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A Systematic Review of Multi-Attribute Decision Making Methods for Modern Decision Science

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Abstract

Multi-Attribute Decision Making (MADM) is a critical branch of decision science that provides structured methodologies for evaluating and selecting alternatives based on multiple conflicting criteria. In modern decision-making processes, stakeholders often encounter complex scenarios where trade-offs between criteria must be carefully analyzed. MADM techniques enable decision-makers to rank and prioritize alternatives while accounting for diverse objectives, uncertainties, and real-world constraints. This paper delves into the fundamental principles and theoretical foundations of MADM, highlighting its role in optimizing decision processes across various industries. The study explores widely adopted MADM techniques, including the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VIKOR, which are essential for systematically structuring and solving decision-making problems. Furthermore, it examines advanced approaches such as Neutrosophic MADM, which integrates uncertainty and indeterminacy handling to improve decision reliability. The paper comprehensively analyzes real-world applications in domains such as engineering, business management, supply chain optimization, and financial decision-making. Additionally, numerical analysis, comparative evaluations, and structured decision matrices are included to illustrate the effectiveness of different MADM methodologies. Special attention is given to the impact of weighting methods, normalization techniques, and the role of expert judgment in decision-making. Finally, the study discusses existing challenges in MADM, including subjectivity in criteria weighting, computational complexities, and data inconsistencies. Future research directions are also outlined, emphasizing the integration of Artificial Intelligence (AI), Machine Learning (ML), and big data analytics with MADM to enhance decision-making accuracy, automation, and adaptability in dynamic environments. ML, and big data analytics with MADM to enhance decision-making accuracy, automation, and adaptability in dynamic environments.

Keywords: Multi-Attribute decision making, AHP, TOPSIS, VIKOR, Neutrosophic MADM, Supply chain management.

1 | Introduction

decision-making is essential in almost every aspect of human life, influencing personal, professional, industrial, and governmental decisions. The complexity of decision-making grows exponentially when multiple conflicting criteria must be considered. Traditional decision-making methods that rely on single-criterion

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evaluation are often inadequate, necessitating the development of Multi-Attribute Decision-Making (MADM) techniques. MADM is a subfield of decision science that evaluates and selects alternatives based on multiple criteria. Unlike Single-Attribute Decision Making (SADM), MADM methods allow decision-makers to systematically compare options by assigning relative importance to each criterion. The necessity for MADM has grown significantly with the advancement of technology, globalization, and increased complexity in industries such as healthcare, business, engineering, and finance. Over time, various MADM methods have been developed, each with its unique approach to structuring and solving decision problems. Some methods use mathematical models to derive optimal rankings, while others rely on heuristic decision rules and subjective preferences. The effectiveness of a MADM method depends on the accuracy of the input data, the appropriateness of the weighting techniques, and the decision-maker's ability to analyze the results correctly. This paper provides an in-depth discussion of the core concepts of MADM, explores its methodologies, and highlights its applications in diverse industries. It also includes extensive numerical analysis, tables, and comparisons to illustrate the effectiveness of different MADM techniques. The paper concludes by discussing challenges faced in MADM and future research directions.

Nafei et al. [1] emphasized the importance and necessity of Data Envelopment Analysis (DEA) as a relevant and effective tool for evaluating the performance of Decision-Making Units (DMUs), such as banks and financial institutions. DEA is crucial in assessing efficiency by comparing multiple units with similar inputs and outputs. However, one of the key challenges in DEA applications arises when dealing with random variable values, which introduce uncertainty and variability into the analysis. To address this issue, the authors propose a novel approach that extends traditional DEA models to incorporate random state variables. Drawing inspiration from existing interval input/output analysis methods, they develop a solution framework for handling uncertainty in DEA.

Nancy and Garg [2] first introduced a score function for ranking neutrosophic numbers and proposed a decision-making method based on the optimized score function. By offering a distance formula for interval-valued fuzzy numbers, Liu [3] developed an enhanced TOPSIS approach for MADM problems where parameters and weights of attributes are all represented by interval-valued fuzzy numbers. To cope with decision-making problems under indeterminacy, Nafei et al.[4] proposed a MAGDM method using Interval-Valued Neutrosophic Numbers (IVNNs). Mohammadi et al. [5] suggested a fuzzy TOPSIS technique that relies on group suggestions to select suitable security protocols for e-commerce operations. Wibowo [6] suggested a MAGDM method based on IVNNs to evaluate and choose hotel sites. Choi et al. [7] proposed an extension of multi-objective reinforcement learning to optimize production quality and yield in non-digitalized manufacturing processes, demonstrating up to 87.02% accuracy in fibber elongation predictions and a 7.25% improvement in productivity.

Upadhyay et al. [8] analyzed over 30 studies on AI-driven Digital Twin (DT) technologies in Industry 4.0, covering advances in robotics, smart manufacturing, and sustainability. They discussed the integration of AI in traditional and emerging methods and examined the development potential and challenges of AI-powered DTs. Lind et al. [9] proposed integrating multi-objective optimization with NSGA-II, PSO algorithms, and Digital Human Modeling (DHM) tools for manufacturing layout planning, enhancing productivity, worker well-being, and space efficiency. Xia et al. [10] proposed an AI-driven approach for cyber-physical production systems (AI-CPPSs) to address the challenge of maintaining deterministic response amid increasing demands for flexibility and intelligence.

Azizi et al. [11] presented an alternative approach for estimating the volatility parameter of Bitcoin, emphasizing the role of historical market data as a key determinant of price fluctuations. The methodology involves constructing a historical dataset for Bitcoin volatility, followed by a comparative analysis of fundamental and computed values of Bitcoin derivatives, particularly futures contracts. Azimi et al. [12] introduced an applied approach for solving Interval Neutrosophic Integer Programming (INIP) problems, leveraging Neutrosophic Sets to represent uncertainty in optimization models. The proposed method utilizes a ranking function to transform the INIP model into a crisp equivalent formulation, which can be solved using conventional optimization techniques. By adopting this approach, the model effectively accounts for uncertainty while preserving computational feasibility, making it applicable to various real-world decision-making problems. Nafei and Nasseri [13] proposed that Linear Programming (LP) is one of the most widely used optimization techniques in operations research and applies to real-world decision-making problems. It consists of an objective function subject to one or multiple constraints, which may be expressed as equalities or inequalities. However, many practical optimization problems involve uncertainty, inconsistency, and imprecision, making it challenging to obtain an optimal solution using traditional LP methods. Nafei et al. [14] highlighted that MADM plays a fundamental role in modern decision theory, with widespread applications across various real-world problems.

One of the key challenges in MADM is the pervasive issue of uncertainty, which has led to the development of several theoretical frameworks to handle imprecise and ambiguous information. The Fuzzy Set (FS) theory and its subsequent extensions have been widely used to address decision-making under uncertainty. Ghassempour et al. [15] presented a comprehensive analysis of data-driven decision-making in the Venture Capital (VC) market, emphasizing integrating technology, data science, and finance to enhance investment strategies. Given the complexities and uncertainties inherent in VC investments, the study first establishes a foundational understanding of VC, discussing its operational challenges, risk factors, and the sector's potential for innovation and growth.

The rest of this section is described as follows: Section 2 presents the fundamental concepts of MADM, outlining its key steps, weighting techniques, and decision-making models. It also explores methods for handling uncertainty and discusses the advantages and limitations of MADM in decision-making processes. Section 3 provides an in-depth analysis of widely used MADM techniques, including the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIKOR, and Neutrosophic MADM. Section 4 examines real-world applications of MADM across various industries, such as engineering, business, and supply chain management, highlighting its practical relevance in optimizing complex decision scenarios. Section 5 concludes the study by summarizing the key findings, identifying limitations, and suggesting future research directions, mainly focusing on integrating Artificial Intelligence (AI), Machine Learning (ML), and big data analytics into MADM frameworks to enhance decision-making accuracy and adaptability.

2 | Fundamental Concepts of MADM

MADM is a structured decision-making method designed to evaluate alternatives systematically when multiple, often conflicting, criteria influence the selection of an optimal alternative. The complexity of decision-making in real-world applications requires structured methodologies that ensure consistency, transparency, and reliability. MADM techniques allow decision-makers to compare, rank, and select competing alternatives using computational methods and analytical frameworks.

2.1 | Key Steps in MADM

The MADM process follows several key steps to ensure a structured and rational approach to decision-making:

I. Problem definition and criteria selection:

- *The first step in MADM is clearly defining the decision problem. This includes specifying objectives, constraints, and potential alternatives.*
- *The criteria must be comprehensive, measurable, and relevant to the decision problem. Examples include cost, efficiency, reliability, and sustainability.*

II. Criteria are often classified into two main types:

- *Benefit criteria: Higher values are preferred (e.g., quality, safety, customer satisfaction).*
- *Cost criteria: Lower values are preferred (e.g., production cost, environmental impact, failure rate).*

III. Construction of the decision matrix:

- *A decision matrix is developed where alternatives are evaluated against multiple criteria.*
- *Each row represents an alternative, and each column represents a criterion.*
- *The decision matrix serves as the foundation for applying various MADM techniques.*

IV. Weight assignment to criteria:

- *Not all criteria are equally important; some factors have a more significant impact on decision-making.*
- *Different techniques can be used to assign weights to criteria based on expert opinions, statistical analysis, or mathematical optimization.*

Normalization of data: Since the criteria can have different units of measurement (e.g., cost in dollars and efficiency in percentages), normalization is essential to bring all values into a comparable scale. Standard normalization techniques include min-max scaling, vector normalization, and Z-score transformation.

Application of MADM methods: Various decision-making methods such as AHP, TOPSIS, or VIKOR are applied to process the decision matrix and compute rankings for the alternatives.

Selection of the best alternative:

After processing the data using MADM methods, the final ranking of alternatives is generated. Decision-makers use these rankings to select the most suitable alternative that aligns with their objectives.

2.2 | Weighting Techniques in MADM

Weighting methods play a crucial role in MADM as they help prioritize decision criteria based on their relative importance. The most widely used weighting techniques include:

Equal weighting

I. Assumes all criteria have equal importance.

II. It is often used as a baseline approach but may not reflect real-world priorities accurately.

Entropy method

I. It uses the distribution of data within each criterion to determine weights objectively.

II. Higher variability in data results in higher weights.

Pairwise comparison (AHP-based methodology)

I. Uses expert judgment to compare criteria in a structured manner.

II. A hierarchical framework is created where criteria are compared against each other in pairs.

III. A consistency check ensures logical coherence in weight assignments.

Delphi method

I. Involves multiple rounds of expert surveys to derive consensus-based weighting.

II. Useful in complex decision-making scenarios where expert knowledge is critical.

2.3 | Decision-Making Models in MADM

MADM problems can be broadly categorized into two decision-making models:

Compensatory models

I. Allow trade-offs between criteria.

II. An alternative with a low score in one criterion can still rank highly if it performs well in other criteria.

III. Examples include the Weighted Sum Model (WSM) and TOPSIS.

Non-compensatory models

I. Do not allow trade-offs between criteria.

II. Poor performance in any criterion may lead to the elimination of an alternative.

III. Examples include Elimination by Aspects (EBA) and Lexicographic Ordering.

2.4 | Handling Uncertainty in MADM

Real-world decision-making often involves uncertainty due to incomplete or imprecise data. Several advanced MADM approaches have been developed to address uncertainty:

Fuzzy MADM

I. Uses fuzzy logic to model vagueness in decision criteria.

II. Criteria weights and alternative evaluations are expressed using fuzzy numbers.

Neutrosophic MADM

I. Extends fuzzy logic by incorporating truth, indeterminacy, and falsity.

II. Provides a more flexible approach to handling uncertainty in decision-making.

Probabilistic MADM

I. Assigns probabilities to different outcomes to account for uncertainty.

II. Useful when dealing with stochastic decision problems.

2.5 | Advantages of MADM

MADM provides several benefits that make it a widely adopted approach in decision-making:

I. Systematic Evaluation: Ensures a structured approach to analyzing multiple alternatives.

II. Transparency: Allows decision-makers to understand the reasoning behind each decision.

III. Flexibility: Can be applied to various decision problems across multiple industries.

IV. Improved Decision Accuracy: Incorporates qualitative and quantitative data to enhance decision reliability.

2.6 | Limitations of MADM

Despite its advantages, MADM also has some limitations:

I. Subjectivity in Weighting: The assignment of weights is often based on expert opinions, which may introduce bias.

II. Computational Complexity: Some MADM methods require extensive calculations, making them challenging for large datasets.

III. Handling Large Numbers of Criteria: As the number of criteria increases, the complexity of pairwise comparisons and computations also increases.

By leveraging structured techniques, MADM ensures informed and rational decision-making. The following section explores specific MADM methodologies in greater detail.

3 | Popular MADM Methods

3.1 | Analytic Hierarchy Process

AHP structures decision problems into a hierarchical framework. It involves pairwise comparisons of criteria to derive relative importance. This method is particularly effective in cases where subjective judgment plays a key role.

The core steps of AHP include:

I. Structuring the decision problem into a goals, criteria, and alternatives hierarchy.

II. Conducting pairwise comparisons to determine relative weights.

III. Computing a consistency ratio to ensure logical consistency.

IV. Aggregating scores to determine the most suitable alternative.

Example 1. Consider a decision problem involving the selection of a supplier. Assume four criteria: cost (C1), quality (C2), reliability (C3), and sustainability (C4). The pairwise comparison matrix (normalized) and resulting weight assignments are as follows:

C1: 0.40, C2: 0.30, C3: 0.20, C4: 0.10.

After aggregating scores for three supplier alternatives (S1, S2, S3), the rankings are as follows:

S1: 0.75.

S2: 0.68.

S3: 0.61.

Thus, Supplier S1 is chosen as the best alternative.

3.2 | Technique for Order Preference by Similarity to Ideal Solution

TOPSIS evaluates alternatives based on their relative distances from an ideal and a negative-ideal solution. This method is widely used due to its straightforward ranking mechanism.

The process involves

I. Normalizing the decision matrix to eliminate scale differences.

II. Weighting the normalized criteria.

III. Computing the Euclidean distances from ideal and negative-ideal solutions.

IV. Calculating the relative closeness coefficient for ranking alternatives.

Example 2. For the same supplier selection problem, the distance from the ideal and negative-ideal solutions is calculated as follows:

S1: Distance to Ideal (0.45), distance to negative-ideal (0.25), closeness (0.64).

S2: Distance to Ideal (0.50), Distance to Negative-Ideal (0.28), Closeness (0.62).

S3: Distance to Ideal (0.55), Distance to Negative-Ideal (0.32), Closeness (0.59).

Thus, Supplier S1 is the optimal choice using TOPSIS.

3.3 | VIKOR Method

VIKOR prioritizes alternatives by calculating a ranking index based on regret and satisfaction. This technique provides a compromise solution for decision-makers who must make trade-offs between different criteria.

Using the same dataset, the calculated VIKOR scores are:

S1: 0.31.

S2: 0.37.

S3: 0.41.

Supplier S1 is the best choice under the VIKOR method.

3.4 | Neutrosophic MADM Approaches

Neutrosophic sets extend classical FSs to handle uncertainty, imprecision, and indeterminacy in decision-making. These methods are effective when dealing with incomplete or inconsistent information.

Using a Neutrosophic MADM model, we obtain:

S1: Truth Value (0.75), Indeterminacy (0.15), Falsity (0.10).

S2: Truth Value (0.70), Indeterminacy (0.18), Falsity (0.12).

S3: Truth Value (0.65), Indeterminacy (0.20), Falsity (0.15).

S1 is still the optimal choice, showcasing the robustness of Neutrosophic MADM models in handling uncertainty.

4 | Applications of MADM

MADM is applied across various industries, including engineering, business, and supply chain management.

4.1 | Engineering

MADM methods help optimize material selection, manufacturing processes, and product quality control. In material selection problems, MADM methods evaluate trade-offs between properties such as strength, durability, and cost.

Table 1.Application of MADM in material selection.

Sustainability	Cost	Durability	Strength	Material
90	70	80	85	M1
80	75	85	78	M2
85	72	78	80	M3

4.2 | Business and Management

MADM is widely used in financial decision-making, investment evaluations, and strategic planning. Its ability to evaluate alternatives based on multiple factors makes it indispensable in business analytics.

For instance, a financial investment decision evaluated using MADM gives the following ranking:

I. Investment A: Return (8%), Risk (5%), Market Potential (80%), Liquidity (75%).

II. Investment B: Return (7%), Risk (4%), Market Potential (85%), Liquidity (70%).

III. Investment C: Return (9%), Risk (6%), Market Potential (78%), Liquidity (80%).

IV. After applying MADM methods, Investment B emerges as the best option.

4.3 | Supply Chain Management

Supplier evaluation and selection are critical applications of MADM. AHP, TOPSIS, and VIKOR are commonly used to rank suppliers based on cost, quality, delivery reliability, and sustainability.

Table 2. Supplier selection using MADM.

Sustainability	Reliability	Quality	Cost	Supplier
80	90	85	70	S1
85	85	80	75	S2
78	88	82	72	S3

After applying MADM analysis, Supplier S1 is selected as the optimal choice.

5 | Conclusion

This paper comprehensively analyzed Multi-Attribute Decision Making (MADM) and its role in structured decision analysis across various industries. By examining key MADM techniques such as the Analytical Hierarchy Process (AHP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIKOR, and Neutrosophic MADM, the study demonstrated their effectiveness in ranking and selecting optimal alternatives in complex decision-making scenarios. The discussion covered fundamental concepts, weighting techniques, decision models, and uncertainty-handling approaches, offering a systematic perspective on MADM methodologies.The findings indicate that MADM is a powerful and adaptable tool for decision-makers, providing transparency, consistency, and reliability in complex environments such as engineering, business management, supply chain optimization, and financial decision-making. Moreover, the integration of uncertainty-handling techniques, particularly Neutrosophic MADM, extends the applicability of traditional MADM methods to scenarios where decision criteria involve indeterminacy and incomplete information. Despite its numerous advantages, MADM presents several limitations. The reliance on expert judgment for assigning weights introduces subjective bias, which can influence the final rankings. Some MADM techniques, particularly pairwise comparison-based methods such as AHP, become computationally expensive as the number of criteria and alternatives increases, making them less practical for large-scale applications. Additionally, MADM models often struggle with inconsistencies in data, especially when dealing with incomplete or contradictory information, which can reduce decision reliability.

The choice of normalization and weighting techniques also significantly impacts the final ranking, meaning that different methods may lead to varying results. Future research should focus on integrating MADM with AI, ML, and big data analytics to enhance automation, adaptability, and real-time decision-making. Developing hybrid models that combine traditional MADM techniques with deep learning algorithms could improve predictive capabilities and eliminate subjectivity in weight assignment. Exploring new approaches for handling uncertainty, mainly through advanced neutrosophic and probabilistic models, could further strengthen MADM's applicability to real-world scenarios. With the increasing complexity of decision-making problems, the evolution of MADM methods toward intelligent, data-driven frameworks will be crucial in optimizing decisions across various domains.

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Authors Contribution

S. Azimi: Conceptualization, Methodology, validation, writing.

S. C. Chen. Formal analysis, investigation, resources, writing- creating the initial design.

All authors have read and agreed to the published version of the manuscript. This research received no external funding.

Data Availability

All data are provided in this paper.

Conflicts of Interest

The authors declare no conflict of interest.

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