence of the comparison burden, the consistence, and the reliability in the weight determination. The method decreases the number of comparisons that need to be made, reducing mental effort and increasing the uniformity of expert opinions. But, Rezaei [40] also mentioned that BWM relies on the correct identification of the best and worst criteria, and the outcomes might be affected by subjective judgments made in the selection of the best and worst criteria. The restrictions have led to the research of fuzzy BWM, interval valued BWM and hybrid BWM to handle uncertainty and robustness in complex decision-making contexts [41].

7.1.4 FUCOM (Full Consistency Method)

The Full Consistency Method (FUCOM) was proposed by Pamucar et al. [42] as a subjective weighting method that minimizes the inconsistency between pairwise comparisons and allows determining the weights of the criteria. FUCOM requires a lot fewer comparisons compared to conventional methods like AHP, and therefore less burden on the decision maker's cognitive resources. The method ranks the criteria by their importance, and then calculates weight coefficients by mathematical optimization but keeps comparisons between all criteria full. The efficiency and reliability of FUCOM received many attentions in engineering, logistics, sustainability assessment, supplier selection, risk management and so on. This research identified some of the strengths in FUCOM, such as fewer pairwise comparisons, higher consistency and computational efficiency. The method produces correct weights and reduces inconsistencies which are often seen in conventional weighting methods. FUCOM's approach, however, is based on the criteria being ranked by experts and is thus subject to the subjectivity of the ranking. Additionally, the ranking of the criteria may affect the final weight distribution if it is incorrect. The inability to deal with uncertainty and robustness in complex decision-making environments has led researchers to combine FUCOM with fuzzy and hybrid MCDM methods.

7.1.5 LBWA (Level Based Weight Assessment)

One subjective weighting method suggested by Zizovic et al. [43] is the Level Based Weight Assessment (LBWA) method which relies on the level-based comparison and the hierarchical grouping of the criteria. The approach is to rank the criteria by importance and allot scores based on the relative importance of the criteria within their respective rank. The weightings process is simplified and decision making is easier for problems involving large numbers of criteria by reducing the number of comparisons required in LBWA. This study highlighted that using LBWA can help save effort from decision makers, be simple and flexible in terms of the criteria weighting process. The method is especially applicable to the large-scale decision problems in which the traditional pairwise comparison methods are cumbersome. The assignment of criteria to levels, however, will rely heavily on professional judgement and may be subjective in the weighting process. Thus fuzzy and hybrid LBWA extensions have been investigated to enhance the level of certainty in decisions and uncertainty management [44].

7.1.6 LMAW (Logarithm Methodology of Additive Weights)

To determine the subjective weights, a novel methodology was introduced by Pamucar et al. [45] called Logarithm Methodology of Additive Weights (LMAW) which is a methodology based on the logarithmic transformation of the expert preferences. The approach transforms experts' evaluations into logarithmic scales and calculates the weights of the criteria by applying an additive aggregation process. LMAW has been created to give a mathematically consistent and stable weighting framework, and minimize the inconsistencies from traditional weighting schemes. This study concluded that LMAW has some benefits such as simplifying the calculation process, it is highly stable and the weight can be determined more consistently. The approach is suitable for representing preferences of experts and is able to yield reliable weighting under complex decision context. However, LMAW relies on evaluations by experts and can be subject to individual interpretation. Furthermore, it is a new method compared to other weighting methods like AHP and BWM and therefore the applications are limited.

7.1.7 DIBR I (Defining Interrelationships Between Ranked Criteria)

Tešić et al. [46] proposed DIBR I - Defining Interrelationships Between Ranked Criteria as a subjective weighting method which aims at determining the weights of the criteria based on the analysis of interrelationships between ranked criteria. The method enables decision makers to articulate the relative importance of the criteria without neglecting the influence between criteria, which makes the decision makers' preferences more realistic. This Study underscored the positive aspects of DIBR I such as the modeling of inter-relation among the criteria, less comparison requirements, and more consistent weighting of the criteria. The method is well suited to strategic planning, environmental assessment and infrastructure evaluations. The approach is based on expert judgment in both ranking and in assessing relationships, however, which can create subjectivity and influence the reliability of the results in uncertain situations.

7.1.7 DIBR II (Defining Interrelationships Between Ranked Criteria – Extended Version)

To enhance the representation of interdependencies among the criteria and to increase accuracy of the weighting, Božanić et al. [47] proposed the enhancement of DIBR I to DIBR II. It incorporates various relationship structures and improved weighting calculations to the original DIBR framework to enable more comprehensive complex decision making problem analysis. The results in this study showed that DIBR II offers higher flexibility, higher accuracy and more consistency than the traditional DIBR. This method is especially applied to engineering management, sustainability evaluation, logistics, and risk analysis studies. An increased number of interrelationship models, however, may demand higher levels of expertise and of computing power. Therefore, there is a need for further research to simplify the implementation of this and enhance its applicability in a larger decision context.

7.2 Objective Weighting Methods

Objective weighting techniques measures the importance of the criteria using a mathematical method and without human judgment. These techniques minimize subjectivity and enhance data-informed decision making.

7.2.1 Entropy Method

The concept of entropy was introduced in information theory by Shannon [48] and adapted into MCDM as an objective weighting technique to measure the importance of the criteria based on the information they contain. The Entropy method uses measures of variability or dispersion of performance values of alternatives to calculate the weights of the criteria. The higher the variation of criteria, the more useful the information and the higher the weight, the lower the variation, the lower the weight. The mathematical nature and the fact that the Entropy method is not based on human judgment, has made it one of the most popular objective weighting methods in engineering, sustainability assessment, supplier selection, and energy planning studies.

The advantages of the Entropy method were also pointed out by Hwang and Yoon [49] which can be summarized as follows: It is completely objective; It is data-based and does not involve human judgment in the weighting process. The method is based only on the data, therefore improving the transparency and consistency of decision-making results. Whereas, Zeleny [50] pointed out that the Entropy method has the drawback of not considering the preferences of experts or managerial experiences, and this might be a disadvantage in cases where the subjective knowledge plays a significant role. In addition, the method is very sensitive to the quality and variability of data, and any inaccuracies or incompleteness in the data can greatly affect the weights that are calculated. Due to these constraints, researchers have started using subjective weighting methods like AHP, BWM, SWARA with Entropy in order to obtain more balanced and reliable decision-making results [51].

7.2.2 CRITIC (Criteria Importance Through Intercriteria Correlation)

Diakoulaki *et al.,* [52] proposed an objective weights determination method called CRITIC (Criteria Importance Through Intercriteria Correlation) which utilizes the contrast intensity and the conflict between the criteria. The method is based on the following principles: using standard deviation to determine the amount of information included in each criterion, and reliability analysis to determine the degree of dependence between criteria. Those criteria with higher variability and lower correlation with other criteria will be more important, because they give more unique and discriminative information to the decision making process. Because of its objective nature, CRITIC has been utilized in a wide variety of engineering design, sustainability assessment, supplier selection, energy planning and performance evaluation studies. The main advantages of CRITIC, according to Diakoulaki et al. [52] was the consideration of conflicts between the criteria, the good reflection of information content, and the objective weighting mechanism, which does not require the expert judgments. These features help to make weight measurement more accurate and transparent. But, Krishnan et al. [53] remarked that the method is relatively complicated to calculate and is sensitive with the underlying correlation structure of the data set. The weights can change greatly if there are changes in the structure of data distribution or the type of correlation. These constraints have inspired researchers to use a hybrid weighting, such as CRITIC in combination with Entropy, MEREC, and other hybrid weighting method to attain more robust and robust decision making in complex environments [54].

7.2.3 MEREC (Method Based on the Removal Effects of Criteria)

Another objective weighting method was proposed by Keshavarz-Ghorabaee et al. [55] which is called MEREC (Method Based on the Removal Effects of Criteria), that calculates the importance of the criteria based on the effects of removing each one from the decision matrix. The concept behind MEREC is that the criteria should be considered more significant the more it is removed without significantly impacting the overall performance of the alternatives. MEREC is an objective approach to weight determination, based on the removal effects of individual criteria, regardless of the expert judgments. The method has gained in popularity for its ability to capture the intrinsic contribution of criteria, and has been utilized in engineering design, supplier selection, sustainability assessment, energy management and hybrid MCDM frameworks.

Keshavarz-Ghorabei et al. [55] called out the advantages of MEREC, which include decreased subjectivity, objective assessment and appropriate weights for incorporation with different MCDM methods. The attributes described above make MEREC a very appropriate technique for hybrid-type decision making models, where objective criteria weighting is needed.

7.2.4 WENSLO (Weights by ENvelope and SLOpe)

Weights by ENvelope and SLOpe (WENSLO) method was proposed by Pamucar et al. [56] to solve MCDM problems with objective criteria weights. Unlike the subjective weighting methods, WENSLO calculates the weights of criteria directly from the decision matrix properties and does not depend on the expert opinions or personal opinions. It was founded on two concepts: the envelope and the slope of the criteria values. If two or more criteria have the same envelope value, the criterion with the smallest slope value is more discriminating and has more stability and is given a larger weight. WENSLO is particularly unique in that it does not depend on whether criteria are considered to be benefit-type or cost-type, and therefore it is a flexible and strong objective weighting approach. Given these properties, WENSLO has become a potential option for evaluating the sustainability of engineering systems, assessing their performance, and making decisions.

Pamucar et al. [56] pointed out the advantages of WENSLO, which is fully objective, not based on expert opinion, and that its criteria importance can be identified based on the intrinsic properties of the decision data. The approach offers a clear and mathematically rigorous approach for weight determination while avoiding subjective weight assessment. Moreover, it is not dependent on benefit–cost classification, thereby making the weighting process simpler and more useful in a variety of decision-making contexts. WENSLO, however, is like many objective weighting methods, dependent on the quality and representativeness of the data set. The weights may vary depending on variations in data structure and distribution; in highly dynamic decision environments, the method may need further validation. A recent trend has been to integrate WENSLO with hybrid MCDM types to enhance robustness and reliability of decision-making in complex applications.

7.2.5 LOPCOW (Logarithmic Percentage Change-Driven Objective Weighting)

Ecer and Pamucar [57] introduced the Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW) method, which is an objective weighting technique for weights of criteria in MCDM problem. The technique adopts the concepts of percentage changes along the log scale and the different values of the criterion, and therefore, weights are computed directly from the decision matrix rather than depending on expert judgments. LOPCOW scheme is able to obtain a more balanced distribution of criterion weights than the Entropy method, because it takes into account both the performance values of the alternatives and the variation of each criterion. An understanding of the use of a logarithmic function allows for a rational and stable weight allocation procedure, while also addressing some of the drawbacks of conventional objective weighting procedures. Because of its robustness and efficiency, the LOPCOW became more and more used in engineering, management, sustainability assessment, financial and social science decision making problems [58].

Ecer and Pamucar [57] pointed out some merits of LOPCOW: 1) it provides a balanced weight of criteria; 2) it is efficient for dealing with large decision matrix; 3) it avoids the negative or zero values problem that frequently occurs with Entropy method. The computation process of LOPCOW is simpler than the CRITIC method, because there is no need for correlation analysis between the criteria, making the process more applicable. Moreover, the technique is not as susceptible to outlier values and does not require criteria sorting when calculating weights. Like other objective weighting procedures, however, LOPCOW is dependent on the quality and representativeness of the data at hand and it does not involve managers or experts in the weighting process. Therefore, recent research has integrated LOPCOW with subjective weightings and advanced MCDM frameworks to enhance the reliability and robustness of the decisions in complex decision processes.

7.3 Hybrid Weighting Approaches

Demir et al. [58] pointed out that hybrid weighting methods have been found to be a good remedy to address the drawbacks of subjective and objective weighting methods in MCDM. The methods are based on expert information and mathematical data analysis, and they produce more balanced and reliable criteria weights. The hybrid weighting models can combine subjective and objective approaches like AHP, BWM, SWARA and Entropy, CRITIC, MEREC, which can enhance the accuracy and robustness of the outcomes of the decision-making process. AHP–Entropy, BWM–CRITIC, SWARA–Entropy, Fuzzy AHP–MEREC, and DEMATEL–ANP are common hybrid methods that have been reported in the literature and proven to be useful in engineering, sustainability assessment, healthcare, supply chain management, and energy planning problems [58,59].

Esmaeilzadeh et al. [59] pointed out that the advantages of hybrid weighting approaches are that they increase the reliability of decisions, balance the subjective and objective knowledge, handle uncertainty better and increase the robustness in a complex decision making environment. Hybrid methods combine the preference of experts and data-driven information often yield more realistic and consistent weighting results than individual methods. But, Esmaeilzadeh et al. [59] pointed out that most of the hybrid models are usually complex and demand a considerable amount of time for implementation procedures, and integration of expert judgments with quantitative data. Despite the difficulties, hybrid weighting methods are becoming increasingly popular and one of the promising directions in the field of advanced applications of MCDM in intelligent decision-support systems [60].

7.4 Comparative Analysis of Weighting Methods

Each weighting method has its own advantages and disadvantages, depending on the decision problem, availability of data, the degree of uncertainty, and the involvement of experts. Objective methods work with quantitative and data-driven environments, subjective with expert knowledge. Hybrid solutions combine both views, as outlined in Table 13.

Table 13
Comparative Analysis of Weighting Methods

Aspect	Subjective Methods	Objective Methods	Hybrid Methods
Weight Source	Expert judgment	Mathematical/statistical data	Combination of both
Human Involvement	High	Low	Moderate
Subjectivity Level	High	Low	Balanced
Computational Complexity	Moderate	Moderate to high	High
Data Requirement	Low	High	Moderate to high
Reliability	Depends on expert consistency	Depends on data quality	Higher reliability
Uncertainty Handling	Good with fuzzy integration	Limited	Better handling capability
Major Limitation	Bias and inconsistency	Ignores expert knowledge	Computational burden
Suitable Applications	Strategic and qualitative decisions	Quantitative evaluations	Complex real-world problems

Weighting techniques are used as a fundamental approach to improve the effectiveness and reliability of MCDM methods. Subjective methods (AHP, SWARA and BWM) are based on the knowledge of experts and human judgment, whereas the objective methods (Entropy, CRITIC and MEREC) give weights based on data. Hybrid weighting approaches combine the benefits of both two types and are widely suitable to the modern intelligent decision support systems with uncertainty, complexity and changing environment.

8. Hybrid and Advanced MCDM Approaches

Real-world problems involved in decision making have become more complex, uncertain and dynamic, which has given rise to the development of hybrid and advanced MCDM approaches. The traditional MCDM techniques may be limited in the situations of vague information, incomplete information, interdependent criteria, and large-scale intelligent systems. Considering these difficulties, the researchers have applied fuzzy logic, grey theory, rough sets, artificial intelligence, machine learning, deep learning, optimization algorithms, and big data analysis with classical MCDM techniques. These cutting-edge systems increase the precision, versatility, flexibility, and handling of uncertainty of all decision-making tasks in multiple sectors, including engineering, healthcare, sustainability, robotics, manufacturing, and smart systems.

8.1 Fuzzy MCDM

Zadeh [61] developed fuzzy set theory to handle uncertainty and imprecision in human reasoning, and fuzzy multiple criteria decision making (Fuzzy MCDM) methods were developed based on fuzzy set theory. Fuzzy MCDM combines the advantages of fuzzy logic and classical MCDM methods to overcome vague, ambiguous and incomplete information which is often encountered in real-life decision-making problems. Fuzzy MCDM uses linguistic variables and fuzzy numbers to better describe expert judgments, rather than precise numerical values, as are used in conventional methods. Among the most popular Fuzzy MCDM techniques one can mention Fuzzy AHP, Fuzzy TOPSIS, Fuzzy VIKOR, and Fuzzy DEMATEL methods, which have been widely used in engineering and management, healthcare, sustainability assessment, and risk analysis problems [61,62].

Kahraman et al. [62] pointed out that Fuzzy MCDM has several advantages: effectiveness in dealing with uncertainty, proximity to human thinking and reliability of decision results. The use of fuzzy sets in the evaluation process makes these methods more flexible in handling vague and subjective information. As a result, Fuzzy MCDM has been applied in various fields such as supplier selection, healthcare diagnosis, sustainability assessment, and risk management. Kahraman et al. [62] observed, however, that the Fuzzy MCDM methods have complex mathematical calculations and require extra calculation load, especially in large scale decision problems. Although there are some drawbacks, Fuzzy MCDM is one of the most influential and widely used advanced MCDM models to address decision problems in uncertainty situations [63].

8.2 Intuitionistic Fuzzy MCDM

Atanassov [64] extended the classical fuzzy set theory by taking into account membership, non-membership and hesitation degrees in a single set, Intuitionistic Fuzzy Sets (IFS). This extra hesitation parameter allows for a wider description of both uncertainty and lack of information in decision making. Based on this idea, Intuitionistic Fuzzy MCDM methods were developed to improve the accuracy and flexibility of decision analysis in decision making problems under complex environments where expert judgments may be imprecise, vague or partially known. Intuitionistic Fuzzy MCDM approaches have been applied to many medical decision-making, robotics, pattern recognition, engineering optimization, supplier selection and risk assessment problems [64,65].

Xu [65] pointed out that the advantages of IFMCDM method are that it has strong uncertainty modeling capability, it can better represent incomplete information, and it can carry out the sensitivity analysis of decision-making more effectively than the fuzzy method. The use of hesitation degrees enables the decision makers to express their uncertainties in a more realistic way and in the end the decision is more precise and reliable. Xu [65] pointed out, however, that IFMCDM methods have high computational complexity and can be difficult to understand the meaning of membership, non-membership and hesitation parameters. Although the method has its drawbacks, Intuitionistic

Fuzzy MCDM is a significant advancement and continues to be a popular topic of study in current research on MCDM [66].

8.3 Neutrosophic MCDM

Inspired by Fuzzy and Intuitionistic Fuzzy theories, Smarandache [67] generalized these two theories into a new one called Neutrosophic Set Theory, where he independently defined the membership functions of truth, indeterminacy and falsity. Unlike the conventional fuzzy methods, Neutrosophic MCDM enables decision makers to explicitly model indeterminate and inconsistent information, which makes it appropriate in high uncertain decision environments. The flexibility of representing uncertainty makes Neutrosophic MCDM a new and improved decision making system for complex decision making problems under conditions of incomplete, inconsistent and ambiguous information. Therefore the Neutrosophic MCDM methods have been used more and more in case of artificial intelligence systems, risk assessment, medical diagnosis, strategic management and sustainability evaluation studies, etc. [67,68].

The advantages of Neutrosophic MCDM were expressed by Ye [68] who pointed out that it could better process the incomplete and inconsistent information, that it had different expressions of truth and falsity values, and that it had higher flexibility in uncertainty modeling. These are the properties that make these features useful for making decisions in very uncertain systems where conventional fuzzy methods are inadequate. Ye [68] also pointed out that Neutrosophic MCDM has complex mathematical representation and there is not a universal standardization for the application of it in the practice. In the context of large-scale decision problems, some difficulties may occur in the interpretation and aggregation of neutrosophic elements. Although it has its drawbacks, Neutrosophic MCDM is increasingly acknowledged as a powerful tool in the realm of uncertainty-based decision making and is attracting the interest of researchers in advanced MCDM applications [69].

8.4 Grey Theory-Based MCDM

Grey System Theory was presented by Deng [70] to solve the decision-making problem when the information is incomplete, uncertain or partially known. According to this theory, Grey Theory based MCDM methods were developed to deal with the case of limited or insufficient data to perform conventional statistical analysis. These methods work well for small data sets and when uncertainty is due to a lack of information, not to randomness. Several Grey MCDM methods are used in various fields such as manufacturing systems, energy planning, environmental management, industrial optimization, and sustainability assessment studies, including Grey Relational Analysis (GRA), Grey TOPSIS, and Grey AHP [70,71].

Liu and Lin [71] pointed out that the advantages of Grey Theory-based MCDM are that it is effective to deal with limited information, easy to implement procedures and has low requirement for large amount of data. In real-world applications where full information is not available, the three properties above are especially important for Grey MCDM. In the meantime, Liu and Lin [71] pointed out that the predictive ability of Grey Theory-based methods might be lower than the advanced intelligent methods and Grey Theory-based methods might be sensitive to the selection of grey parameters and relational coefficients. These restrictions can affect the outcomes of decisions and decision stability. Despite the difficulties mentioned above, Grey Theory-based MCDM has proven to be useful in the decision-making process in situations of incomplete information and has been widely applied in engineering, energy, environmental and industrial fields [72].

8.5 Rough Set Theory in MCDM

Pawlak [73] proposed Rough Set Theory (RST) as a mathematical tool for dealing with uncertainties, vagueness and inconsistencies of information without making any prior assumption of probability distribution, membership functions etc. before using it. Rough Set Theory can be used to express uncertain knowledge by lower and upper approximations, and it is proving to be an important tool in data-driven decision analysis. For decision makers, RST can be of great significance in MCDM applications in terms of attribute reduction, feature selection, rule extraction and knowledge discovery and helps them identify the most relevant attributes while keeping all the relevant information. As a result, Rough Set Theory has become a popular application in data mining, pattern classification, decision support systems and knowledge management problems [73,74].

Pawlak [74] pointed out some advantages of Rough Set Theory, especially its ability to deal with inconsistent information effectively, to facilitate knowledge discovery and to efficiently select features without prior knowledge of the distribution of data. These are the properties that make RST particularly appropriate for complex decision-making situations with large amounts of data and/or uncertain information. But, Polkowski [74] pointed out that the Rough Set Theory was sensitive to data quality and noise or incompleteness can introduce errors in the decision rules generated from the data. In addition, traditional RST is not very efficient at dealing with continuous variables and sometimes needs to be discretized prior to analysis. Although there are some restrictions, Rough Set Theory is a significant uncertainty-handling method in MCDM and still plays important role in intelligent decision-making support and data analysis applications [75].

8.6 AI and Machine Learning Integrated MCDM

Artificial Intelligence (AI) and Machine Learning (ML) have played a significant part in elevating the capability of various decision-support systems, thereby providing data-driven, adaptive, and intelligent decision-making [76]. These hybrid MCDM methods can improve prediction accuracy, automate decision-making and provide real-time analytics support, by combining AI and ML techniques with traditional decision-making methods. In MCDM, the most common techniques used to solve the decision problems are the following and are increasingly being applied in complex decision problems in dynamic environments: Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest and Reinforcement Learning. Several of the above-mentioned smart applications have been applied in smart healthcare, autonomous systems [76,77], smart cities, industrial automation, and predictive maintenance systems.

Goodfellow et al. [77] highlighted the benefits of using AI and ML in MCDM, such as enhanced predictive accuracy, intelligent analysis in real-time, and AI-driven decision support. Through past experience and real-time data, they can adapt their responses to meet evolving situations and enhance the quality of decisions made in complex systems. Goodfellow et al. [77] acknowledged, however, that in data-limited settings AI-based MCDM models might not be as applicable due to their demand of vast datasets for training and validation. Furthermore, there are still large concerns to the interpretability, transparency, and high demand of computational resourcing concerns in issues. The restrictions have spurred the development of explainable AI (XAI) based MCDM frameworks that aim to enhance the trustworthiness, transparency and reliability of intelligent decision-support systems [78].

8.7 Deep Learning and Big Data in MCDM

LeCun *et al.,* [79] pointed out that the development of deep learning and big data technologies has greatly broadened the MCDM field of applications, making it possible to deal with high dimensional, large-scale and heterogeneous datasets. By automatically discovering intricate patterns, relationships, and hidden elements within the decision context, deep learning models can boost the precision and efficiency of decision-support systems. The most common deep learning architectures applied to MCDM are Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deep Neural Networks (DNN), which are increasingly used in predictive analytics, classification, optimization and intelligent decision-making applications. These technologies are very important for image-based decision systems, smart transport, financial forecasting and healthcare analytics [79,80].

Goodfellow et al. [80] pointed out the benefits of DBC-DCM and its high predictive value, unstructured data processing and the intelligent automation in the complex decision-making environment. These methods can deliver real-time analytical insights and enhance decision making quality with the leverage of massive data and sophisticated learning algorithms. Goodfellow et al. [80] also pointed out that deep learning models need a significant number of computational resources and training data to attain best performance. Moreover, the explainability and transparency of deep neural networks are still an important challenge to be overcome for their wide-spread adoption in critical decision-making applications. Such limitations have spurred researchers to find methods for increasing the trustworthiness and transparency of intelligent MCDM systems, such as Explainable AI (XAI) and interpretable deep learning [81].

8.8 Optimization-Based Hybrid Models

Genetic Algorithms (GA) have been introduced by Goldberg [82] as powerful optimization methods inspired by the natural evolution, and since then, they have been extensively applied to the MCDM methods to cope with complex decision problems. Optimization based hybrid MCDM models have been developed to enhance the solution quality, convergence speed, and decision accuracy using optimization techniques like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA) along with decision-making methods. These hybrid methods can find optimal or near-optimal solutions in multi-objective problems and efficiently search large and complex search space. The optimization-based hybrid MCDM models have been widely used in robot path planning, scheduling optimization, renewable energy systems, and supply chain management problems, etc., due to their global optimization ability and improved search efficiency [82,83].

Kennedy and Eberhart [83] pointed out the advantages of optimization-based hybrid models of MCDM, which are able to find better solutions, enhance the scalability of the model, and solve complex engineering and management problems with multiple conflicting objectives. These can be used to combine optimization algorithms with MCDM techniques to improve the quality of decision and to generate good quality multi-objective solutions. But the hybrid models typically require significant computing power and complex parameter tuning procedures that can impact the efficiency of implementation and stability of the solution [84]. However, optimization-based hybrid MCDM approaches are still one of the most promising methods for solving large scale, dynamic and intelligent decision-making problem in modern engineering and industrial system [85].

As outlined below in Table 14, hybrid and advanced MCDM tools have greatly enhanced the capability of traditional MCDM systems by incorporating uncertainty modeling, intelligent learning, optimization and big data analytics. These solutions offer a more accurate, flexible, adaptive and real-time decision-making solution for modern and complex applications. In the future, the use of artificial intelligence, machine learning, deep learning and optimization techniques is likely to be a key element in the development of intelligent and autonomous decision support systems and Industry 5.0 applications.

Table 14
Comparative Overview of Hybrid and Advanced MCDM Approaches

Approach	Key Feature	Major Advantage	Limitation	Major Applications
Fuzzy MCDM	Fuzzy uncertainty handling	Handles vagueness effectively	Computational complexity	Healthcare, sustainability
Intuitionistic Fuzzy MCDM	Membership and hesitation modeling	Better uncertainty representation	Difficult interpretation	Robotics, engineering
Neutrosophic MCDM	Truth-indeterminacy-falsity modeling	Handles inconsistent information	Complex formulation	AI systems, risk analysis
Grey Theory-Based MCDM	Incomplete information analysis	Effective with small datasets	Limited prediction capability	Manufacturing, energy
Rough Set Theory	Rule extraction and data reduction	Knowledge discovery	Sensitive to data quality	Data mining, classification
AI-Integrated MCDM	Intelligent learning-based decisions	Automated adaptive systems	Large data requirement	Smart systems
Deep Learning MCDM	Complex pattern recognition	High prediction accuracy	High computational cost	Big data analytics
Optimization-Based Hybrid Models	Optimization-assisted decisions	Better global solutions	Parameter tuning difficulty	Engineering optimization

9. Application Areas of MCDM

The MCDM methods have been widely used in a wide range of fields to address complex decision issues with multiple conflicting criteria. Due to the flexibility, adaptability, and ability of MCDM methods to deal with uncertainty and optimize decision making processes, it has been used in a wide range of engineering, healthcare, energy systems, finance, transportation, robotics, sustainability, etc. and many other fields. In recent years, the application of MCDM techniques in intelligent and autonomous systems has been further extended with the help of the modern development of artificial intelligence, machine learning, fuzzy logic and optimization. In this section, the major application areas of MCDM are introduced, key applications and methods for each application area are explained, and the related applications are summarized.

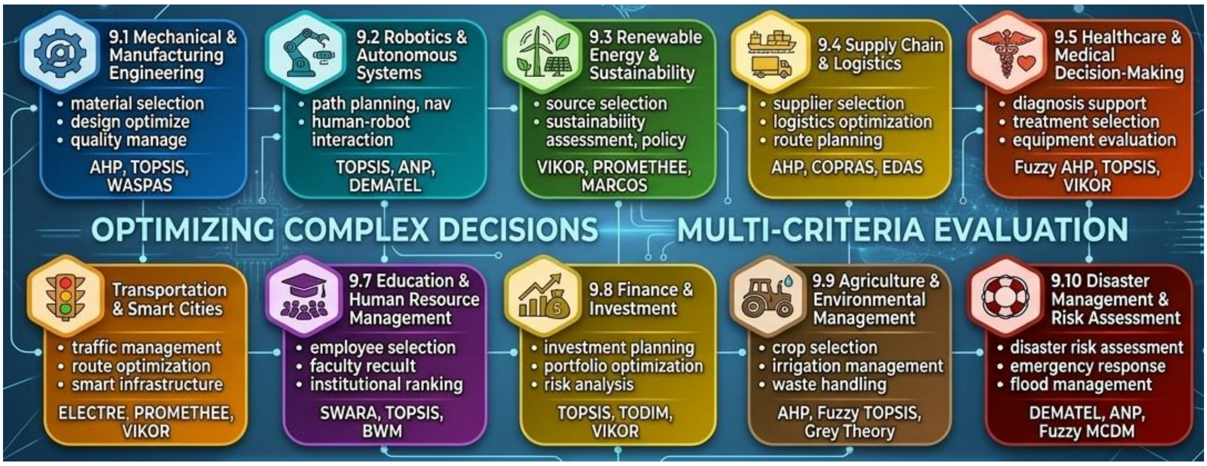

Fig. 9. Classification and mapping across major application areas.

Figure 9 provides a structured framework to consider 10 different application domains of MCDM and shows how they can be put together in a coherent way in the context of Optimizing Complex Decisions and performing a thorough multi-criteria Evaluation. The highest layer covers engineering, industrial and clinical applications, spanning from Mechanical Engineering and Robotics, to Supply Chain and Healthcare, with the criteria matrix focusing on safety, efficiency and reliability. The bottom layer, on the other hand, is dedicated to socio-economic, urban and environmental aspects, including Smart Cities, Human Resource Management, Finance, Agriculture and Disaster Risk Assessment.

10. Comparative Analysis of MCDM Methods

There are many differences among Multiple Criteria Decision Making (MCDM) methods ranging from computational complexity, accuracy, mathematical structure, uncertainty handling capability to suitability of application. There are advantages and disadvantages to each method, depending on the type of decision problem, dataset properties, dependency of the criteria, and degree of uncertainty. There are some methods that are simple and efficient to computer, while others give more accurate and robust solutions to more complicated and uncertain environments. So, it is necessary to choose the right MCDM technique to get decision results that are reliable and effective.

10.1 Comparison Based on Complexity

The computational complexity of MCDM methods is influenced by several factors such as the number of alternatives, criteria, pairwise comparisons, mathematical operations and interdependency calculations that are used for the decision-making process. The computational cost of simple methods (SAW and MOORA) is low, while the computational cost of methods like ANP, DEMATEL and AI-integrated MCDM is high as demonstrated by the numbers in Table 15.

Table 15
Comparison Based on Complexity

Method	Complexity Level	Reason for Complexity
SAW	Low	Simple weighted summation
MOORA	Low	Ratio-based normalization
TOPSIS	Moderate	Distance calculations
COPRAS	Moderate	Utility degree computation
VIKOR	Moderate	Compromise ranking analysis
AHP	Moderate	Pairwise comparisons and consistency checking
PROMETHEE	High	Preference flow analysis
ELECTRE	High	Concordance-discordance computations
DEMATEL	High	Cause-effect matrix analysis
ANP	Very High	Supermatrix and interdependency calculations
AI-based MCDM	Very High	Machine learning and intelligent computation

10.2 Comparison Based on Accuracy

Accuracy of MCDM methods is defined as the ability to give the same rankings with consistency and reliability in various decision situations. Hybrid and intelligent methods usually offer increased accuracy because of their improved ability to deal with uncertainty and adaptive learning. The proof is given in Table 16.

Table 16
Comparison Based on Accuracy

Method	Accuracy Level	Key Strength
SAW	Moderate	Simple evaluation process
TOPSIS	High	Ideal solution-based ranking
VIKOR	High	Compromise solution capability
AHP	High	Structured pairwise comparisons
DEMATEL	High	Interdependency analysis

Table 16
Comparison Based on Accuracy

Method	Accuracy Level	Key Strength
Fuzzy MCDM	Very High	Uncertainty handling
ANP	Very High	Network relationship modelling
AI-integrated MCDM	Very High	Adaptive intelligent learning
Deep Learning-based MCDM	Extremely High	Complex pattern recognition

10.3 Comparison Based on Computational Requirements

The mathematical complexity, optimization process, and data sets size are a few of the factors that influence the computational needs of different MCDM methods. The classical methods are less power demanding while the AI and integrated deep learning methods are more power demanding and need advanced computational infrastructure, as shown in Table 17.

Table 17
Comparison Based on Computational Requirements

Method	Computational Requirement	Suitable Dataset Size
SAW	Very Low	Small datasets
MOORA	Low	Small to medium datasets
TOPSIS	Moderate	Medium datasets
VIKOR	Moderate	Medium datasets
AHP	Moderate	Small to medium datasets
ELECTRE	High	Medium to large datasets
DEMATEL	High	Complex systems
ANP	Very High	Large interdependent systems
Machine Learning-integrated MCDM	Very High	Large datasets
Deep Learning-based MCDM	Extremely High	Big data environments

10.4 Advantages and Limitations

There are specific benefits and constraints associated with each of the MCDM methods, depending on the characteristics of the problem and the decision-making environment as listed in Table 18.

Table 18
Advantages and Limitations of Major MCDM Methods

Method	Major Advantages	Major Limitations
AHP	Simple and intuitive	Subjective inconsistency
TOPSIS	Easy implementation and ranking	Sensitive to normalization
VIKOR	Effective compromise solution	Parameter sensitivity
ELECTRE	Handles conflicting criteria	Complex calculations
PROMETHEE	Flexible preference modelling	Requires parameter tuning
DEMATEL	Identifies cause-effect relationships	Difficult interpretation
ANP	Handles interdependencies	High computational burden
MOORA	Computationally efficient	Limited uncertainty handling
COPRAS	Simultaneous benefit-cost evaluation	Weight dependency
WASPAS	Improved ranking stability	Computational sensitivity
Fuzzy MCDM	Effective uncertainty handling	Complex mathematical formulation
AI-integrated MCDM	Intelligent adaptive decisions	Interpretability challenges

10.5 Suitability for Different Problem Types

In Table 19, we illustrate the variety of decision environments and the selection of different MCDM methods for different levels of uncertainty, complexity, availability of data, and the interrelationship of the decision criteria.

Table 19
Suitability of MCDM Methods for Different Problems

Problem Type	Suitable MCDM Methods	Reason
Simple ranking problems	SAW, MOORA	Easy and fast computation
Engineering optimization	TOPSIS, VIKOR	Accurate ranking capability
Interdependent criteria problems	ANP, DEMATEL	Dependency modeling
Uncertain and vague environments	Fuzzy MCDM, Grey MCDM	Uncertainty handling
Strategic planning	AHP, PROMETHEE	Structured evaluation
Big data decision systems	AI-integrated MCDM	Intelligent data analysis
Real-time autonomous systems	Deep learning-based MCDM	Adaptive intelligent learning
Sustainability assessment	VIKOR, MARCOS, CoCoSo	Multi-dimensional evaluation

10.6 Comparative Summary Table

The comparative summary gives an overall evaluation of the major MCDM methods as regards their complexity, handling of uncertainty, computational requirements and suitability for their applications as presented in Table 20.

Table 20
Comparative Summary of Major MCDM Methods

Method	Complexity	Accuracy	Uncertainty Handling	Computational Requirement	Best Suitable Applications
AHP	Moderate	High	Moderate	Moderate	Supplier and project selection
TOPSIS	Moderate	High	Moderate	Moderate	Engineering optimization
VIKOR	Moderate	High	Good	Moderate	Sustainability assessment
ELECTRE	High	High	Good	High	Policy and strategic decisions
PROMETHEE	High	High	Moderate	High	Environmental management
DEMATEL	High	Very High	Good	High	Risk and dependency analysis
ANP	Very High	Very High	Good	Very High	Complex interdependent systems
MOORA	Low	Moderate	Low	Low	Manufacturing evaluation
COPRAS	Moderate	High	Moderate	Moderate	Construction and logistics
WASPAS	Moderate	High	Moderate	Moderate	Material and energy selection
Fuzzy MCDM	High	Very High	Very High	High	Uncertain decision environments
AI-based MCDM	Very High	Extremely High	Very High	Very High	Intelligent autonomous systems

Comparative studies of MCDM methods indicate that none of the methods is always the best for all decision problems. In the uncertain, complex, and intelligent decision-making environment, while the classical approaches like AHP, TOPSIS and VIKOR are still popular because of their simplicity and effectiveness, the advanced approaches like fuzzy, hybrid, and AI-integrated MCDM are performed better. The choice of the MCDM technique is determined by the degree of complexity of the decision, uncertainty level, computational resources as well as application requirements.

11. Challenges and Research Gaps

Although MCDM methods have been developed considerably during the last 30 years, there are still some problems and gaps for their application in a complex decision problem in real world. Most of the classical MCDM methods are not applicable to uncertainty, scalability, computational requirement and changing decision situation. In addition, the rapid adoption of artificial intelligence, machine learning, big data analytics and autonomous systems has added further complexities of interpretability, transparency and real-time processing. It is crucial to recognize the need for more robust, intelligent, and adaptive decision support systems to address these limitations. The major challenges and gaps in the existing research regarding current methods of MCDM is discussed in this section. This is shown in Figure 10, as the transition from legacy constraints to optimized next-generation MCDM systems. Traditional Struggles (data uncertainty, computational complexity and scalability problem) and AI Complexities (interpretability and integration problem) are considered to form a "black-box" bottleneck in the context of current decision processes. Five key Research Gaps & Opportunities are identified, which address these specific bottlenecks: unified uncertainty modeling, scalable and distributed computing, standardized evaluation frameworks, with explainable and transparent AI (XAI), and adaptive, real-time systems. It is these gaps that are directly addressed, systematically building up to a real-time, autonomous peak in Next-Generation MCDM Frameworks. A continuous improvement loop underpins this entire ecosystem, resulting in high decision effectiveness, trust and applicability.

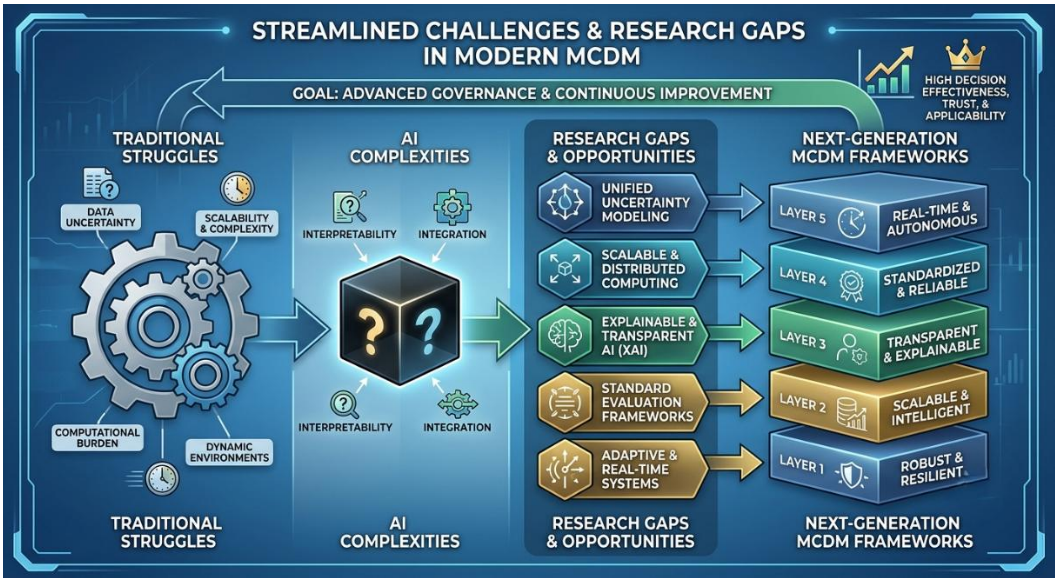

Fig. 10. A Mapping of Challenges, Research Gaps, and Solutions for Next-Generation MCDM Frameworks.

12. Future Research Directions

The field of Multiple Criteria Decision Making (MCDM) keeps evolving as AI, machine learning, big data analytics, quantum computing, Internet of Things (IoT), and autonomous systems rapidly change the landscape of decision-making. The traditional MCDM approaches are shifting to become more intelligent, adaptive, explainable, and real-time decision support systems that can cope with dynamic and uncertain environments. Future research is anticipated to be directed towards enhancing transparency, computational efficiency, scalability, sustainability, and autonomous decision making capabilities. The combination of new technologies and MCDM techniques will be important for the construction of future intelligent decision-support systems in Industry 5.0, smart cities, health care, robotics and cyber-physical systems.

The architecture of the next-generation MCDM framework, shown in Figure 11, is divided into four steps progressively leading to the establishment of intelligent, sustainable and autonomous decision support in highly uncertain environments. The foundation of computational power and model transparency is Pillar 1 (Foundation & Technology Integration), which integrates the Internet of Things (IoT), Cyber-Physical Systems, Quantum Computing and Explainable AI (XAI) at the base. On top of this information-rich layer, Pillar 2 (Intelligent Systems & Analytics) facilitates the processing of information in a quick and context-rich way, using Real-Time Intelligent Decision Systems in conjunction with Human-Centered Decision Intelligence, which keeps the processing information in line with cognitive support and values. These analytics directly support Pillar 3 (Strategic Applications), including Digital Twin and Industry 5.0 applications as well as Sustainable and Green Decision-Making paradigms, and they are tailored for addressing the needs of today's industry and environment. Lastly, Pillar 4 (Advanced Governance) presents a new concept of Autonomous Decision-Making Frameworks to enable self-governing and safe decisions. This whole system is an ongoing learning and improvement cycle that continually feeds the outcomes of the process back into the lower layers, enabling the MCDM system to adapt and evolve in dynamic environments.

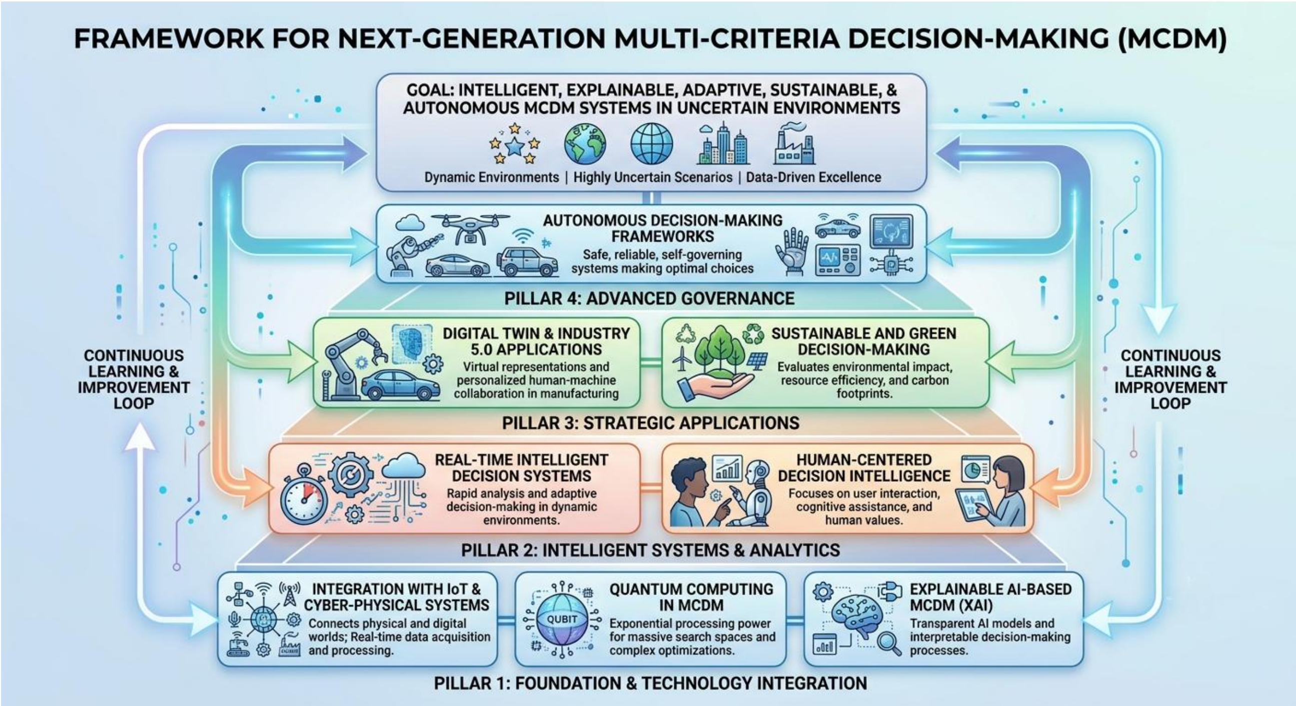

Fig. 11. Framework for Next-Generation MCDM in Dynamic and Uncertain Environments.

13. Conclusion

This review paper reviewed MCDM methods comprehensively covering their development, advancement, application, challenges, and future directions for the period from 1996 to 2026. It was found that the studies on the application of MCDM techniques have advanced greatly in the past three decades, from classical mathematical decision models to advanced intelligent, hybrid, and AI integrated decision-support systems. Traditional methods like AHP, TOPSIS, AHP, ELECTRE, PROMETHEE and VIKOR are still essential in addressing multi-criteria decision problems, and modern approaches combining fuzzy logic, grey theory, machine learning, deep learning, optimization algorithms and explainable artificial intelligence have significantly improved the precision, flexibility and coping ability of decisions under uncertainty.

The study pointed out that the MCDM methods have been widely used in various fields like mechanical and manufacturing engineering, robotics, health science, renewable energy, transportation, supply chain management, finance, agriculture, sustainability, and disaster management. Moreover, the study revealed the rising significance of hybrid and intelligent MCDM methods in solving complex real-world problems under uncertainty, dynamism of data and interdependence of criteria. Bibliometric and comparative analysis revealed the growing research interests in autonomous decision-making systems, IoT and AI-assisted.

The most significant contribution of this review is the comprehensible, systematic integration of more than three decades of MCDM research that is organized into the following topics: historical evolution, MCDM classification, weighting methods, advanced hybrid MCDM methods and applications, comparative analysis, research gaps and future directions. The study also gives a detailed comparative analysis of the major MCDM methods based on complexity, computational needs, uncertainty handling capacity and suitability for application, which can be useful for the researchers and practitioners to choose the appropriate decision-making technique for their application.

Although significant advances have been made in the research on MCDM, there are still some issues that have not been resolved, such as uncertainty management, scalability problems, computational complexity, the lack of uniform evaluation systems, the limitation of interpretation of the results, and the problem of real-time intelligent decision-making. These constraints highlight the need for more transparent, scalable, adaptive and computationally efficient decision-support systems. Research directions for the future will concentrate on explainable AI based MCDM, integration of quantum computing, digital twin application, applications of Industry 5.0, human-centered decision intelligence, IoT based cyber-physical system, and self-decision system.

In general, MCDM methodologies will remain a key component of resolving increasingly complex decision problems in the world, supporting intelligent, data-driven, sustainable, and autonomous decision-making processes. With the ongoing integration of advanced computational technologies into MCDM, its applicability and effectiveness will continue to grow in the future smart systems and intelligent industrial environments.

Acknowledgement
We would like to offer our warmest thanks to our mentors, our colleagues and sources of research, whose support and help were of value to this research.

Conflicts of Interest
The authors declare no conflicts of interest.

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