



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

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ABSTRACT

This research paper presents a comprehensive review of Multiple Criteria Decision-Making (MCDM) methods, encompassing their advancements, applications, and future directions. The study begins with an introduction emphasizing the significance of MCDM in complex decision-making scenarios. Through a systematic literature review, recent developments in MCDM techniques are examined, including multi-objective methods, fuzzy-based approaches, data-driven models, and hybrid methodologies. The strengths and limitations of each method are critically analyzed. Furthermore, the paper investigates the diverse applications of MCDM in domains such as business, engineering, environment, healthcare, and public policy, highlighting the practical implications through real-world case studies. The study then identifies emerging trends and challenges in MCDM research, discussing the integration of MCDM with emerging technologies, enhancing robustness and adaptability, addressing uncertainty, and identifying unexplored domains for potential application. This comprehensive review serves as a valuable resource for decision-makers and researchers, providing insights into the advancements, applications, and future directions of MCDM methods.

1. Introduction

In today's complex and rapidly evolving world, decision-makers face multifaceted challenges that demand a structured and informed approach to decision-making. Multiple Criteria Decision-Making (MCDM) methods offer a systematic framework to tackle decision problems involving multiple objectives, diverse criteria, and varying preferences [1]. The objective of this research paper is to provide a comprehensive review of MCDM methods, exploring their advancements, applications, and future directions. The advancements in MCDM techniques have been significant in recent years. Traditional approaches, such as the Analytic Hierarchy Process, TOPSIS, and ELECTRE, have served as foundations for decision-making [2]. However, novel methodologies have emerged, including multi-

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objective MCDM methods that consider conflicting objectives, fuzzy-based approaches that handle uncertainty and imprecision, data-driven models leveraging machine learning and big data analytics, and hybrid methodologies that integrate multiple techniques.

A critical analysis of the strengths and limitations of each method will provide insights into their applicability in different decision contexts. Moreover, MCDM methods have found diverse applications across various domains. From business and management to engineering, environmental decision-making, healthcare, and public policy, these techniques have proven their efficacy in addressing complex decision problems [3]. By examining real-world case studies, this review will shed light on the practical implications of MCDM methods in different fields, highlighting their effectiveness and challenges encountered in their application. Looking ahead, it is crucial to identify the future directions and emerging trends in MCDM research. The integration of MCDM with emerging technologies, such as artificial intelligence, Blockchain, and Internet of Things, holds immense potential for enhancing decision-making processes. Furthermore, improving the robustness and adaptability of MCDM methods, addressing uncertainty and vagueness, and exploring unexplored domains present exciting opportunities for further research and development. This research paper aims to provide decision-makers and researchers with a comprehensive review of MCDM methods, encompassing their advancements, applications, and future directions [4,5]. By synthesizing the existing knowledge and identifying gaps, this study seeks to contribute to the ongoing discourse in MCDM research, empowering decision-makers with valuable insights and guiding future investigations in this dynamic field.

1.1. Significance of MCDM methods

The significance of MCDM methods lies in their ability to address the complexities inherent in decision-making processes that involve multiple objectives, criteria, and stakeholders [6]. Here are a few key aspects that highlight the significance of MCDM methods.

- **Systematic and structured approach:** MCDM methods provide a systematic and structured framework for decision-making. They enable decision-makers to break down complex problems into a set of criteria, evaluate alternatives against these criteria, and make informed choices based on well-defined decision rules [7]. This structured approach helps in reducing ambiguity, ensuring transparency, and facilitating consistent decision-making.
- **Incorporation of multiple objectives and criteria:** Many real-world decisions involve multiple objectives that need to be considered simultaneously. MCDM methods provide a way to explicitly account for multiple objectives and criteria, enabling decision-makers to strike a balance among competing goals [8,9]. By capturing the preferences and trade-offs between objectives, MCDM methods help in identifying optimal or satisfactory solutions that align with the decision-maker's preferences.
- **Handling uncertainty and subjectivity:** Decision-making often involves dealing with uncertainty and subjectivity. MCDM methods offer techniques to handle uncertain information, such as fuzzy logic or probabilistic models, allowing decision-makers to make robust decisions even in the presence of incomplete or imprecise data [10]. Moreover, MCDM methods provide mechanisms to incorporate subjective judgments and preferences of decision-makers, ensuring their perspectives are adequately represented in the decision-making process.
- **Consideration of stakeholder perspectives:** In many decision contexts, multiple stakeholders with diverse interests and preferences are involved. MCDM methods facilitate the inclusion of multiple stakeholder perspectives by allowing for the explicit consideration of their criteria

and preferences [11]. This participatory approach promotes fairness, inclusivity, and stakeholder engagement, leading to more acceptable and well-supported decisions.

- Wide range of applications: MCDM methods have found applications in various fields, including business, engineering, environmental management, healthcare, public policy, and more [12]. From strategic planning and project selection to resource allocation and risk assessment, MCDM methods provide valuable tools for addressing complex decision problems in different domains. Their versatility and adaptability make them applicable to a wide range of decision-making scenarios.

The significance of MCDM methods lies in their ability to enhance decision-making by providing a structured, comprehensive, and inclusive approach [13]. By incorporating multiple objectives, criteria, and stakeholder perspectives, MCDM methods facilitate informed choices, improve transparency, and promote better decision outcomes in complex and uncertain decision environments.

1.2. Objective of Research Paper

The objective for the review paper is as follows.

- To conduct a comprehensive review of the advancements in MCDM methods, examining the evolution and development of traditional techniques and identifying recent innovations in the field.
- To explore the diverse applications of MCDM methods in various domains, including business, engineering, environmental decision-making, healthcare, public policy, and other interdisciplinary contexts, by analyzing real-world case studies and identifying their practical implications.
- To identify and discuss the emerging trends and future directions in MCDM research, including the integration of MCDM with emerging technologies, enhancing the robustness and adaptability of MCDM methods, addressing uncertainty and vagueness, and identifying unexplored domains for potential application.
- To critically evaluate the strengths and limitations of different MCDM methods, facilitating a comparative analysis of their suitability in different decision-making contexts and providing insights into their applicability, effectiveness, and challenges.
- To serve as a valuable resource for decision-makers and researchers, offering a comprehensive understanding of MCDM methods, their advancements, applications, and future directions, and guiding future research and development efforts in the field.

2. Literature Review

MCDM methods play a crucial role in assisting decision-makers in complex decision problems that involve multiple conflicting objectives and criteria [14]. This literature review aims to provide an overview of the existing research on MCDM methods, highlighting their advancements, applications, and key findings.

2.1. Advancements in MCDM methods

MCDM methods have undergone significant advancements over the years, driven by the need to handle complex decision scenarios. Traditional techniques such as the Analytic Hierarchy Process (AHP) [15], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [16], and

Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [17] have laid the foundation for MCDM research. These methods provide structured frameworks for decision-making by prioritizing criteria, ranking alternatives, and establishing preference relationships. In recent years, researchers have developed innovative MCDM approaches to address the limitations of traditional methods. Multi-objective MCDM methods have gained prominence, allowing decision-makers to consider conflicting objectives simultaneously. These methods, such as the Weighted Sum Model (WSM) [18], the Weighted Product Model (WPM) [19], and the TOPSIS, enable the identification of Pareto-optimal solutions that represent trade-offs between objectives. Additionally, fuzzy-based MCDM approaches have been introduced to handle uncertainty and imprecision in decision-making processes. Fuzzy AHP, Fuzzy TOPSIS, and fuzzy sets-based methods provide mechanisms to capture and quantify vague and subjective information, enhancing the flexibility and robustness of MCDM models. Fuzzy AHP [20] and Fuzzy TOPSIS [21] are notable examples of fuzzy-based MCDM methods. These approaches allow decision-makers to express subjective judgments and capture imprecise information, enhancing the flexibility and robustness of decision models.

The integration of MCDM with data-driven approaches has also been explored. Machine learning algorithms, such as neural networks, decision trees, and support vector machines, have been combined with MCDM methods to improve accuracy and prediction capabilities. Big data analytics and optimization algorithms have further enhanced the efficiency and effectiveness of MCDM processes. Machine learning algorithms, such as neural networks, decision trees, and support vector machines, have been combined with MCDM methods to improve prediction accuracy and decision support. For instance, Sharma & Sehrawat [22] proposed a hybrid method combining TOPSIS and decision trees for supplier selection in supply chain management. Hybrid MCDM methods, which combine multiple techniques, have emerged as a promising direction for achieving more comprehensive and accurate decision-making frameworks. These methods leverage the strengths of individual techniques, creating synergistic models that overcome the limitations of standalone approaches. For example, the integration of Analytic Network Process (ANP) with TOPSIS has been proposed by Coban et al. [23], providing a comprehensive framework that considers both hierarchy and interdependence among criteria. Hybrid methods offer enhanced decision support by addressing the limitations of individual techniques. These models are exceptionally strong to handle any kind of decision-making problems in diverse areas.

2.2. Applications of MCDM Methods

MCDM methods have found diverse applications across various domains, providing valuable support to decision-makers in complex decision problems. This literature review aims to provide an overview of the applications of MCDM methods, highlighting key studies and their corresponding citations [5,6]. In business and management, MCDM techniques have been utilized for strategic planning, project selection, supplier evaluation, and investment decisions. In engineering and technology, these methods have supported product design, process optimization, and technology selection. Environmental decision-making has benefited from MCDM methods for evaluating environmental impact, resource allocation, and sustainability assessments.

- Business and management applications: In strategic planning, AHP has been used to prioritize strategic objectives and evaluate alternative strategies [12]. In supplier selection, TOPSIS has been employed to rank potential suppliers based on multiple criteria [14,15]. In investment decisions, ELECTRE has been utilized to assess investment alternatives considering financial and non-financial factors [21]. These studies demonstrate the efficacy of MCDM methods in enhancing decision-making processes in the business domain.

- Engineering and technology applications: In product design, fuzzy-based MCDM methods, such as Fuzzy AHP, have been employed to evaluate design alternatives based on criteria such as cost, performance, and reliability [2,3]. In project management, PROMETHEE has been utilized to prioritize project activities and allocate resources [10]. In technology selection, ELECTRE and TOPSIS have been applied to assess and rank different technological alternatives [18,19]. These studies highlight the significance of MCDM methods in supporting engineering and technology decision-making processes.
- Environmental decision-making applications: In environmental impact assessment, PROMETHEE has been used to evaluate and rank alternative actions based on environmental criteria [24]. In sustainable development, AHP has been employed to prioritize sustainability goals and guide decision-making processes [24,25]. In resource allocation, TOPSIS has been utilized to assess different resource management options based on ecological, social, and economic criteria [12].
- Healthcare applications: In medical diagnosis, AHP has been used to prioritize diagnostic criteria and guide the selection of appropriate diagnostic tests [3,4]. In treatment selection, PROMETHEE has been employed to evaluate treatment alternatives considering multiple effectiveness and cost criteria [17,18]. In healthcare management, ELECTRE has been utilized to assess and rank hospitals based on quality and performance indicators [9].
- Public policy applications: MCDM methods have been applied in various public policy domains. In urban planning, AHP has been utilized to prioritize urban development projects based on social, economic, and environmental criteria [26]. In transportation planning, TOPSIS has been employed to evaluate and rank different transportation alternatives based on criteria such as cost, efficiency, and environmental impact [21]. In social welfare, fuzzy-based MCDM methods have been applied to assess and prioritize social programs considering multiple social factors [22]. These studies highlight the significance of MCDM methods in public policy decision-making and resource allocation.
- Energy planning applications: MCDM methods have been utilized in energy planning to support decision-making related to energy generation, distribution, and utilization. In energy efficiency measures, AHP has been used to evaluate and rank various energy-saving alternatives [13,14]. These studies emphasize the relevance of MCDM methods in energy-related decision-making processes.
- Risk assessment applications: In project risk management, ANP has been utilized to assess project risks, their impacts, and interdependencies [4]. In environmental risk assessment, TOPSIS has been employed to rank potential risks and guide risk mitigation strategies [14]. These studies demonstrate the effectiveness of MCDM methods in supporting risk assessment and management.
- Supply chain management applications: In supplier selection and evaluation, AHP and TOPSIS have been used to assess suppliers based on criteria such as quality, cost, delivery, and sustainability [27]. In supply chain optimization, MCDM methods have been employed to balance conflicting objectives such as cost, service level, and sustainability [21].

This literature review has provided an overview of the applications of MCDM methods in various domains. The reviewed studies have demonstrated the effectiveness of MCDM methods in supporting decision-making processes in business, engineering, environment, healthcare, public policy, energy planning, risk assessment, and supply chain management [28]. The cited works serve as key references for further exploration and understanding of the applications of MCDM methods, guiding future research and practical implementation in diverse fields of decision-making contexts.

2.3. Novelty and Research Gap

While several literature reviews exist on MCDM methods, there is a need for a comprehensive review that not only focuses on the advancements and applications of MCDM methods but also identifies the research gaps and future directions in the field. The novelty of this research paper lies in its comprehensive nature, covering a wide range of MCDM methods, advancements, and applications. It aims to go beyond summarizing existing literature by critically analyzing the strengths and limitations of different MCDM methods and identifying areas for further research and development. One significant research gap that this paper addresses is the lack of a consolidated overview of recent advancements in MCDM methods. While previous reviews have covered specific techniques or applications, there is a need to synthesize the latest developments across various MCDM methods, such as multi-objective approaches, fuzzy-based models, data-driven techniques, and hybrid methodologies. By providing an up-to-date and comprehensive overview, this research paper fills the gap in the literature by offering a holistic understanding of the advancements in MCDM methods. Another research gap that this paper addresses is the limited focus on the practical applications and case studies of MCDM methods. While many studies have proposed and evaluated MCDM techniques, there is a lack of comprehensive analysis of their real-world applications and the outcomes achieved.

This paper aims to bridge this gap by reviewing and synthesizing empirical case studies across different domains, including business, engineering, environment, healthcare, and public policy. By highlighting the practical implications and lessons learned from these applications, this research paper provides valuable insights for decision-makers and researchers seeking to apply MCDM methods in their respective fields. Furthermore, the paper aims to identify the future directions and research opportunities in the field of MCDM. By analyzing the limitations and challenges of existing methods, it will identify areas where further research and innovation are needed. These may include addressing the computational complexity of MCDM models, incorporating dynamic and uncertain decision environments, integrating emerging technologies like artificial intelligence and blockchain, and exploring the ethical and social implications of decision-making using MCDM methods. This research paper fills a research gap by providing a comprehensive review of MCDM methods, advancements, applications, and future directions. It offers a unique contribution by synthesizing the latest developments across various MCDM techniques, highlighting practical applications through case studies, and identifying research opportunities for further advancements in the field. By doing so, it provides a valuable resource for decision-makers, researchers, and practitioners interested in MCDM methods.

3. Discussion of Recent Advancements in MCDM Techniques

In recent years, MCDM techniques have undergone significant advancements to enhance their effectiveness and applicability in complex decision problems [6]. This discussion focuses on the recent developments in MCDM techniques, highlighting their key advancements and contributions. One major advancement in MCDM techniques is the integration of multi-objective approaches. Traditional MCDM methods often assume a single objective or aggregate multiple objectives into a single criterion. However, with the increasing recognition of the importance of considering multiple conflicting objectives, researchers have developed multi-objective MCDM methods. These methods allow decision-makers to simultaneously optimize multiple criteria and consider trade-offs between them. Techniques such as the WSM and the TOPSIS have been widely used in multi-objective decision-making, enabling the identification of Pareto-optimal solutions that represent the best

trade-offs between different objectives. Another significant advancement is the incorporation of fuzzy logic in MCDM methods. Fuzzy-based MCDM techniques address the challenges of dealing with uncertainty and vagueness in decision-making processes [10,11]. By allowing decision-makers to express subjective judgments and capture imprecise information, these techniques enhance the flexibility and robustness of decision models. Fuzzy-AHP and Fuzzy-TOPSIS are notable examples of fuzzy-based MCDM methods. These approaches enable decision-makers to handle decision problems with fuzzy criteria and linguistic assessments, providing more realistic and practical decision support.

Hybrid MCDM methods have also emerged as a notable advancement in the field. Hybrid methods combine multiple decision-making techniques to leverage their strengths and overcome their limitations. For instance, the integration of ANP with TOPSIS has been proposed, providing a comprehensive framework that considers both the hierarchy of criteria and the interdependence among them [25]. By combining the advantages of different methods, hybrid MCDM approaches offer enhanced decision support and facilitate more comprehensive decision analysis. The integration of MCDM techniques with data-driven approaches is another noteworthy advancement. Machine learning algorithms, such as neural networks, decision trees, and support vector machines, have been combined with MCDM methods to improve prediction accuracy and decision support. This integration allows decision-makers to leverage large datasets and extract valuable insights for decision-making. For instance, a hybrid method combining TOPSIS, and decision trees has been proposed for supplier selection in supply chain management [26,27]. This approach combines the robustness of MCDM methods with the predictive power of machine learning algorithms, resulting in improved decision outcomes.

Additionally, evolutionary algorithms have been applied to solve complex MCDM problems. These algorithms, such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO), provide efficient and effective solutions by exploring the solution space and optimizing decision outcomes. For example, a GA-based method has been proposed for portfolio selection, demonstrating the capabilities of evolutionary algorithms in handling multi-objective decision problems [11,12]. These methods offer an alternative approach to solving MCDM problems, particularly when traditional mathematical optimization techniques face challenges in scalability and computational complexity. Recent advancements in MCDM techniques have significantly contributed to their effectiveness and applicability in addressing complex decision problems [21]. The integration of multi-objective approaches, fuzzy logic, hybrid methods, data-driven techniques, and evolutionary algorithms has expanded the capabilities of MCDM methods and provided decision-makers with more comprehensive and robust decision support [16,19]. These advancements offer valuable tools for decision-making in various domains, ranging from business and engineering to environmental management and healthcare. Further research and innovation in MCDM techniques hold the potential to tackle emerging challenges for enhancing the daily life needs and provide more sophisticated decision support in an increasingly complex and uncertain world.

3.1. Fuzzy-based MCDM Approaches

Fuzzy-based MCDM approaches have been applied in various decision-making contexts, allowing decision-makers to handle uncertainties and vagueness in a more realistic and practical manner. One notable application of fuzzy-based MCDM is in the field of supplier selection, where decision-makers need to evaluate and rank potential suppliers based on multiple criteria [1,2]. For instance, in the study conducted by Tan et al. [29], a fuzzy TOPSIS method was utilized for supplier selection in a semiconductor manufacturing company. The authors applied the fuzzy TOPSIS approach to address the imprecise and uncertain information associated with the evaluation criteria. The method allowed decision-makers to express their subjective judgments through linguistic terms and effectively handle

the vagueness inherent in supplier evaluation. The study demonstrated that the fuzzy TOPSIS method provided a comprehensive and robust evaluation framework for supplier selection, enhancing the decision-making process in a complex and uncertain business environment.

Another application of fuzzy-based MCDM is found in environmental impact assessment. In the study conducted by Khose et al. [30], a fuzzy extension of the PROMETHEE method was employed to evaluate and rank alternative wastewater treatment technologies for a food processing industry. The fuzzy PROMETHEE approach allowed decision-makers to consider the imprecision and uncertainty associated with the environmental criteria. By incorporating fuzzy logic, the method enabled a more realistic assessment of the alternatives' environmental impacts and provided decision-makers with valuable insights for selecting the most suitable wastewater treatment technology. These examples highlight the practical applications of fuzzy-based MCDM approaches in supplier selection and environmental impact assessment. By employing fuzzy logic, these methods enable decision-makers to handle imprecise and uncertain information, providing a more comprehensive and accurate evaluation of alternatives. The cited studies demonstrate the effectiveness of fuzzy-based MCDM approaches in supporting decision-making processes in different domains, emphasizing their relevance and applicability in real-world decision contexts.

Fuzzy-based MCDM methods have been applied in project evaluation and selection processes, where decision-makers need to assess and rank alternative projects based on multiple criteria. In the study by Khan et al. [31], a fuzzy TOPSIS method was employed to evaluate and prioritize potential construction projects considering factors such as cost, schedule, quality, and environmental impact. The fuzzy TOPSIS approach allowed decision-makers to handle the uncertainties and imprecisions associated with the project evaluation criteria, resulting in more accurate and reliable project selection outcomes. Fuzzy-based MCDM techniques have been utilized in healthcare decision-making to assist in medical diagnosis, treatment selection, and resource allocation. For instance, in the study conducted by Chauhan et al. [32], a Fuzzy-AHP method was employed to evaluate and prioritize different treatment alternatives for stroke patients. The fuzzy AHP approach allowed decision-makers to handle the uncertainties and subjectivity associated with medical experts' judgments, enabling a more accurate and comprehensive assessment of the treatment options. Fuzzy-based MCDM methods have been applied in environmental management to support decision-making processes related to pollution control, waste management, and environmental planning. In a study by Liu et al. [33], a fuzzy TOPSIS approach was utilized to prioritize pollution sources in a textile manufacturing facility. The fuzzy TOPSIS method considered linguistic assessments and uncertainty in pollution levels, facilitating a more accurate identification of critical pollution sources and guiding effective pollution control measures.

Fuzzy-based MCDM techniques have found applications in transportation and logistics decision-making, such as route selection, fleet management, and facility location. In a study by Ozkan et al. [34], a fuzzy AHP approach was employed to evaluate and select transportation modes for intermodal freight transportation. The fuzzy AHP method accommodated uncertainties in criteria weights and preference assessments, aiding in the identification of optimal transportation modes considering factors such as cost, time, and environmental impact. Fuzzy-based MCDM methods have been utilized in water resources management for decision-making processes related to water allocation, reservoir operation, and water quality management. In a study by Zhao et al. [35], a fuzzy TOPSIS approach was applied to prioritize water quality improvement measures in a river basin. The fuzzy TOPSIS method incorporated uncertainty in water quality data and expert opinions, facilitating the identification of effective water quality improvement strategies for decision-makers. These examples demonstrate the diverse applications of fuzzy-based MCDM approaches in various domains, including environmental management, transportation and logistics, and water resources

management. By incorporating fuzzy logic, these methods provide a more realistic and robust decision support framework, accommodating uncertainties and vagueness in decision-making processes. The cited studies highlight the effectiveness of fuzzy-based MCDM approaches in addressing complex decision problems and aiding decision-makers in making informed and optimal decisions.

3.2. Data-driven MCDM Models

Data-driven MCDM models have gained significant attention and have been widely applied in various domains to leverage large datasets and extract valuable insights for decision-making. Here are a few examples of applications of data-driven MCDM models along with relevant citations.

Data-driven MCDM models have been used in financial risk assessment to support investment decision-making. In a study by Hariri et al. [36], a data-driven MCDM model based on an improved random forest algorithm was proposed for credit risk evaluation. The model utilized a large dataset of financial indicators and historical credit information to assess the creditworthiness of borrowers. The data-driven approach provided accurate and reliable risk assessment, aiding decision-makers in making informed investment decisions. Data-driven MCDM models have been applied in customer relationship management to enhance customer satisfaction and loyalty. In a study by Islam et al. [37], a data-driven MCDM model based on the combined use of fuzzy TOPSIS and the k-nearest neighbors algorithm was proposed for customer satisfaction analysis. The model incorporated customer feedback and historical data to evaluate and rank service alternatives, enabling organizations to identify areas for improvement and tailor their services to meet customer preferences. Data-driven MCDM models have been utilized in energy management to optimize energy consumption and improve energy efficiency. In a study by Rezk et al. [38], a data-driven MCDM model based on the combination of deep learning and TOPSIS was proposed for energy consumption prediction and optimization in buildings. The model incorporated historical energy consumption data, weather data, and building characteristics to predict future energy consumption and recommend energy-saving measures. The data-driven approach provided accurate predictions and effective energy management strategies.

Data-driven MCDM models have been used in supply chain management to optimize supply chain performance and decision-making. In a study by Patil et al. [39], a data-driven MCDM model based on the integrated use of fuzzy set theory and data envelopment analysis (DEA) was proposed for supplier selection. The model utilized supplier performance data and evaluated suppliers based on multiple criteria, such as cost, quality, delivery, and flexibility. The data-driven approach provided a systematic and objective method for supplier evaluation and selection in supply chain management. Data-driven MCDM models have been applied in healthcare decision-making to support clinical diagnosis, treatment selection, and resource allocation. In a study by Tey et al. [40], a data-driven MCDM model based on machine learning techniques was proposed for cancer diagnosis. The model utilized patient data, including clinical and genomic information, to predict cancer types and assist in treatment decision-making. The data-driven approach provided accurate and personalized diagnostic insights, aiding clinicians in delivering tailored treatments for better patient outcomes. Data-driven MCDM models have been utilized in marketing and consumer behavior analysis to understand customer preferences and enhance marketing strategies. In a study by Mardani et al. [41], a data-driven MCDM model based on the combination of principal component analysis (PCA) and multiple regression analysis was proposed for product preference analysis. The model utilized consumer survey data and assessed the relative importance of product attributes to predict consumer preferences. The data-driven approach provided valuable insights for product development and targeted marketing campaigns for the data driven MCDM algorithms.

Data-driven MCDM models have been applied in risk management to assess and prioritize risks based on multiple criteria. In a study by Zahraee et al. [42], a data-driven MCDM model based on Bayesian networks was proposed for risk assessment in construction projects. The model utilized historical project data and expert judgments to quantify and analyze risks, providing a comprehensive understanding of the project's risk profile. The data-driven approach facilitated more accurate risk evaluation and supported effective risk mitigation strategies. Data-driven MCDM models have been used in urban planning to support decision-making processes related to land use, transportation, and infrastructure development. In a study by Kartal et al. [43], a data-driven MCDM model based on geographic information system (GIS) and AHP was proposed for land suitability assessment. The model integrated spatial data and expert judgments to evaluate the suitability of different land parcels for specific purposes, such as residential, commercial, or industrial use. The data-driven approach facilitated objective and informed land use decision-making. Data-driven MCDM models have been utilized in energy systems to optimize energy generation, distribution, and consumption. In a study by Hosouli et al. [44], a data-driven MCDM model based on machine learning algorithms was proposed for energy demand forecasting. The model utilized historical energy consumption data, weather data, and socio-economic factors to predict future energy demand at different time horizons. The data-driven approach provided accurate demand forecasts, supporting efficient energy planning and resource allocation. This also helps in finding the proper way to reach final decisions involving large number of conflicting parameters and alternatives that can be very essential in the terms of finding the optimum choices.

3.3. Hybrid MCDM Methods

Hybrid MCDM methods combine multiple decision-making approaches or techniques to improve the accuracy and robustness of decision outcomes [36-40]. Here are a few examples of applications of hybrid MCDM methods along with relevant citations.

Hybrid MCDM methods have been applied in sustainable supplier selection to consider both economic and environmental criteria. In a study by Agyekum et al. [45], a hybrid MCDM method combining the TOPSIS, and the Weighted Aggregated Sum Product Assessment (WASPAS) was proposed for sustainable supplier selection. The method integrated multiple criteria, including cost, quality, delivery, and environmental impact, to evaluate and rank potential suppliers. The hybrid approach provided a comprehensive and balanced assessment of suppliers' sustainability performance. Hybrid MCDM methods have been used in project portfolio selection to consider multiple objectives and constraints. In a study by Garg et al. [46], a hybrid MCDM method combining the AHP and the TOPSIS was proposed for project portfolio selection in the construction industry. The method integrated criteria such as project profitability, risk, and resource availability to rank and select projects for optimal portfolio composition. The hybrid approach facilitated more informed and effective project portfolio decisions. Hybrid MCDM methods have been utilized in supplier evaluation within the context of green supply chain management. In a study by Castelló-Sirvent & Meneses-Eraso [47], a hybrid MCDM method combining the ANP and the VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenje) method was proposed for green supplier selection. The method considered multiple criteria, including environmental performance, social responsibility, and economic factors, to assess and rank potential suppliers. The hybrid approach provided a comprehensive evaluation framework for green supplier selection in the supply chain.

Hybrid MCDM methods have been applied in investment decision-making to consider both financial and non-financial criteria. In a study by Alghofaili & Rassam [48], a hybrid MCDM method combining the AHP and the TOPSIS was proposed for investment project selection. The method integrated criteria such as return on investment, risk, market potential and environmental impact to

evaluate and rank investment projects. The hybrid approach provided a comprehensive assessment of investment opportunities, considering both quantitative and qualitative factors. Hybrid MCDM methods have been used in supplier performance evaluation to consider various performance indicators and their relative importance. In a study by Omerali & Kaya [49], a hybrid MCDM method combining the AHP and the TOPSIS was proposed for supplier performance evaluation. The method incorporated criteria such as quality, cost, delivery, and responsiveness to assess and rank suppliers. The hybrid approach facilitated a comprehensive evaluation of supplier performance, considering multiple dimensions and their relative weights. Hybrid MCDM methods have been utilized in the selection of renewable energy projects to consider various economic, environmental, and social factors. In a study by Jamwal et al. [50], a hybrid MCDM method combining the AHP and WSM method was proposed for renewable energy project selection. The method incorporated criteria such as investment cost, energy generation, environmental impact, and social acceptance to evaluate and rank renewable energy projects. The hybrid approach facilitated a comprehensive assessment of project alternatives, considering multiple dimensions and their relative importance.

Hybrid MCDM methods have been used in product design and development to consider multiple design criteria and optimize product performance. In a study by Ortiz-Barrios et al. [51], a hybrid MCDM approach combining the AHP and the TOPSIS was proposed for product design evaluation. The method integrated criteria such as functionality, reliability, cost, and aesthetics to assess and rank different design alternatives. The hybrid approach facilitated a comprehensive evaluation of product designs, considering both technical and market-driven factors. Hybrid MCDM methods have been applied in supplier selection within the context of green supply chains to consider both environmental and economic aspects. In a study by Coelho et al. [52], a hybrid MCDM approach combining the Grey Relational Analysis (GRA) and the VIKOR method was proposed for green supplier selection. The method integrated criteria such as environmental performance, cost, quality, and delivery to evaluate and rank potential suppliers. The hybrid approach enabled a comprehensive assessment of suppliers' green capabilities and economic performance. Hybrid MCDM methods have been utilized in project risk assessment to consider multiple risk factors and prioritize risk mitigation strategies. In a study by Battaïa & Dolgui [53], a hybrid MCDM approach combining the AHP and the Fuzzy TOPSIS was proposed for project risk assessment. The method integrated criteria such as project complexity, financial risks, technical risks, and market risks to evaluate and rank different project risks. The hybrid approach facilitated a comprehensive assessment of project risks, considering both qualitative and quantitative factors.

These examples showcase the diverse applications of hybrid MCDM methods in product design, green supply chain management, and project risk assessment. By combining different decision-making approaches or techniques, hybrid methods enable a more comprehensive evaluation of alternatives, considering multiple criteria and objectives. The cited studies demonstrate the effectiveness and relevance of hybrid MCDM methods in addressing complex decision problems and providing practical solutions in various domains.

4. Strength and Limitations of Different MCDM Methods

MCDM methods offer valuable tools for decision-makers to address complex decision problems involving multiple criteria and objectives [54,55]. However, each MCDM method has its own strengths and limitations, which should be carefully considered when selecting and applying them. In this discussion, we will explore the strengths and limitations of some commonly used MCDM methods.

4.1. Analytic Hierarchy Process (AHP)

Strengths:

- AHP allows decision-makers to decompose complex problems into a hierarchy of criteria and alternatives, making it easier to understand and analyze.
- It incorporates both qualitative and quantitative factors, facilitating a comprehensive evaluation of alternatives.
- AHP provides a consistent framework for pairwise comparison of criteria and alternatives, ensuring transparency and reducing biases.

Limitations:

- AHP heavily relies on the accuracy and consistency of pairwise comparisons, which can be subjective and influenced by individual biases.
- AHP may not adequately capture the interactions and dependencies among criteria, leading to potential oversimplification of the decision problem.
- The calculation of AHP weights can be time-consuming and requires significant effort to obtain reliable and meaningful results.

4.2. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Strengths:

- TOPSIS offers a straightforward and intuitive approach for ranking alternatives based on their similarity to the ideal solution and dissimilarity to the worst solution.
- It allows for the consideration of both positive and negative aspects of criteria, accommodating trade-offs and conflicting objectives.
- TOPSIS provides a clear and easily interpretable ranking of alternatives, facilitating decision-making and communication.

Limitations:

- TOPSIS assumes a linear relationship between criteria and may not capture non-linear relationships or complex interactions among criteria.
- The selection of the ideal and worst solutions in TOPSIS can significantly impact the ranking results and may require subjective judgments.
- TOPSIS does not consider uncertainty or imprecision in the decision data, limiting its applicability in situations with uncertain information.

4.3. ELECTRE (Elimination and Choice Translating Reality)

Strengths:

- ELECTRE allows for the consideration of multiple criteria with different importance levels, enabling flexible and customizable decision-making.
- It incorporates the concept of outranking, which considers the relative performance of alternatives rather than absolute scores.
- ELECTRE can handle imprecise and uncertain data by using fuzzy sets and linguistic terms to represent preferences.

Limitations:

- ELECTRE may generate intransitive results in certain situations, where the ranking of alternatives is not consistent or logical.
- The performance thresholds and preference parameters in ELECTRE are subjective and require careful calibration, which can be challenging and time-consuming.
- ELECTRE may not be suitable for large-scale decision problems due to its computational complexity and the need for extensive pairwise comparisons.

4.4. PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations)

Strengths:

- PROMETHEE provides a flexible framework for ranking and comparing alternatives based on multiple criteria.
- It allows decision-makers to incorporate different preference functions and criteria weights, accommodating diverse decision contexts.
- PROMETHEE offers graphical representations, such as the PROMETHEE Gaia and PROMETHEE outranking flow, which enhance the visualization and interpretation of results.

Limitations:

- PROMETHEE assumes that criteria are independent and does not explicitly consider interactions or dependencies among criteria.
- The choice of preference functions and criteria weights in PROMETHEE can significantly influence the ranking results and may require subjective judgments.
- PROMETHEE is sensitive to changes in the preference parameters, which can lead to different ranking outcomes.

It is important to note that the strengths and limitations mentioned above are contingent upon the specific application context and the decision problem at hand [56]. The suitability of each MCDM method depends on factors such as the nature of the decision problem, the availability of data, the preferences of decision-makers, and the level of complexity involved.

4.5. Multi-Attribute Utility Theory (MAUT)

Strengths:

- MAUT allows decision-makers to explicitly express their preferences through utility functions, providing a structured approach to decision-making.
- It accommodates uncertainty by incorporating probabilistic models and decision analysis techniques, enabling robust decision-making under uncertainty.
- MAUT can handle both qualitative and quantitative criteria, facilitating a comprehensive evaluation of alternatives.

Limitations:

- MAUT requires precise quantification of utility functions, which can be challenging and subjective, especially for complex and subjective criteria.
- It assumes independence and additivity of criteria, which may not hold true in real-world decision problems with interdependencies among criteria.
- The complexity of MAUT models increases with the number of criteria, making it computationally demanding and potentially difficult to manage.

4.6. Grey Relational Analysis (GRA)

Strengths:

- GRA is particularly suitable for decision problems with limited or imprecise data, as it can handle uncertain and incomplete information effectively.
- It can capture the relative closeness or similarity between alternatives and reference points, providing a comprehensive understanding of the decision problem.
- GRA is less sensitive to outliers and extreme values, making it robust against data variations and measurement errors.

Limitations:

- GRA assumes a linear relationship between criteria and their performance, which may not always reflect the true nature of the decision problem.
- The determination of the weighting scheme and the selection of reference points in GRA can be subjective and require expert judgment.
- GRA may not adequately capture complex decision scenarios where there are non-linear relationships or interactions among criteria.

4.7. Data Envelopment Analysis (DEA)

Strengths:

- DEA provides an efficient method for evaluating the relative efficiency and performance of decision-making units, such as companies or organizations.
- It allows for benchmarking and identifying best practices by comparing units' performance against the most efficient ones.
- DEA can handle multiple inputs and outputs, accommodating various dimensions of performance evaluation.

Limitations:

- DEA assumes a constant returns to scale (CRS) or variable returns to scale (VRS) production function, which may not accurately represent the production process in certain industries or sectors.
- The selection of appropriate inputs, outputs, and decision-making units in DEA requires careful consideration, as incorrect specifications can lead to biased results.
- DEA focuses on relative efficiency rather than absolute performance, limiting its ability to provide a complete assessment of individual units' performance.

4.8. Analytic Network Process (ANP)

Strengths:

- ANP allows decision-makers to model complex decision problems with interdependencies among criteria and alternatives using a network structure.
- It accommodates both tangible and intangible criteria, enabling a comprehensive evaluation of alternatives.

- ANP incorporates feedback loops and interactions among criteria, capturing the dynamic nature of decision problems.

Limitations:

- ANP requires the specification of a network structure, which can be time-consuming and subjective, particularly for large and complex decision problems.
- The calculation of weights and priorities in ANP involves matrix operations, which can be computationally intensive and may require specialized software.
- ANP heavily relies on the accuracy and consistency of pairwise comparisons, which can be influenced by individual biases and subjectivity.

4.9. Fuzzy TOPSIS

Strengths:

- Fuzzy TOPSIS allows decision-makers to handle uncertainties and vagueness in decision data using fuzzy sets and linguistic variables.
- It provides a clear and intuitive ranking of alternatives based on their similarity to the ideal solution and dissimilarity to the worst solution.
- Fuzzy TOPSIS incorporates both positive and negative aspects of criteria, accommodating trade-offs and conflicting objectives.

Limitations:

- Fuzzy TOPSIS requires the definition of membership functions and linguistic variables, which can be subjective and challenging, especially when dealing with complex and ambiguous criteria.
- The selection of appropriate weights for criteria and the determination of the fuzzy similarity measures can significantly impact the ranking results and may require expert knowledge or consensus.
- Fuzzy TOPSIS assumes a linear relationship between criteria and their performance, which may not accurately capture non-linear relationships or complex interactions.

4.10. Multi-Objective Optimization (MOO)

Strengths:

- MOO methods allow decision-makers to optimize multiple conflicting objectives simultaneously, facilitating the exploration of trade-offs and Pareto optimal solutions.
- They can handle decision problems with many criteria and alternatives, providing a flexible and scalable approach.
- MOO methods provide a range of solution options, enabling decision-makers to make informed choices based on their preferences and priorities.

Limitations:

- MOO methods require the specification of objective functions, constraints, and decision variables, which can be challenging and may require expert knowledge or sophisticated modeling techniques.
- The identification and interpretation of Pareto optimal solutions in MOO methods can be complex, particularly when dealing with high-dimensional decision spaces.

- MOO methods often focus on quantitative criteria and may not adequately capture qualitative or subjective aspects of the decision problem.

These additional strengths and limitations highlight the diverse characteristics and considerations associated with different MCDM methods [57]. By understanding these aspects, decision-makers and researchers can make informed choices and advancements in selecting and improving the most appropriate MCDM methods for various decision contexts.

5. Future Directions in MCDM Research

The field of MCDM has witnessed significant advancements over the years, but there are still several avenues for future research and development [58]. Here are some potential future directions in MCDM research.

- **Integration of Artificial Intelligence (AI) and Machine Learning (ML):** The integration of AI and ML techniques can enhance the capabilities of MCDM methods by automating data analysis, decision modeling, and decision-making processes [59]. Exploring the potential of AI and ML algorithms, such as neural networks, genetic algorithms, and reinforcement learning, in MCDM can lead to more efficient and accurate decision support systems.
- **Handling big data and real-time decision-making:** With the advent of big data technologies, there is a need for MCDM methods that can handle large volumes of data and enable real-time decision-making [44,45]. Developing MCDM approaches that can effectively process and analyze big data streams, incorporate real-time updates, and adapt to dynamic decision environments will be crucial.
- **Incorporating sustainability and environmental considerations:** Sustainable decision-making is becoming increasingly important across various domains [39,40]. Future research in MCDM can focus on integrating sustainability metrics and environmental considerations into decision models [52]. This includes developing MCDM methods that explicitly address environmental impacts, resource management, carbon footprint reduction, and social responsibility.
- **Addressing uncertainty and risk:** Decision problems often involve various sources of uncertainty and risk. Future research can concentrate on developing MCDM techniques that explicitly consider uncertainty modeling, risk analysis, and robust decision-making [60,61]. This includes incorporating probabilistic approaches, fuzzy logic, stochastic optimization, and scenario analysis to handle uncertain data and support decision-making under risk.
- **Multi-objective evolutionary optimization:** Evolutionary algorithms have shown promise in solving complex optimization problems with multiple conflicting objectives [62]. Future research can explore the application of multi-objective evolutionary optimization algorithms in MCDM, integrating them with decision-making approaches to identify Pareto optimal solutions and enable interactive decision support.
- **Decision-making in dynamic environments:** Decision problems often evolve over time, requiring decision-makers to adapt their strategies and decisions accordingly. Future research can focus on developing MCDM methods that can handle dynamic decision environments, considering changing criteria, preferences, and constraints [63]. This includes dynamic optimization, adaptive decision-making, and real-time decision support systems.
- **Incorporating human factors and cognitive biases:** Understanding the role of human factors, cognitive biases, and decision heuristics in MCDM is essential. Future research can explore how human behavior, emotions, and biases influence decision-making processes and develop MCDM methods that account for these factors [54,64]. This includes integrating behavioral economics, psychology, and decision neuroscience into MCDM frameworks.

- **Application-specific MCDM approaches:** Different domains and industries have unique decision requirements and challenges. Future research can focus on developing specialized MCDM methods tailored to specific application areas, such as healthcare, finance, logistics, energy, and sustainability [65]. This includes considering domain-specific constraints, criteria, and decision-making contexts to provide more accurate and practical decision support.
- **Collaborative and group decision-making:** Decision-making is often a collaborative process involving multiple stakeholders and decision-makers. Future research can explore MCDM methods that facilitate collaborative decision-making, group consensus building, and conflict resolution [61,66]. This includes developing decision support systems that enable efficient communication, negotiation, and aggregation of preferences in group decision-making settings.
- **Evaluation and comparison of MCDM methods:** As the number of MCDM methods continues to grow, there is a need for systematic evaluation, benchmarking, and comparison studies [67]. Future research can focus on developing standardized evaluation frameworks and criteria to assess the performance, applicability, and robustness of different MCDM methods. This can aid decision-makers in selecting the most appropriate method.

6. Conclusion

This comprehensive review has shed light on the advancements, applications, and future directions in MCDM methods. We have explored various MCDM techniques, including fuzzy-based approaches, data-driven models, hybrid methods, and more, highlighting their strengths, limitations, and applications in diverse domains. The review has revealed that MCDM methods play a crucial role in supporting complex decision-making processes by considering multiple criteria and objectives. These methods provide decision-makers with valuable insights, aiding in the evaluation and selection of alternatives based on their preferences and priorities. Moreover, we have identified several areas for future research in MCDM. Integration of AI and ML techniques can enhance decision support systems, while handling big data and real-time decision-making requires the development of efficient algorithms. The incorporation of sustainability and environmental considerations is essential, as is addressing uncertainty, risk, and decision-making in dynamic environments. Furthermore, the understanding of human factors, cognitive biases, and collaborative decision-making should be further explored. Lastly, standardized evaluation frameworks and comparison studies will contribute to the selection and improvement of MCDM methods.

By embracing these future directions, researchers can further enhance the effectiveness and applicability of MCDM methods in various domains. Decision-makers can benefit from improved decision support tools that provide robust, efficient, and context-specific solutions. In summary, this review serves as a comprehensive resource for understanding the advancements, applications, strengths, and limitations of MCDM methods. It provides a foundation for future research and encourages the exploration of innovative approaches to address complex decision problems. With continuous efforts in advancing MCDM, we can facilitate more informed and effective decision-making processes in diverse fields, leading to improved outcomes and sustainable development.

6.1. Practical Implication

The comprehensive review of Multiple Criteria Decision-Making (MCDM) methods presented in this paper has several practical implications for decision-makers and practitioners in various domains. The following are some key practical implications derived from the review.

- **Improved decision-making:** Decision-makers can benefit from the wide range of MCDM methods discussed in this review. By understanding the strengths and limitations of each method, decision-makers can select the most appropriate approach based on the specific characteristics of their decision problem. This knowledge empowers decision-makers to make more informed and robust decisions, considering multiple criteria and objectives.
- **Enhanced evaluation and selection processes:** MCDM methods provide systematic frameworks for evaluating and selecting alternatives. By employing these methods, decision-makers can overcome the challenges associated with subjective judgment and biases. The review highlights various MCDM methods, such as fuzzy-based approaches, data-driven models, and hybrid methods, enabling decision-makers to choose the most suitable method based on the available data, decision context, and decision complexity.
- **Application specific decision support:** The review demonstrates the applications of MCDM methods in diverse domains, including healthcare, finance, logistics, energy, and sustainability. Decision-makers can leverage these applications to address specific decision challenges within their respective fields. The knowledge gained from this review can guide decision-makers in tailoring MCDM methods to their unique requirements and incorporating domain-specific criteria, constraints, and preferences.
- **Future research and development:** The future directions outlined in the review provide guidance for researchers and practitioners interested in advancing the field of MCDM. By focusing on integrating AI and ML techniques, handling big data and real-time decision-making, addressing sustainability and environmental considerations, and exploring collaborative decision-making, researchers can contribute to the development of more efficient, accurate, and practical MCDM methods. The review acts as a roadmap for future research endeavors in MCDM, encouraging the exploration of innovative approaches and methodologies.
- **Standardized evaluation and comparison:** The review emphasizes the importance of standardized evaluation frameworks and comparison studies for MCDM methods. Decision-makers and practitioners can benefit from these efforts by having access to reliable and consistent performance metrics for different MCDM methods. This enables them to make well-informed choices when selecting the most appropriate method for their decision problem.

6.2. Limitations

While the comprehensive review on Multiple Criteria Decision-Making (MCDM) methods provides valuable insights into advancements, applications, and future directions, there are certain limitations to acknowledge:

- **Scope and coverage:** Given the vastness of the field of MCDM, it is challenging to cover all the existing methods and their applications comprehensively within a single review. The review may not include some relatively recent or niche MCDM methods, which could have valuable contributions to decision-making.
- **Bias in method selection:** The selection of MCDM methods discussed in the review might be influenced by the author's expertise or the availability of literature sources. As a result, certain methods or approaches may receive more attention compared to others, potentially leading to an incomplete representation of the MCDM landscape.
- **Evolving nature of MCDM:** The field of MCDM is constantly evolving, with new methods, algorithms, and applications emerging over time. The review's focus on advancements up to

a specific cutoff date means that the latest developments might not be fully captured. Decision-makers and researchers should refer to more recent literature to stay up to date with the latest advancements in MCDM.

- **Context-specific limitations:** The limitations of individual MCDM methods discussed in the review may vary depending on the specific decision context, criteria, and objectives. Certain limitations may only be applicable to specific types of decision problems or industries. Decision-makers should consider these context-specific factors when applying MCDM methods in practice.
- **Implementation challenges:** While MCDM methods provide valuable decision support, their implementation in real-world scenarios can be challenging. Practical limitations such as data availability, computational complexity, and stakeholder acceptance may hinder the widespread adoption and practical application of certain MCDM methods.
- **Subjectivity and uncertainty:** Despite efforts to address subjectivity and uncertainty in decision-making, MCDM methods still rely on subjective judgments and assumptions. The accuracy and reliability of the results are influenced by the quality of input data, criteria weighting, and decision-maker preferences. The review acknowledges that MCDM methods cannot eliminate subjectivity and uncertainty but rather provide systematic frameworks to handle them.
- **Lack of consensus:** The review highlights the diversity of MCDM methods and their respective strengths and limitations. However, there is no consensus on a universally superior method, as the selection of the most appropriate method depends on the decision context and preferences. Decision-makers should carefully evaluate and adapt the methods to suit their specific needs.

6.3. Future Work

Based on the comprehensive review of MCDM methods presented in this paper, several avenues for future work and research can be identified.

- **Development of new MCDM methods:** Despite the vast array of existing MCDM methods, there is still room for the development of new techniques that address specific decision-making challenges. Future research can focus on devising innovative MCDM approaches that integrate emerging technologies, such as artificial intelligence, machine learning, and big data analytics, to enhance decision support capabilities.
- **Comparative studies and evaluation frameworks:** Conducting comprehensive comparative studies that evaluate the performance of different MCDM methods across various decision contexts and domains can be valuable. Future work should emphasize the development of standardized evaluation frameworks and performance metrics to enable objective comparisons and facilitate informed decision-making.
- **Integration of multiple disciplines:** MCDM is an interdisciplinary field that can benefit from the integration of various domains. Future research should encourage collaboration between decision scientists, domain experts, and practitioners from diverse fields, such as economics, operations research, environmental science, and social sciences. This collaboration can lead to the development of more holistic and context specific MCDM methods.
- **Application-specific research:** Further research is needed to explore the application of MCDM methods in specific domains and industries. Future work should focus on tailoring MCDM approaches to address the unique requirements and challenges of various sectors, including healthcare, finance, logistics, energy, and sustainability. This includes considering domain-

specific criteria, constraints, and decision-making contexts to provide practical and effective decision support.

- **Incorporation of dynamic and real-time decision-making:** Decision problems often occur in dynamic and rapidly changing environments. Future research should concentrate on developing MCDM methods that can handle real-time data updates, evolving criteria, and dynamic decision contexts. This includes incorporating adaptive decision-making techniques and real-time decision support systems to ensure the relevance and timeliness of decision support.
- **Addressing ethical and social implications:** As MCDM methods become more powerful and influential, it is important to address the ethical and social implications associated with their application. Future work should investigate the ethical considerations, biases, and fairness issues in MCDM decision-making processes. This includes exploring approaches to mitigate biases, incorporate social preferences, and ensure transparent and accountable decision-making.
- **Decision-making under uncertainty:** Decision problems often involve various sources of uncertainty. Future research should focus on advancing MCDM methods that explicitly address uncertainty modeling, risk analysis, and decision-making under uncertainty. This includes integrating probabilistic approaches, robust optimization techniques, and scenario analysis to enhance decision robustness in uncertain environments.
- **User-friendly decision support tools:** As MCDM methods become more sophisticated, there is a need to develop user-friendly decision support tools that can be easily applied by decision-makers in practice. Future work should concentrate on the development of user-friendly software interfaces, visualization tools, and decision support systems that simplify the implementation of MCDM methods and enhance their usability.
- **Longitudinal studies:** Longitudinal studies that examine the long-term effectiveness and impact of MCDM methods in decision-making processes can provide valuable insights. Future research should consider conducting longitudinal studies that assess the practical outcomes and benefits of applying MCDM methods in real-world decision contexts over extended periods.
- **Stakeholder engagement and decision transparency:** Future research should emphasize the involvement of stakeholders in the decision-making process to ensure their active participation and acceptance. This includes developing participatory decision-making approaches, incorporating stakeholder preferences, and promoting decision transparency to enhance decision legitimacy and implementation.

By addressing these future research directions, the field of MCDM can continue to evolve and provide more effective and practical decision support tools. These research avenues have the potential to enhance decision-making.

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Conflicts of Interest

The authors declare no conflicts of interest.

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