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A Comprehensive Review of MCDM Methods, Applications, and Emerging Trends

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ABSTRACT

Multiple-criteria decision-making (MCDM) approaches have become vital for tackling complicated, multi-objective decision-making issues in dynamic and unpredictable situations. This paper covers the history of MCDM methodologies, ranging from conventional methods like the analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) to sophisticated innovations embracing fuzzy logic, hybrid models, and artificial intelligence (AI). It analyses the numerous uses of MCDM in business, engineering, healthcare, and environmental management, highlighting their adaptation to both qualitative and quantitative criteria. The approaches adopted include an examination of conventional and current frameworks, identifying their strengths and shortcomings. Emerging technologies such as integrating Blockchain, the Internet of Things, and big data analytics are studied, revealing their potential for real-time and dynamic decision-making. Key findings underscore the limitations of uncertainty modeling, computational complexity, and scalability while also revealing potential for multidisciplinary research and sustainability-focused applications. This study finds by offering actionable recommendations for researchers and practitioners, advocating for the establishment of AI-integrated, real-time decision-making frameworks and standardized evaluation standards to address contemporary challenges and enhance the practical relevance of MCDM methods.

1. Introduction

In today's world, which is becoming more complicated and changing quickly, people who make decisions have to deal with many problems that need complex tools to help them compare different goals, criteria, and stakeholder opinions. Real-world problems are often too complicated for traditional ways of making decisions to handle. For example, there may be competing goals, different levels of doubt, and the need to balance trade-offs.

Multiple-criteria decision-making (MCDM) has become an important tool for dealing with these

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problems because it gives you a structured way to find, evaluate, and rank your choices [1]. MCDM techniques help people make decisions by breaking down difficult issues into manageable parts. This makes it possible to compare options using both quantitative and qualitative factors [2]. Over the years, MCDM has changed a lot. It used to use old methods like the analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) but now it uses new mixed and data-driven methods [3]. As the need for strong, adaptable, and flexible models that can deal with uncertainty and incorporate new technologies grows, these models are changing too. MCDM is used in many areas, such as public policy, engineering design, strategic business planning, environmental management, and making decisions about healthcare. By taking into account multiple factors at the same time and including feedback from stakeholders, MCDM improves clarity, consistency, and the quality of decisions. This review looks at the latest developments, uses, and new trends in MCDM [4]. It shows how important it is for solving real-life decision problems and suggests ways that study and development can go in the future.

The paper is organized as follows: Section 1 introduces the study; Section 2 reviews advancements in MCDM methods; Section 3 explores applications in various domains; Section 4 discusses emerging trends; Section 5 highlights strengths and limitations; Section 6 concludes the findings; and Section 7 outlines future research directions.

1.1 Significance of the Study

The significance of this work resides in tackling the increasing complexity of decision-making in today’s dynamic, data-driven situations. Traditional MCDM approaches, such as AHP, TOPSIS, and elimination and choice translating reality (ELECTRE), have proved significant in solving issues with numerous competing criteria. However, these shortcomings become obvious when applied to real-time, high-dimensional, and fast-moving scenarios. In particular, business management has experienced an increasing demand for adaptable, scalable, and effective decision-making frameworks to handle difficulties such as strategy planning, supplier selection, and performance optimization [5].

This research focuses on the progression of MCDM methodologies from classic approaches to cutting-edge models using artificial intelligence (AI), big data, and blockchain technology. These developments provide transformative potential by making decision-making systems more accurate, responsive, and context-aware. For studying their applications in business management and other sectors such as healthcare and environmental sustainability, this study bridges gaps in the existing literature while delivering actionable insights for practitioners and researchers alike [6]. Also, as industries such as supply chain management, smart cities, and financial markets continue to grow, the demand for frameworks that can handle real-time, adaptive, and sustainability-focused decision-making difficulties has become crucial. This study underscores the importance for future MCDM models to combine these skills, thus meeting the ever-changing needs of decision-makers in a quickly shifting global environment [7]. With the rapid adoption of technologies like AI and the Internet of Things (IoT), MCDM frameworks must evolve to handle real-time data, uncertainty, and sustainability challenges. This research bridges this gap by evaluating contemporary techniques and their potential applications.

1.2 Scope of the Study

The development of MCDM techniques and their practical implementations are the main topics of this review. Analyzing contemporary developments like fuzzy logic, hybrid models, and AI-driven procedures as well as more conventional approaches like AHP and TOPSIS is part of the focus. Their use in business management, where MCDM techniques are widely employed for strategic planning, supplier selection, and performance evaluation, is given special attention. The research also emphasizes their contribution to other sectors like infrastructure development, healthcare, and environmental sustainability. To solve current issues, the combination of sustainability measures, real-time data, and interdisciplinary approaches is investigated. This review focuses on analyzing the evolution of MCDM methods, their diverse applications, and emerging trends to address the increasing complexity of decision-making in modern contexts.

1.3 Research Objectives

In the evolving arena of MCDM, decision-makers frequently encounter intricate issues necessitating the reconciliation of several, often contradictory, criteria. Over the years, MCDM techniques have progressed from conventional methods such as AHP and TOPSIS to more sophisticated methodologies that use fuzzy logic, hybrid models, and AI-driven systems. This research seeks to investigate these advancements and analyze how MCDM is evolving to address the problems presented by modern decision-making contexts. The research will examine the application of these approaches in critical sectors including business management, healthcare, environmental sustainability, and infrastructure. Additionally, it aims to identify emerging trends, evaluate the effects of new technologies, and reveal significant research deficiencies in the domain.

This project will enhance MCDM methodologies and offer a systematic method for real-time, adaptive decision-making. The following key research objectives (RO) guide this study:

i. *RO1* – To analyze the evolution of MCDM techniques.
ii. *RO2* – Investigate the application of MCDM in business management.
iii. *RO3* – To identify emerging trends in MCDM.
iv. *RO4* – To address research gaps and propose future directions.
v. *RO5* – To provide a comprehensive resource for researchers and practitioners.

1.4 Review of Literature

Relevant literature was retrieved from Scopus, Web of Science, and Google Scholar using keywords like "MCDM", "AHP", and "fuzzy logic". Studies published between 2000 and 2024 were included based on relevance, peer-reviewed status, and contribution to the field of MCDM.

1.4.1 Historical Development of MCDM

MCDM methods have changed greatly since their inception [8]. Alsheref [9] stressed breaking complex choices into hierarchical structures, making decision-making clearer and more systematic. Ren et al. [10] presented the idea of finding solutions based on their closeness to an ideal solution. Abad et al. [11] brought forward the idea of outranking for handling choice problems involving qualitative data. The shift from traditional to cutting-edge techniques marked the integration of fuzzy logic and mixed models, addressing the limitations of rigidity in classical approaches [11]. For instance, fuzzy MCDM models presented by Zhang et al. [12] added doubt and vagueness, improving decision-making in imprecise settings. Salih et al. [13] combined the benefits of multiple methods to improve robustness and flexibility in multi-criteria evaluations [13].

1.4.2 Key Contributions Across Domains

MCDM methodologies have found broad applications across different fields. In business and management, tools like the preference ranking organization method for enrichment evaluations (PROMETHEE) have been applied for investment research and supplier selection [14]. Engineering and technology fields widely utilize AHP and hybrid models for project management and product development [15]. Environmental decision-making has seen the uptake of methods like TOPSIS for sustainability studies and resource allocation [16]. Healthcare apps have leveraged MCDM methods for diagnostic help and treatment priority. For instance, fuzzy AHP has been used for evaluating medical tools and treatment choices [17]. In public policy, ELECTRE has eased urban planning and governance choices, showing its applicability in handling qualitative and quantitative factors effectively [18].

1.4.3 Research Gaps

MCDM has matured in various areas, but major study gaps exist. Dynamic decision-making, which accounts for changing criteria and stakeholder opinions over time, is underexplored. Similarly, the integration of AI into MCDM, though hopeful, remains in nascent stages. Current models often struggle to combine real-time data, limiting their applicability in fast-paced settings such as emergency management and social media analytics. Furthermore, uncertainty modeling continues to be a problem, especially in situations involving high-dimensional and heterogeneous data. Although fuzzy and stochastic models handle some of these problems, their computational complexity often hinders practical application.

The historical development of MCDM shows its adaptability and usefulness across diverse sectors. However, new trends like AI integration, real-time data analysis, and interdisciplinary study demand innovative methods to bridge existing gaps. Future studies must focus on improving computing speed and solving the challenges brought by doubt and high-dimensional data.

2. Advancements in MCDM Methods

2.1 Traditional Approaches: AHP, TOPSIS, PROMETHEE, ELECTRE

MCDM techniques, such as the AHP, TOPSIS, PROMETHEE, and ELECTRE, have been foundational in the field. These methods offer structured models for fixing choice problems that feature multiple conflicting factors. AHP focuses on pairwise comparisons to derive the relative importance of decision factors, easing decision-making in difficult situations [19]. TOPSIS, on the other hand, ranks alternatives based on their geometric distance to the ideal answer, making it particularly effective in situations where alternatives can be compared quantitatively [20]. PROMETHEE focuses on outranking alternatives and rating them based on a set of choice relationships, while ELECTRE uses pairwise comparisons to remove inferior alternatives and rank the remaining options. Despite their robustness, traditional methods often deal with uncertainties and interdependencies between criteria, limiting their application in more complicated choice settings [21].

2.2 Modern Innovations: Fuzzy Logic-based Approaches

Recent advances in MCDM have been driven by the need to handle doubt and imprecision in decision-making. Fuzzy logic-based MCDM methods have gained popularity due to their ability to handle individual opinions and vague data. Techniques such as fuzzy AHP and fuzzy TOPSIS allow decision-makers to state opinions and judgments in linguistic terms, thus fitting the natural uncertainty present in many real-world scenarios. These methods utilize fuzzy sets to describe vague information, making them particularly useful in areas such as environmental management, medical diagnostics, and urban planning, where exact data is often unavailable. The ability to record and process imprecise data improves the flexibility and usefulness of MCDM models, enhancing their strength in dealing with human emotion and complex decision criteria [22].

2.3 Hybrid Models Integrating Multiple Techniques

The integration of multiple MCDM techniques into hybrid models has appeared as a potential way to overcome the limits of individual methods. These models combine the strengths of different MCDM methods to provide more complete answers. For instance, combining AHP with TOPSIS allows for the prioritization of criteria and ranking of options, while integrating fuzzy AHP with PROMETHEE can address both subjective opinions and complex choice structures [23]. Hybrid MCDM models are highly suitable for multi-dimensional choice problems, especially in industries such as supply chain management, energy planning, and product design. By combining methods that handle doubt with those that manage trade-offs between clashing goals, hybrid models offer a more robust decision-making framework capable of handling complex real-world challenges.

2.4 AI and Machine Learning Decision Models

The integration of AI and machine learning (ML) with MCDM methods marks a major development in decision-making processes. AI and ML algorithms, such as neural networks, support vector machines, and decision trees, can be added to MCDM frameworks to improve choice accuracy and support dynamic, data-driven decision-making [24]. These models shine in environments where big datasets and complex patterns need to be processed, making them ideal for use in healthcare, finance, and smart cities. Machine learning improves MCDM models by giving predictive insights, finding hidden trends in data, and changing decision models in real-time.

The merger of MCDM and AI allows for the optimization of decision processes in settings with massive and continuously updating data, reshaping industries like e-commerce, autonomous systems, and precise medicine.

2.5 Data-driven Models Leveraging Big Data and Analytics

In recent years, the rise of Big Data has changed decision-making models. Data-driven MCDM models harness vast amounts of organized and unstructured data to guide decision-making. These models utilize advanced analytics techniques such as predictive modeling, clustering, and regression analysis to process real-time data and forecast results under varying situations. Big Data MCDM applications are especially beneficial in fields such as supply chain management, marketing, and risk management, where choices need to be made quickly based on big datasets. These models offer high levels of accuracy by combining past data, customer behavior, and real-time market trends. By improving decision-making skills with data-driven insights, these models allow more precise and useful outcomes, especially in environments marked by high unpredictability and rapid changes [25].

2.6 Comparative Analysis: Strengths, Weaknesses, and Suitability for Various Applications

Each MCDM method has its own set of benefits and limits, which make it suitable for different types of decision problems. Traditional methods, such as AHP and TOPSIS, excel in cases where choice factors are well-defined and the data is stable and precise [26]. However, they face difficulties in dealing with uncertainty and complicated interrelationships between criteria. Fuzzy logic-based methods handle this by incorporating subjective, uncertain data, making them suitable for areas where human opinion plays a crucial role. Hybrid models, by combining the benefits of multiple methods, offer increased freedom and stability, especially in multidimensional situations involving both qualitative and quantitative data. On the other hand, these models can become computationally intensive and may require significant expertise to apply successfully. AI and machine learning-based models provide exceptional powers for large-scale, real-time decision-making, but they require huge datasets and significant computational resources, making them more suited to dynamic, data-rich environments. Data-driven models are ideal for settings where decision-making depends heavily on big data, giving high levels of accuracy and adaptability, but they are also dependent on the availability of quality data and robust analytical infrastructure. Ultimately, the choice of the MCDM method depends on the unique decision context, the availability of data, and the complexity of the problem at hand [27].

3. Applications of MCDM in Business and Management

3.1 Strategic Planning and Supplier Evaluation

MCDM methods have become important tools in business and management for strategy planning and supplier evaluation. In strategic planning, methods such as the AHP are applied to examine multiple strategic options based on factors like cost, market trends, and long-term sustainability. These frameworks help decision-makers select projects and allocate resources efficiently. Additionally, MCDM is widely applied in supplier evaluation, where methods like TOPSIS and PROMETHEE allow businesses to rank suppliers based on factors such as price, quality, delivery reliability, and service [28]. With the rise of digital technologies, the integration of AI with MCDM methods has improved source selection processes by automating data analysis and optimizing buying choices. Recent developments also show how MCDM helps in reviewing digital transformation strategies, allowing more informed choices in the competitive global market.

3.*2 Engineering and Technology: Product Design and Project Management*

In engineering and technology, MCDM offers a robust framework for product design and project management choices. For product design, fuzzy-based MCDM models, such as fuzzy ahp and fuzzy TOPSIS, allow engineers to assess design alternatives by considering factors such as cost, performance, and longevity, aligning technical requirements with market needs. These methods are important in ensuring product innovations meet both customer expectations and engineering requirements. In project management, MCDM methods are applied to prioritize and pick tasks, measure resource allocation, and analyze risks. By considering multiple criteria, such as project cost, time, and risk, methods like PROMETHEE and the analytic network process (ANP) help project managers make more balanced and informed choices. The merging of hybrid MCDM models, mixing optimization algorithms with decision-making techniques, has further improved project management through better decision-making under dynamic conditions [29].

3.3 Environmental Decision-Making: Sustainability Assessments, Impact Analysis

Environmental decision-making strongly leans on MCDM to measure sustainability and evaluate environmental impacts. MCDM methods like AHP and TOPSIS are widely used to evaluate alternative energy projects, waste management strategies, and environmental policies by combining economic, social, and ecological factors. These tools help decision-makers select projects that reduce environmental footprints while promoting sustainable growth. Additionally, fuzzy logic-based MCDM models improve the robustness of environmental studies by dealing with uncertainties in data, such as imprecise environmental effect predictions [30]. As environmental worries continue to rise, the integration of MCDM with new technologies such as blockchain and IoT is paving the way for more efficient and open environmental government, especially in the context of climate change mitigation and resource management.

3.4 Healthcare: Diagnosis and Treatment Selection

In healthcare, MCDM is essential to better decision-making processes linked to diagnostic and treatment selection. For diagnosis, AHP methods are used to rank medical conditions based on signs, patient history, and diagnostic tests, allowing faster and more accurate diagnoses. In treatment selection, MCDM methods like Fuzzy AHP and TOPSIS are applied to evaluate the best treatment choices based on factors like effectiveness, side effects, patient preferences, and cost [31]. This is especially important in complicated healthcare areas like oncology, where treatment choices must be tailored to individual patient needs. Moreover, personalized medicine has gained from the integration of MCDM with genetic data, allowing more exact and individualized treatment plans. Recent advancements show how AI and machine learning are further enhancing MCDM uses in healthcare by offering decision support systems that study big datasets to predict the most effective treatments.

Table 1
Applications of MCDM in various fields

Domain	Example applications	MCDM methods used	Technologies integrated
Business Management	Supplier selection, project prioritization	AHP, TOPSIS	AI, IoT
Engineering	Product design, project management	Fuzzy AHP, PROMETHEE	Fuzzy logic, optimization algorithms
Healthcare	Diagnosis, treatment selection	Fuzzy AHP, AI-driven models	Machine learning, genetic data
Environmental Studies	Sustainability assessments, energy planning	TOPSIS, fuzzy models	Blockchain, IoT
Public policy	Urban planning, resource allocation	AHP, PROMETHEE	Big data analytics, IoT

4. Discussion on Emerging Trends

4.1 Integration with Emerging Technologies: Blockchain, IoT, and Advanced AI

The combination of blockchain, IoT, and AI with MCDM methods has appeared as a transformative development in decision science. Blockchain, with its decentralized and safe nature, offers improved data integrity in MCDM systems, especially in cases involving multiple parties, such as in supply chain management and financial services. By offering a transparent and immutable ledger, Blockchain ensures that the data coming into decision-making models stays unchanged, thereby increasing trust in the results [32].

The IoT revolution has enabled real-time data collection from interconnected devices, allowing MCDM systems to work in dynamic settings. In smart cities, IoT-enabled MCDM models improve resource allocation, energy usage, and traffic management, among other aspects, by constantly processing real-time data. These technologies allow for more responsive decision-making, where models change based on new, arriving information.

AI and machine learning further elevate the capabilities of MCDM models by allowing them to handle big datasets, learn from previous results, and predict future scenarios. Machine learning algorithms, such as deep learning, can identify buried patterns in complex datasets, enabling better decision-making in environments marked by doubt and rapid change. AI-powered MCDM models are particularly useful in healthcare, automated systems, and financial modeling, where the ability to analyze vast, dynamic datasets provides critical insights and supports faster, more informed decisions.

4.2 Decision-Making in Dynamic and Real-Time Environments

Traditional MCDM methods are usually static, depending on pre-defined datasets and parameters. However, many current decision-making problems occur in dynamic and real-time environments, where the facts and conditions are constantly changing. The need for MCDM systems capable of real-time change has become important, especially in sectors such as driverless cars, disaster management, and financial markets [33].

In driverless cars, for example, real-time data from sensors, cameras, and GPS systems must be handled to make choices about navigation, speed control, and obstacle avoidance. Similarly, in financial markets, algorithmic trading systems leverage real-time data feeds to perform trades based on changing market conditions. The inclusion of real-time data processing into MCDM models improves their flexibility and accuracy, allowing decision-makers to respond to unforeseen changes or new information quickly [34].

By adding feedback loops and dynamic modeling, real-time decision-making systems allow the continuous refinement of choices. MCDM models are changing to include adaptive algorithms, which allow decision systems to learn and change based on newly available data, improving their speed in real-time decision-making situations.

4.3 Addressing Challenges: Handling Uncertainty through Fuzzy and Stochastic Models

Uncertainty remains a major challenge in decision-making, especially when data is missing, unclear, or contradictory. Fuzzy logic and stochastic models have emerged as important tools for handling such doubt in MCDM. Fuzzy-based models, such as fuzzy AHP and fuzzy TOPSIS, allow decision-makers to add subjective judgments stated in linguistic terms, such as "high", "medium", or "low", rather than depending solely on exact numerical data. This flexibility makes fuzzy models ideal for complicated decision problems in areas like environmental management, healthcare, and urban planning, where human judgment and imprecision are inevitable [35].

Stochastic models, such as Monte Carlo simulations and Markov chains, bring probabilistic methods to MCDM, allowing the modeling of uncertainty through random variables and probability distributions. These models are particularly effective in situations such as financial risk analysis and resource allocation in unclear settings, where the results are not fixed but are affected by various random factors. By considering a range of possible outcomes, stochastic MCDM models provide decision-makers with a complete view of potential risks and benefits, improving the reliability of decision-making under uncertainty.

4.4. Enhancing Computational Efficiency

As choice problems become increasingly complicated, there is a growing need to improve the processing efficiency of MCDM methods. Traditional MCDM approaches often fight with scalability and high-dimensional decision spaces, especially when working with big datasets or numerous factors. To handle these issues, new developments rely on optimizing algorithms and leveraging high-performance computing techniques to improve working speeds [36].

The use of parallel computing and cloud-based computing platforms has made it possible to handle bigger datasets more efficiently, thus allowing real-time decision-making in environments where timely answers are important. Additionally, metaheuristic optimization algorithms, such as genetic algorithms and particle swarm optimization have been combined into MCDM frameworks to improve the speed and accuracy of choice outcomes. These algorithms offer faster transitions to optimal or near-optimal solutions, making them particularly useful in large-scale optimization problems across industries like transportation, manufacturing, and energy management.

4.5 Unexplored Areas: Novel Domains like Social Media, Fintech, and Disaster Management

While MCDM has been widely applied in traditional domains such as engineering, healthcare, and business, there remain several new domains where its potential is largely unexplored. The emergence of social media, fintech, and emergency management offers exciting possibilities for the application of MCDM in new settings.

In social media, MCDM models can help in mood analysis, content recommendation, and influencer recognition by studying vast amounts of user-generated data. Social network analysis mixed with MCDM methods can provide useful insights into user behavior, interaction patterns, and the success of marketing strategies.

The fintech sector, defined by rapid technological developments and huge amounts of financial data, can benefit from MCDM in areas like investment portfolio optimization, credit risk assessment, and fraud discovery. By combining real-time market data and machine learning, MCDM models can help financial institutions make more informed, data-driven choices.

In emergency management, MCDM models can improve resource allocation, evacuation plans, and crisis reaction strategies by integrating data from IoT devices, satellite images, and crowd-sourced information. These models can help governments and groups make timely, effective choices during natural disasters, pandemics, or other emergencies [37].

Exploring these novel areas offers significant possibilities for MCDM to provide decision support in cutting-edge fields, further increasing its applicability and effect in the digital age.

4.6 Public Policy and Governance: Urban Planning and Resource Allocation

MCDM plays a vital role in public policy and government, especially in urban planning and resource allocation. Urban development projects, including transportation infrastructure and land-use planning, require evaluation across multiple opposing factors, such as social effect, environmental sustainability, and economic success. MCDM methods like AHP, VIKOR, and PROMETHEE allow lawmakers to rank alternative projects and select those that offer the best trade-offs among various stakeholders [38]. Additionally, in resource allocation, MCDM helps in choices regarding public services, disaster relief, and healthcare funds by measuring urgency, effect, and available resources. As cities grow increasingly complicated, the merging of real-time data with

MCDM frameworks, such as through the use of big data analytics, allows for more dynamic and adaptive policy choices, improving the overall efficiency and responsiveness of government.

5. Strengths and Limitations

5.1 Strengths of the MCDM Method

One of the key benefits of MCDM methods is their ability to offer organized models for decision problems that involve multiple goals or criteria. By breaking down complicated choices into smaller, doable components, MCDM methods allow decision-makers to evaluate and compare options consistently. This structured method provides a clear decision route, ensuring transparency and uniformity, which is crucial for informed decision-making [39].

Strength is the adaptability of MCDM methods to different decision-making situations. From business strategy to environmental sustainability and healthcare management, MCDM has proven its flexibility in handling a broad spectrum of choice problems. This adaptability stems from the fact that MCDM allows for the addition of both qualitative and quantitative data, making it perfect for a wide range of areas and uses. Whether the choice criteria are financial, environmental, or social, MCDM methods can be customized to meet unique needs.

Furthermore, MCDM's inclusion of diverse factors is another significant strength. In real-world decision-making scenarios, multiple parties often have conflicting goals, and MCDM methods provide a structured way of bringing these diverse viewpoints into the decision process. By allowing decision-makers to organize, rank, and analyze options based on a complete set of criteria, MCDM ensures that all relevant factors are considered. This inclusivity is especially useful in complicated, multi-stakeholder environments such as public policy and project management, where decisions have wide-ranging effects and must account for various competing interests [40].

Table 2
Strengths and limitations of different MCDM methods

MCDM Methods	Strengths	Limitations	Best-suited application
AHP	Structured, easy to use	Struggles with large datasets	Strategic planning, resource allocation
TOPSIS	Easy ranking based on ideal solutions	Limited uncertainty handling	Supplier selection, risk analysis
Fuzzy methods	Handles subjective and vague data	Computationally intensive	Healthcare, environmental management
AI-driven models	Real-time, adaptive decision-making	Requires massive datasets and high expertise	Smart cities, autonomous systems

5.2 Limitations of MCDM Methods

Despite the strength, MCDM methods also have inherent limits, mainly related to the complexity of data modeling and challenges in dynamic and high-dimensional situations. One major drawback of MCDM methods is their complexity in data models. MCDM often needs a large amount of data to perform meaningful analysis, and this data is not always widely accessible or easily structured [41]. In many cases, choice factors must be quantitatively measured and weighted, a job that may involve subjective judgments [42]. When decision-makers need to deal with big, complex datasets or criteria that are difficult to measure, the process of gathering, structuring, and analyzing data can become cumbersome and time-consuming [43]. Additionally, ensuring the truth and consistency of this data, especially when drawn from diverse systems or parties, can be a significant challenge [44].

Another limitation is the trouble MCDM methods face in dynamic and high-dimensional decision-making settings. In real-world applications, decision problems are rarely static; they change over time due to changing market conditions, technical improvements, or moving stakeholder goals. Traditional MCDM methods often struggle to change to these changing conditions, as they tend to rely on set, predefined criteria and data [45, 46]. When faced with rapidly changing data or the need for real-time decision-making, standard MCDM models may fail to offer fast or accurate solutions. Moreover, as the number of criteria and options grows, MCDM models can become increasingly high-dimensional, leading to difficulties in processing, analyzing, and combining large amounts of information. This can result in a computational burden and possible errors in choice outcomes, especially when the relationships between criteria are complicated or non-linear [47, 48].

The need to balance complexity and accuracy in decision-making is one of the most important issues for MCDM methods. As decision problems grow more complex and involve multiple factors and goals, the models may require more advanced algorithms and computing resources to process the information effectively [49]. However, the trade-off between computational feasibility and the need for accuracy remains a persistent issue, especially in large-scale decision problems such as those found in financial markets, supply chain management, and healthcare systems [50].

6 Conclusions

6.1 Summary of the Findings

This study offers an extensive examination of MCDM procedures, emphasizing their progression from conventional techniques such as AHP, TOPSIS, PROMETHEE, and ELECTRE to contemporary advancements that include fuzzy logic, hybrid models, and AI-driven methodologies. The results highlight the adaptability of MCDM in tackling intricate decision-making issues across several fields, such as business, engineering, environmental management, and healthcare. Moreover, the incorporation of emerging technologies like blockchain, IoT, and big data analytics has broadened the scope of MCDM, facilitating dynamic and real-time decision-making. The report finds substantial obstacles, such as data complexity, uncertainty modeling, and scalability, while suggesting future research areas to mitigate these deficiencies.

6.2 Implications for Researchers and Practitioners

The findings provide researchers with significant insights into current developments and upcoming trends in MCDM, establishing a basis for investigating novel approaches and multidisciplinary applications. The research emphasizes the potential for incorporating AI, sustainability indicators, and real-time frameworks, which can substantially improve the relevance of MCDM in addressing practical issues. Professionals, especially in dynamic sectors like finance, healthcare, and disaster management, can utilize MCDM models to enhance decision-making by integrating several factors and adjusting to evolving conditions. The practical value of MCDM is obvious in its capacity to establish organized, transparent, and inclusive decision-making frameworks.

6.3 Concluding Observations

The continuous advancement of MCDM techniques signifies the increasing intricacy of contemporary decision-making. Innovation remains crucial to solving difficulties like unpredictability, data scalability, and computing efficiency. By embracing developments in AI, big data, and multidisciplinary cooperation, MCDM can continue to change decision-making processes across disciplines. As the discipline evolves, creating defined standards and assessment frameworks will assure the reliability and consistency of MCDM approaches, supporting their adoption as a crucial tool for both academic and practical applications. This work serves as a call to action for continuing innovation, cooperation, and investigation in MCDM research.

7. Future Research Directions

7.1 Focus Areas

i. *The development of AI-integrated MCDM models* – The integration of AI with MCDM methods offers a promising study path. AI techniques, such as ML and deep learning can greatly increase MCDM by allowing the system to learn from historical data, adapt to new patterns, and improve decision-making processes in real-time. AI-driven MCDM models would ease the study of big datasets, allowing decision-makers to improve choices in dynamic, data-intensive environments such as automated systems, healthcare, and financial markets. Future studies should focus on creating MCDM models that leverage AI to provide more adaptive, predictive, and efficient decision-making solutions.
ii. *Incorporating sustainability metrics* – As global sustainability becomes increasingly important, there is a growing need to combine sustainability measures into MCDM frameworks. Future studies should explore methodologies for embedding environmental, social, and economic factors into decision-making processes. Sustainability measures such as carbon footprint, resource economy, and social effect need to be formally examined and added alongside traditional criteria. This integration will be particularly important in industries such as supply chain management, green technology, and corporate social responsibility, where businesses are expected to make decisions that align with both profitability and environmental/social responsibilities.
iii. *Real-time decision-making frameworks* – The demand for real-time decision-making is growing, especially in healthcare, emergency management, and banking industries. Traditional MCDM models often rely on static data, which can be a weakness in settings where conditions change quickly. Research should focus on building real-time decision-making frameworks that combine big data, IoT, and sensor technologies to handle dynamic, real-time information. This method will improve decision-making accuracy in fast-paced situations such as autonomous vehicles, stock trading, and emergency reaction.

7.2 Interdisciplinary Research: Collaboration across Engineering, Social Sciences, and Data Analytics

MCDM is naturally an interdisciplinary area, and its future growth will benefit greatly from collaboration across fields such as engineering, social sciences, and data analytics. Engineering will add to the design of efficient algorithms capable of handling large-scale decision problems, while social sciences will provide insights into human behavior and decision flaws, helping improve subjective assessments in MCDM. Data analytics, especially in the form of big data and predictive analytics, can improve decision processes by finding patterns and trends. Future studies should encourage interdisciplinary collaboration to develop more holistic decision-making models that are both technically advanced and socially important.

7.3 Standardization: Creation of Benchmarks and Evaluation Frameworks

As MCDM methods are applied across diverse sectors, creating uniform evaluation frameworks is critical for ensuring their effectiveness and trustworthiness. Future studies should focus on building benchmarking methods that allow the comparison of different MCDM techniques across applications. These frameworks should describe measures to evaluate efficiency, accuracy, and robustness in different choice situations. Additionally, the creation of best practices for applying MCDM models in particular industries will help standardize approaches, improving the credibility and usability of MCDM as a decision-support tool.

This study underscores the need for collaborative, interdisciplinary approaches to enhance MCDM techniques, ensuring their adaptability to dynamic and data-driven environments.

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Conflicts of Interest
The authors declare no potential conflicts of interest in relation to this study.

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