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Large Language Models in Multi Criteria Decision Making: A Systematic Review, Taxonomy, and Future Research Agenda

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ABSTRACT

This study presents a systematic review, bibliometric analysis, and taxonomy development of the integration between Large Language Models (LLMs) and Multi-Criteria Decision-Making (MCDM). A total of 63 publications from the Scopus database were analyzed using PRISMA guidelines and VOSviewer tools. The findings indicate that this research field is still highly nascent, with a rapid increase in publications since 2025. The bibliometric analysis reveals that the field has gained global attention, with contributions from 37 countries, among which China and India account for the highest number of publications. The study introduces a novel classification system based on the roles of LLMs, integration stages, and application domains. Comparative analyses demonstrate that LLM-enhanced MCDM approaches improve automation, scalability, and the processing of unstructured data; however, they remain susceptible to biases, limited interpretability, and prompt sensitivity. The study concludes by identifying key research gaps and future opportunities for developing robust, explainable, and hybrid intelligent decision-making systems.

1. Introduction

Decision-making is a core process in a broad array of fields, such as engineering design, healthcare planning, supply chain management, energy systems, and financial analysis. Decision-makers in these areas are frequently obliged to consider several, and occasionally opposing, criteria to come up with an ideal resolution. Indicatively, in engineering design both cost, performance, durability and sustainability have to be considered concurrently whereas in healthcare treatment effectiveness, risk factors and patient preferences are vital. Such complicated situations underscore the need to have systematic decision support methodologies [1].

Multi-Criteria Decision-Making (MCDM) methods have been widely elaborated and used to handle such issues. Some of the most popular techniques like Analytic Hierarchy Process, TOPSIS, and

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VIKOR, as well as other popular techniques like Analytic Network Process, ELECTRE, PROMETHEE, Simple Additive Weighting, Weighted Product Method, Decision-Making Trial and Evaluation Laboratory, Complex Proportional Assessment, Multi-Attributive Border Approximation Area Comparison, Additive Ratio Assessment. These procedures allow decision-makers to break down complicated issues, weight criteria and rank alternatives systematically and clearly [2]. The MCDM approaches have been extensively used in academia and industry because of their flexibility and interpretability.

1.1 Problem Statement

Although they are widely used, the traditional MCDM methods have a number of limitations. Subjectivity is one of the main problems because the value of weights and preferences is frequently based on the expert opinion that can be subjected to bias and inconsistency. Despite the fact that this problem has been partially solved in hybrid fuzzy-related methods- like Fuzzy Analytic Hierarchy Process and Fuzzy MCDM- that are based on uncertainty and vagueness in human judgment, they still require expert input and do not necessarily avoid biasness and inconsistency [3].

Moreover, most classical MCDM methods are also challenged with scalability issues, especially with large data, dynamic systems, or unstructured information like textual data. The majority of traditional and even fuzzy-extended models are mostly set up to work with structured numerical data with limited capacity to compute data sources of complex real-world problems. The other major weakness is the fixedness of traditional MCDM models that in most cases are not flexible to dynamic environments and are incapable of accommodating the diverse type of data.

These limitations lower the usefulness and efficiency of classical and hybrid MCDM methods in the contemporary decision-making environment, which is marked by big data, uncertainty and a flowing stream of information. This has led to an increased requirement of smart, flexible and data driven decision-support systems that can supplement available MCDM methods by managing both structured and unstructured data, decreasing residual human bias, increasing decision-making processes efficiency, flexibility and robustness.

1.2 Emergence of LLMs

The recent breakthrough in artificial intelligence, especially the creation of Large Language Models, has provided new opportunities to improve decision-making systems. Transformer-based LLM models can comprehend, produce, and reason high-quality natural language with impressive accuracy [4]. These models are able to process enormous volumes of unstructured data, derive pertinent information, and give context-sensitive insights, thus they are very appropriate in complex decision-support applications. Within the framework of MCDM, LLMs may serve a variety of functions, including helping in the identification of criteria, creation or refinement of weights, alternative evaluation, and even automating some of the decision making. Moreover, the development of prompt engineering methods, including zero-shot, few-shot, and chain-of-thought reasoning, allow LLMs to complete structured reasoning tasks that are very similar to MCDM methodologies [5].

The rest of this paper is structured as follows. Section 2 gives the literature of MCDM methods and Large Language Models. Section 3 describes the research methodology, including the systematic review process based on the PRISMA framework. Section 4 presents a bibliometric review of the chosen literature with the help of visualizing tools. In section 5, we present a detailed taxonomy of the applications of LLM in MCDM. Section 6 provides a comparative study of the existing studies.

Section 7 addresses the benefits, constraints, and difficulties of combining the use of LLMs and MCDM. The future research directions are outlined in Section 8, and, finally, the paper gives the key findings and insights in Section 9.

2. Literature Review

In this section, a detailed description of the background ideas on the basis of this study will be presented with references to MCDM methods, Large Language Models, and prompt engineering methods as presented in Tables 1 and 2. MCDM techniques have traditionally been used to assist complicated decision-making contexts with numerous competing criteria, providing order, and mathematically based systems to assess and rank. The traditional methods of decision making are however being challenged with the rapid increase in the complexity of the data and the increase in the unstructured information.

Simultaneously, the latest developments in LLMs have shown impressive reasoning, knowledge extraction, and textual data processing abilities. These models, coupled with timely engineering methods, have the capability to model systematic decisions making them potential solutions to augment or improve traditional MCDM models. This section compares the two fields in order to form a solid theoretical framework to base integration on.

Table 1
Comparative Overview of MCDM Methods

Method	Key Principle	Strength	Limitation	Application
Analytic Hierarchy Process (AHP)	Pairwise comparison	Simple, intuitive	Subjectivity, consistency issues	Product development [6], Supplier selection [7]
Analytic Network Process (ANP)	Network relationships	Handles interdependence	Complex structure	Risk analysis [8]
TOPSIS	Distance from ideal solution	Logical ranking	Sensitive to normalization	Material selection [9]
VIKOR	Compromise ranking	Resolves conflicts	Weight sensitivity	Sustainable planning [10]
ELECTRE	Outranking relations	Handles uncertainty	Complex interpretation	Sustainable development [11]
PROMETHEE	Preference ranking	Flexible	Needs preference functions	Environmental decision [12]
Simple Additive Weighting (SAW)	Weighted sum	Easy to use	Oversimplification	Energy harvesting devices [13]
Weighted Product Method (WPM)	Multiplicative aggregation	Avoids scale issues	Complex calculation	Manufacturing [14]
Multi-Attribute Utility Theory (MAUT)	Utility maximization	Strong theoretical base	Requires utility functions	Economics, policy [15]
Multi-Attribute Value Theory (MAVT)	Value-based evaluation	Handles multiple preferences	Complex modeling	Strategic decisions [16]
Best-Worst Method (BWM)	Best vs worst comparison	High consistency	Needs expert input	Optimization problems [17]
SWARA	Stepwise weighting	Simple weighting process	Expert dependency	Resource allocation [18]
DEMATEL	Cause–effect modeling	Visual insight	Subjective inputs	Risk assessment [19]

Table 1
Continued

Method	Key Principle	Strength	Limitation	Application
CoCoSo	Combined compromise solution	High ranking accuracy	Method complexity	Engineering decisions [20]
ARAS	Utility degree ranking	Simple and efficient	Weight sensitive	Energy planning [21]
COPRAS	Proportional assessment	Handles benefit/cost	Data dependency	Facility layout [22]
MABAC	Border approximation	Stable results	Less intuitive	Logistics [23]
EDAS	Distance from average	Robust evaluation	Sensitive to data	Automotive Industry Sector [24]
TODIM	Prospect theory-based	Considers human behavior	Complex calculation	Green energy [25]
MOORA	Ratio analysis	Simple, fast	Limited flexibility	Manufacturing [26]
Grey Relational Analysis (GRA)	Grey system theory	Works with incomplete data	Limited precision	Engineering [27]
Fuzzy AHP	Fuzzy pairwise comparison	Handles uncertainty	Complex computation	Product development [28]
Fuzzy TOPSIS	Fuzzy distance measure	Deals with vagueness	Parameter sensitivity	Risk assessment [29]
Intuitionistic Fuzzy Macont Method	Membership/non-membership	Better uncertainty modeling	Higher complexity	Decision analysis [30]
Neutrosophic EDAS MCDM	Truth–indeterminacy–falsity	Handles ambiguity well	Hard to interpret	Advanced decision systems [31]
Rough Set MCDM	Approximation sets	No need for prior info	Limited scalability	Data mining [32]
Entropy Weight Method	Information entropy	Objective weighting	Ignores expert opinion	Public Procurements [33]
CRITIC	Correlation-based weighting	Considers contrast intensity	Sensitive to correlation	Financial analysis [34]
WASPAS	Weighted sum + product	High accuracy	Computational effort	Engineering [35]
MARCOS	Compromise ranking	Stable results	New, less explored	Sustainability analysis [36]

Table 2
Overview of LLMs and Prompt Engineering Techniques

Category	Technique	Key Idea	Strength	Limitation	Application
LLM	Large Language Models	NLP-based reasoning	Handles unstructured data	Black-box	Decision support [37]
Prompt	Zero-shot	No examples	Quick, flexible	Lower accuracy	General queries [38]
Prompt	Few-shot	Few examples	Improved accuracy	Example dependent	Classification [39]
Prompt	Chain-of-thought	Step-by-step reasoning	Better logical output	Longer prompts	Complex decisions [40]
Prompt	Role prompting	Assign expert role	Context-aware	Bias risk	Domain decisions [41]
Prompt	Self-consistency	Multiple reasoning paths	More reliable	Computational cost	Robust decision-making [42]

2.1 Research Gap & Novelty of the Study

Although MCDM methods are widely employed, and the development of LLMs is rather rapid, their combination has not been explored extensively. The vast majority of current research is aimed at enhancing the conventional MCDM algorithms with the help of fuzzy logic, hybridization, or optimization, yet they tend to overlook the problems associated with unstructured data and intelligent automation. Additionally, there is a lack of:

i. A systematic and comprehensive review combining LLMs and MCDM
ii. Well-defined taxonomy of the role of LLMs in decision-making.
iii. A comparative assessment framework of the analysis of MCDM based on LLM.

Novel contributions of this study include:

i. Development of a PRISMA-based systematic review
iv. Suggestion of a new taxonomy of integrating LLM in MCDM.
v. In-depth comparative and critical examination.
vi. Determination of new research trends and future directions.

2.2 Research Questions

This study aims to address the following research questions:

i. RQ1: What are the functions of LLMs in the decision-making process?
vii. RQ2: How do LLM-based approaches compare with traditional MCDM methods?

2.3 Research Objective

The primary objectives of this study are to perform a methodical literature review on the application of large language models (LLMs) in multi-criteria decision-making (MCDM), examine current methods, tools, and approaches, develop a systematic taxonomy of LLM-based decision systems, conduct a comparative analysis of selected studies, identify existing research gaps and limitations, and propose future research directions for intelligent decision-making systems.

3. Research Methodology

This research aims to investigate the new research format at the crossroads of MCDM and Large Language Models. A mixture of systematic literature review and bibliometric analysis is taken to achieve this. Bibliometric analysis is commonly perceived as an objective and quantitative methodology of analysing vast amounts of scientific information and establishing research trends, patterns and intellectual frameworks within a field [43].

This research has been divided into two sections. The initial aspect of this paper is a systematic literature review to investigate the level of knowledge in the field of the LLM-aided MCDM. The major task is to generalize the research already available, categorize methodologies and discover new trends and future directions of research. Systematic review approach guarantees the collection and analysis of relevant studies in a transparent and reproducible way. This paper is based on PRISMA 2020 to achieve methodological rigor. The second one is devoted to bibliometric analysis with VOSviewer (version 1.6.20) that allows visualizing the relationship between publications. This analysis offers information about distribution of publications, source coupling, geographical distribution and co-occurrence networks of keywords per year. The bibliometric analysis data were mainly obtained at the Scopus database that is reputed to have the biggest coverage of peer-reviewed literature in a variety of fields.

3.1 Search Strategy and Keyword Query

A systematic keyword search strategy was adopted to access the appropriate publications. The main keywords were chosen according to the main themes of this paper, such as LLMs and MCDM, as presented in Table 3. This was done through the search using Boolean operators in order to create different query combinations.

3.2 Data Collection and Selection Process

The literature search was made in the title-abstract-keywords fields without any initial time limiting. Nonetheless, it was noted that after 2025, the first major publications in this field started to emerge, which is associated with the active growth of the LLM technologies. The final data extraction was conducted in April 2026.

The inclusion criteria were defined as follows:

i. Articles on LLMs, MCDM, or their combination.
ii. Types of documents: Journal article, Conference paper, Conference review, Review.
iii. English language publications

Exclusion criteria included:

i. Non-relevant areas that do not fit in decision-making.
ii. Duplicate records

Table 3
Keyword Query Search Terms Used

No.	Keywords Query or Search String	Number of Articles
1	“Large language model” AND “multi-criteria decision making" AND "decision support system”	5
2	“LLM” AND " MCDM " AND "optimization"	1
3	“Large language model” AND “MCDM” AND "evaluation"	15
4	“LLM” AND “multi-criteria decision making" AND "ranking"	9
5	“Generative AI” AND “MCDM” AND "selection”	6
6	“Large language model” AND “multi-criteria decision making" OR "MCDM" AND "decision analysis"	4
7	“Large language models” AND “multi criteria decision making”	32
8	("large language model" OR "LLM*" OR "generative AI" OR "GPT" OR "transformer model") AND ("multi-criteria decision making" OR "multi criteria decision making" OR "MCDM" OR "multi-attribute decision making" OR "MADM" OR "multi-objective decision making" OR "MODM") AND ("decision support system" OR "optimization" OR "evaluation" OR "ranking" OR "selection" OR "decision analysis")	65
9	("large language model" OR "LLM*" OR "GPT") AND ("multi-criteria decision making" OR "MCDM" OR "MADM")	54

3.3 PRISMA-Based Screening

The research is based on the PRISMA 2020 protocol to have a systematic and clear selection procedure. There are four major stages involved in the screening process:

i. Identification: Database recordings.
ii. Screening: Elimination of duplicates and irrelevant studies.
iii. Eligibility: Full-text evaluation of the selected papers.
iv. Inclusion: Final set of studies for analysis

This systematic methodology will help in selecting only the best and most pertinent studies to be part of the review as presented in Figure 1.

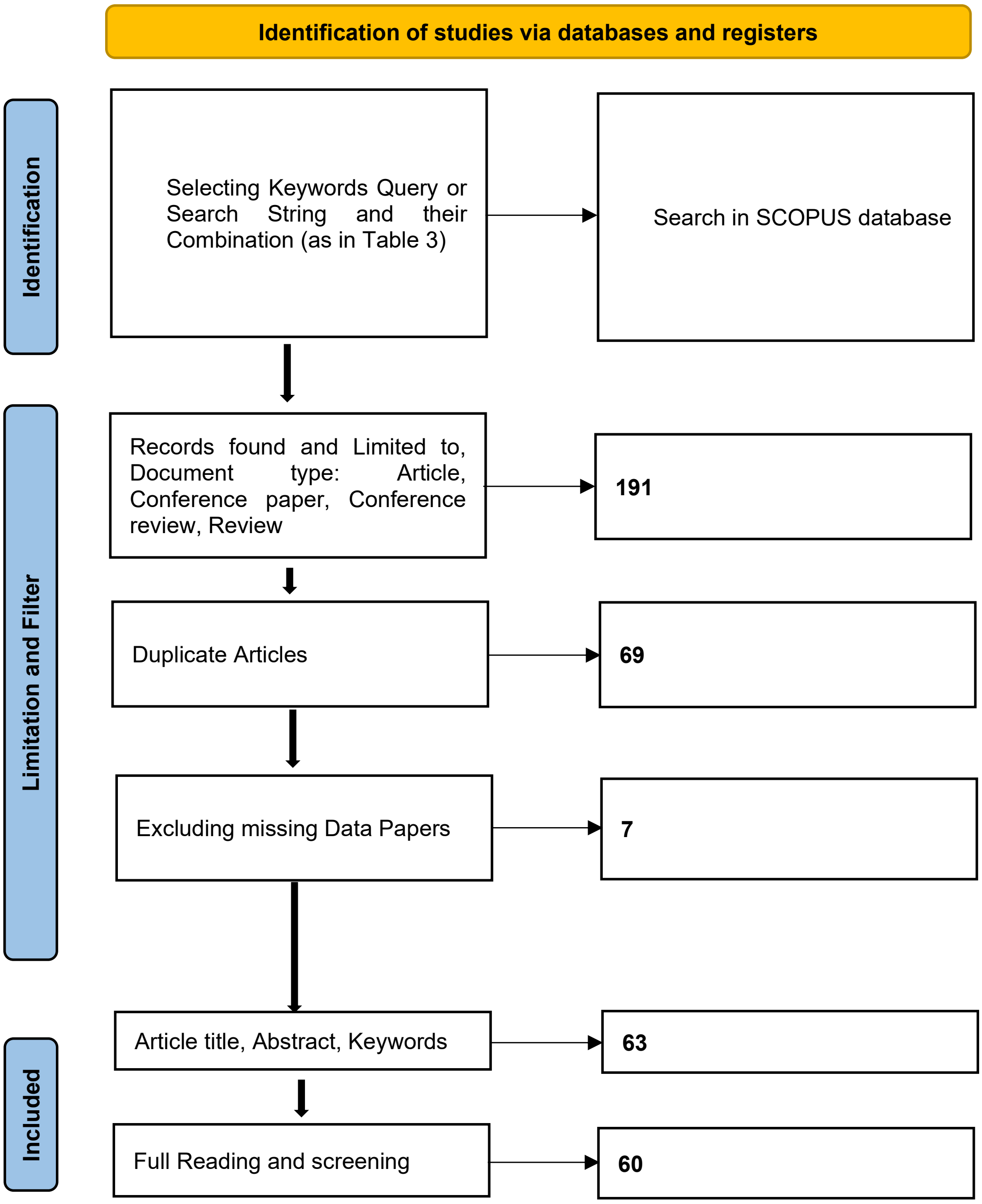


Fig. 1. PRISMA 2020 flow diagram for new systematic reviews

First, the databases were searched and about 191 publications were found. Having eliminated duplicates (121 records), approximately 70 records were left. They were filtered according to titles, abstracts, and keywords which left about 63 relevant studies. This was followed by a full-text review to confirm the relevance to the scope of this study resulting in the final selection of 60 high-quality publications.

4. Bibliometric Analysis

Bibliometric analysis is more of a quantitative method that is employed to assess the organization, progress and effects of research in a particular field. It allows determining the trends of publications, their impactful authors, most prominent journals, and networks of collaboration based on a large amount of bibliographic information [44]. The bibliometric analysis will be used in this work to thoroughly investigate the development of the research at the intersection of MCDM and Large Language Models. Through analysis of trends like frequency of publishing, citation, and geographical distribution, keyword analysis, this analysis offers an in-depth view of the state of the research, as well as novel trends in this fast-expanding field.

4.1 Annual Publication, Citation Trends

Large Language Models in MCDM are a very new field of research, with no publications reported since 2024. There is a significant increase in 2025 (40 papers), and in early 2026 (23 papers) the research trend is growing at a rapid pace and has a promising future, as demonstrated in Figure 2.

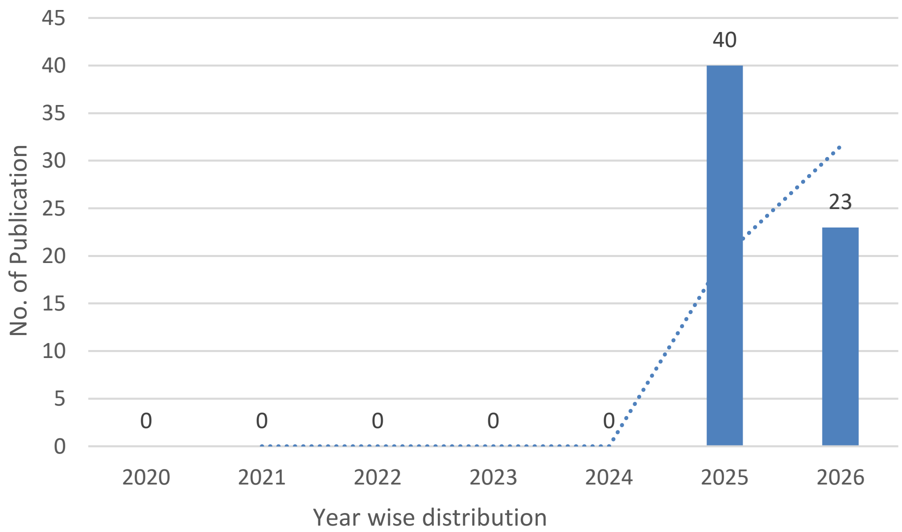


Fig. 2. Publication Trends

The trend in citation indicates the newness of the research on Large Language Models in MCDM, as no additional citation sources were found since 2024. Figure 3 indicate a significant rise in 2025 with 88 citations, and only 3 citations in early 2026 as the time available to accrue is limited.

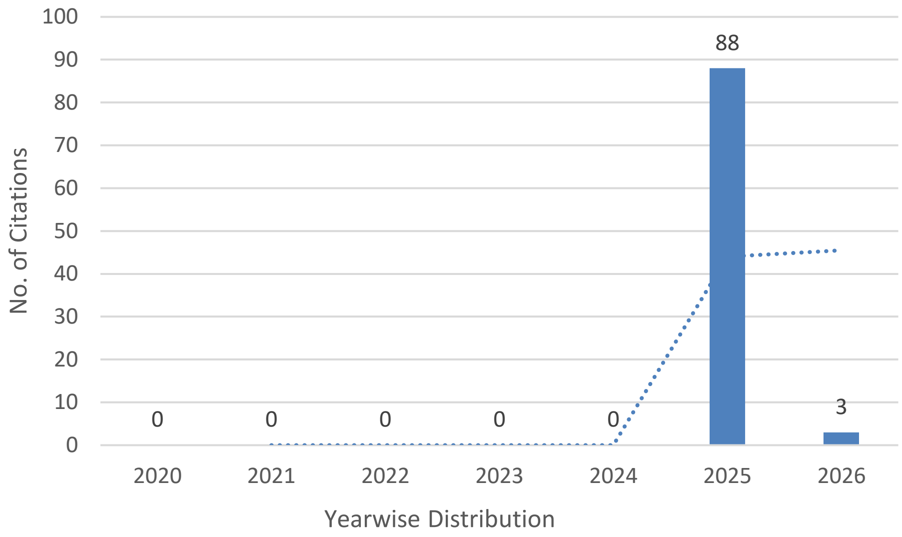


Fig. 3. Citation Trends

4.2 Most Productive Journals

The top 10 sources analysis reveals that the research on the Large Language Models in MCDM is spread through high impact and interdisciplinary journals. Top journals like IEEE Robotics and Automation Letters, Scientific Reports and IEEE Transactions on Fuzzy Systems (Q1) indicate good citation performance, indicating high quality of research and relevance as indicated in Table 4. The availability of journals in engineering, computer science and social sciences point to the interdisciplinary nature of the field. The major publishers include IEEE, Springer, and MDPI, which means that there is a widespread interest among academics and that the new studies are disseminated fast.

Table 4
Most productive sources

Sl. No.	Sources	Publication	Citation	Quartile	Cite Score	Impact Factor	Publisher
1	IEEE Robotics and Automation Letters	1	21	Q1	10.3	5.3	IEEE
2	Scientific Reports	2	11	Q1	6.7	3.9	Nature Research
3	Ln Computer Science	1	11	Q2	2.4	-	Springer Science
4	Cogent Social Sciences	1	8	Q2	2.8	1.9	Cogent OA
5	Applied Sciences	2	6	Q2	5.5	2.5	MDPI
6	Cognitive Computation	1	6	Q1	9.3	4.3	Springer New York
7	Electronics	1	4	Q2	6.1	2.6	MDPI
8	Buildings	1	4	Q1	4.4	3.1	MDPI
9	IEEE Transactions on Fuzzy Systems	2	3	Q1	20	11.9	IEEE
10	International Journal of Advanced Computer Science and Applications	1	3	Q3	2.7	0.9	Science and Information Organization

4.3 Leading Authors

According to the analysis of the top 10 authors, the research on Large Language Models in MCDM is in a developing phase and has a low level of author dominance and low publication numbers. Lanndon Ocampo is the most productive individual with three documents and Alpana Agarwal has the highest impact on citation (8 citations), which is an emerging influence. The publications and citation numbers are low, the majority of authors have only one publication and few citations, which was an indicator of a disjointed and developing research space with much possible room to create a leadership in this field as indicated in the density visualisation in Figure 4.

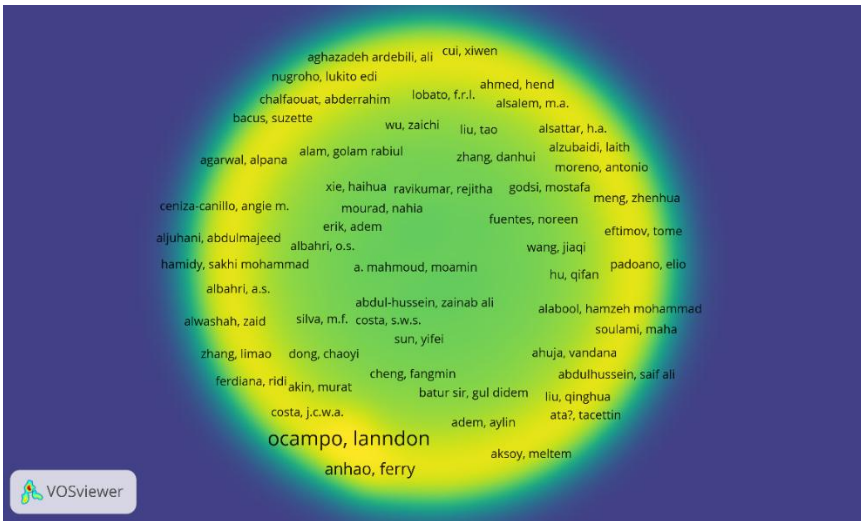


Fig. 4. Density Visualisation of Leading Authors

4.4 Top Institutions

The fact that the top 10 organizations analysis shows that research on Large Language Models in MCDM is geographically dispersed yet remains fragmented. Cebu Technological University is early institutional with two publications by various departments. There are also minor contributions of institutions in India, China, Morocco, Turkey, and Jordan with few outputs and citations. The low number of publications and citation by organizations indicate that the field is still immature and no strong research centre has been established yet and considerable potential to international academic growth and collaboration is still available as indicated in the density visualisation in Figure 5.

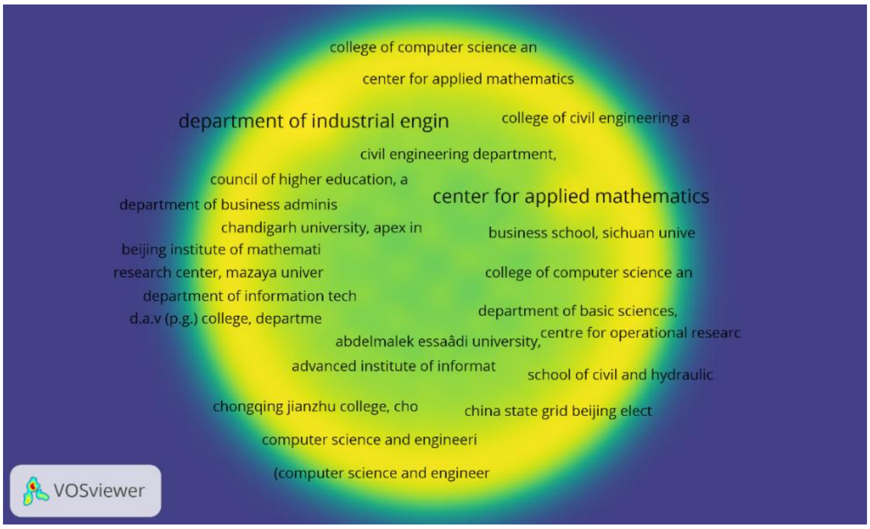


Fig. 5. Density Visualisation of Top Institutions

4.5 Top Country-wise Research Contribution

The analysis by country reveals that the study of Large Language Models in MCDM is spread all over the world, with 37 countries having publications, with China having the highest number of publications (17) and high impact in terms of citation. It is important to note that Saudi Arabia has the greatest citation impact (20) although with less publications, meaning that they conduct quality research. Other countries such as Turkey, Malaysia and Morocco contribute moderately with general results indicating an increasing but disparate global research environment with emergent international engagement as indicated in the density visualisation in Figure 6.

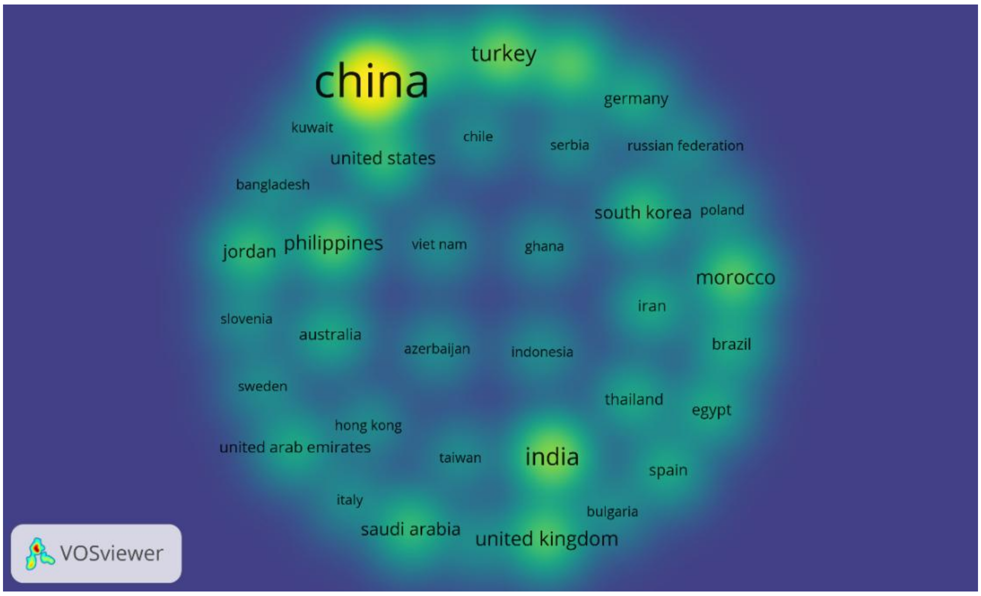


Fig. 6. Density Visualisation of Top Country

4.6 Keyword Analysis

The thematic analysis based on the dataset of keywords and the visualization provided by VOSviewer shows that there is a clear and changing structure of knowledge in the field of Large Language Models integration with MCDM. The theme of decision making is the most dominant theme of the research landscape (39 occurrences) and it is the center of all the other research directions. The terms that closely relate to this central word are language model (26 times), large language model (22 times), and various combinations of the term multi-criteria decision-making (22, 20, 20, 11, 8 times), which means that there is a high degree of convergence between artificial intelligence and decision science. This core group underscores the point that the main theme of the current research is to use the capabilities of LLM to improve the structured decision-making process as it is depicted in the density visualisation in Figure 7.

The second theme is artificial intelligence and computational technologies with the number of mentions of artificial intelligence (18 times), natural language processing systems (9), machine learning (3), transformer modeling (3) and generative AI (6). This cluster represents the technological backbone of the field, emphasizing how advancements in deep learning and transformer-based architectures are driving innovation in decision-support systems. The availability of new terminology like ChatGPT (3 times), retrieval-augmented generation (RAG) (2), and attention mechanisms (2) also reflects the increased significance of enhanced methods of prompting and reasoning to the effectiveness and dependability of LLM-based decision models.

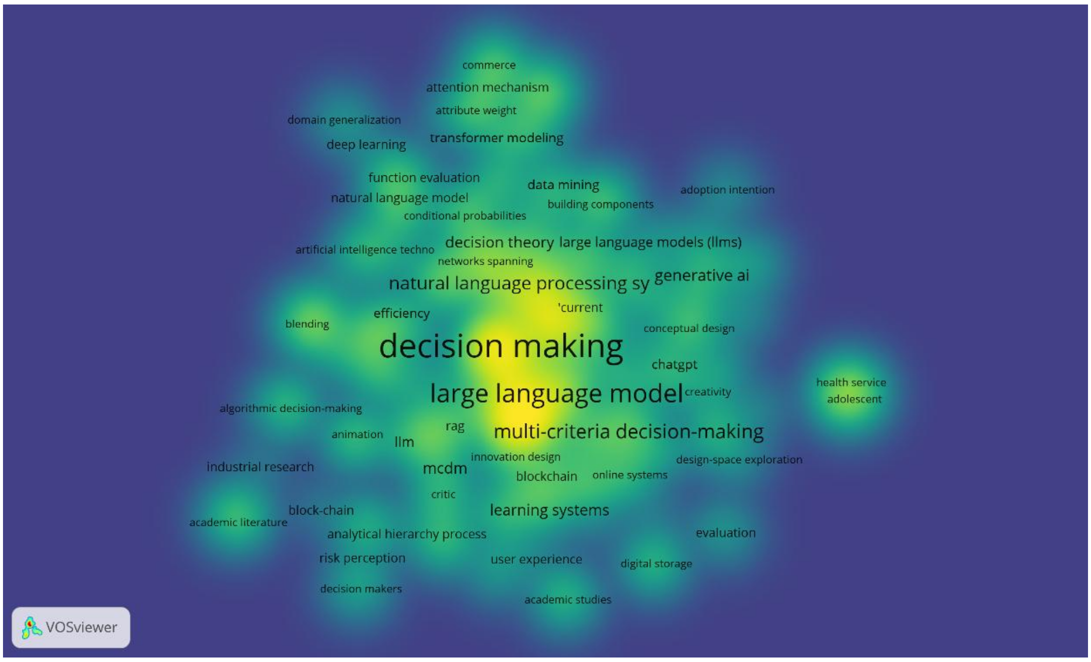


Fig. 7. Density Visualisation of Keyword Analysis

The other important thematic cluster is connected with classical and hybrid MCDM methodologies. Such keywords like analytic hierarchy process (7 times), fuzzy sets (4 times), fuzzy logic (3 times), sensitivity analysis (7 times), uncertainty (5 times) and hierarchical systems (6 times) imply that conventional methods of decision-making remain highly important. Rather than being replaced, these methods are increasingly integrated with LLMs to form hybrid models that combine mathematical rigor with data-driven intelligence. It signifies a distinct research inclination to strengthen, dependable, and versatile decision-making structures.

Moreover, an application-based theme is also evident, which includes various fields including healthcare, sustainability, energy, and industrial systems. Some keywords like behavioural research (15 times), sustainable development (6), economic and social effects (6), decision support systems (8), renewable energy (2), and user experience (2) show that MCDM strategies based on the use of LLM are already implemented in various fields. This demonstrates the adaptability and magnitude of these approaches in solving real-life, decision problems, which are complex.

Lastly, new themes point to the move towards explainable and human-centric AI systems. The keywords human computer interaction (3 times), bias reduction (1), explainability (1), trustworthiness (1) and ethical AI (1) show increasing worries about transparency, fairness and reliability in automated decision-making. Moreover, the emergence of such concepts as intelligent agents (3), recommender systems (3), and interactive systems (1) can indicate that the future research will be shifted towards collaborative human-AI decision-making settings. On the whole, the thematic structure proves that this area is fast growing, interdisciplinary, and innovation-based, and the shift towards traditional MCDM methods to hybrid and AI-based decision-making systems is strong, and confirmed by the keyword dataset.

5. Taxonomy of LLMs in MCDM

The adoption of Large Language Models into MCDM has brought a paradigm shift in formulating, analysing, and solving complex decision problems. A detailed taxonomy is formed, based on the systematic review of 60 research articles included in the dataset and based on functional role, the purpose of methodological focus, the level of integration, and the way of uncertainty treatment. This taxonomy does not just emphasize the use of the LLMs but also their advantages and intrinsic limitations in the applications.

5.1 LLMs as Criteria Generators and Knowledge Extractors

A significant group of studies utilizes LLMs for criteria identification and knowledge extraction, which is traditionally one of the most time-consuming steps in MCDM. To illustrate, Aghazadeh Ardebili *et al*. [45] suggested an AI-based system to automatically identify decision criteria in a large-scale literature utilizing LLMs. The aim of this project was to minimize the amount of manual experience and enhance scalability of criteria selection. Likewise, Park *et al*. [46 used the fine-tuned LLMs to form AHP hierarchies and discover latent connections between criteria. The benefit of this type is that it can handle large unstructured data sets and can produce extensive sets of criteria in a short period of time. However, the drawback is that the criteria generated by LLM might not be validated by experts and can introduce redundancy or bias unless validated by experts.

5.2 LLMs as Weight Assigners (Virtual Experts)

The other significant taxonomy type is that of the LLMs as weight assigners, which substitute or assist human professionals. Memduholu *et al*. [47] tested the use of LLMs as virtual experts in AHP-based weighting of solar site selection. Their goal was to determine the capabilities of the LLMs in imitating expert judgment. The results were highly correlated with human experts ($r \approx 0.838$), thus indicating good reliability. Likewise, Vahidnia [48] suggested the multi-agent LLM system to execute collaborative weight assignment. It was done to minimize bias and enhance uniformity in group decisions. Its benefits are that it will be less expensive, quicker to make decisions and it will remove human inconsistency. Limitations include however, bias in some criterion (e.g., too much emphasis on infrastructure), and lack of contextual sensitivity in complex areas.

5.3 LLMs as Decision-Makers and Ranking Engines

In this category, LLMs directly contribute to scoring, ranking, and decision-making processes. As an example, Phoka *et al*. [49] created an LLM based MCDM recommender system in which a series of LLMs provide scores on food recommendations. The objective was to enhance recommendation accuracy using consensus-based weighting. Equally, Xue *et al*. [50] used TOPSIS with evaluation metrics produced by the LLCM when analyzing the sentiment. Anhao and Ocampo [51] applied ChatGPT to produce semantic scores combined with fuzzy EDAS to assess the SDG alignment. Its benefits are that it automates the decision processes and has increased scalability. Limitations, however, are that it relies on the timely quality, is sensitive to changes in the input, and cannot be explained in some instances.

5.4 LLMs as Hybrid Components in Advanced MCDM Frameworks

Many recent studies integrate LLMs with advanced AI models and hybrid MCDM techniques. To illustrate, Meng *et al*. [52] have suggested ID-GMLM, which is an intelligent decision-maker, based on the combination of the LLM and the graph neural network. The task was to process complicated relational data and enhance the accuracy of ranking. In the same way, Ahmed *et al*. [53] combined LLMs with neutrosophic and CRITIC-MAIRCA blockchain selection techniques. Its benefits are in its high accuracy, capability to model complex relations and durability in the face of uncertainty.

Limitations are however, computational complexity, difficulties in interpretation of the model and high data dependency.

5.5 LLMs for Uncertainty Modeling in MCDM

One of the strengths of the modern integration of LLM-MCDM is coping with uncertainty. Qahtan *et al*. [54] proposed a circular q-rung orthopair fuzzy model of ranking LLMs , in which the uncertainty in the evaluation tasks is considered. Ilieva [55] generalized the fuzzy TOPSIS with interval-valued hesitant Fermatean sets to chatbot assessment. On the same note, Aksoy *et al*. [56] employed hesitant fuzzy AHP to assess the trustworthiness of LLMs. Its strengths are improved management of vagueness, ambiguity and linguistic uncertainty. The limitations, however, are compounded complexity in the model and inability to interpret it by the decision-makers.

5.6 LLMs as Explainable Decision Support Systems

The other new category is explainability and decision support using LLMs. Darm *et al*. [57] incorporated the use of LLMs in satellite collision avoidance systems to give human understandable explanations of the decisions. On the same note, Chasanidou *et al*. [58] incorporated the use of LLMs within the tourism systems to describe recommendations. The aim is to enhance user confidence and transparency in decision systems. The benefits are the better interpretability and involvement of the user, whereas the drawbacks are the susceptibility to hallucinations and irrelevant explanations that are sometimes provided.

Large Language Models have been a major change to the way decisions are made, adding intelligent, data-driven, and automated features to the process. In contrast to traditional methods that require human knowledge and systematized numerical inputs, LLMs are able to handle large volumes of unstructured data, generate insights, and support various steps in decision-making. LLM can be applied to multiple roles in MCDM, though; not restricted to one particular function, it can be represented by various roles, such as knowledge extraction and complete automation of the decision-making process as outlined in Table 5. These functions increase efficiency, minimize human bias, and provide more adaptive and scalable decision-support systems.

Table 5
Roles of LLMs in Decision-Making Processes

Role of LLM	Description	Function in MCDM	Advantage	Limitation
Criteria Generator	Extracts and generates decision criteria from text data	Pre-processing stage	Reduces manual effort, scalable	Requires validation, possible redundancy
Weight Assigner	Assigns importance weights to criteria	Weight determination (AHP, BWM)	Consistent and fast	May introduce model bias
Decision-Maker / Evaluator	Scores and ranks alternatives	Ranking stage (TOPSIS, VIKOR)	Enables automation	Sensitive to prompts
Decision Assistant	Provides recommendations and explanations	Supports human decision-makers	Improves understanding	May generate irrelevant outputs
Hybrid Component	Integrates with AI, fuzzy, or optimization models	Enhances full MCDM framework	High accuracy and robustness	High computational complexity
Knowledge Extractor	Analyzes large datasets for insights	Data preparation stage	Handles unstructured data	Needs domain tuning
Uncertainty Handler	Works with fuzzy/linguistic data	Supports uncertain environments	Improves realism	Complex modeling

Table 5
Continued

Role of LLM	Description	Function in MCDM	Advantage	Limitation
Explainability Tool	Generates human-readable explanations	Post-decision analysis	Improves transparency and trust	Risk of hallucination
Multi-Agent Participant	Acts as part of multiple LLM agents	Group decision-making	Reduces bias, improves consensus	System complexity
Decision Automation Engine	Performs end-to-end decision processes	Full decision pipeline	High efficiency, real-time decisions	Limited reliability in critical systems

6. Comparative Analysis

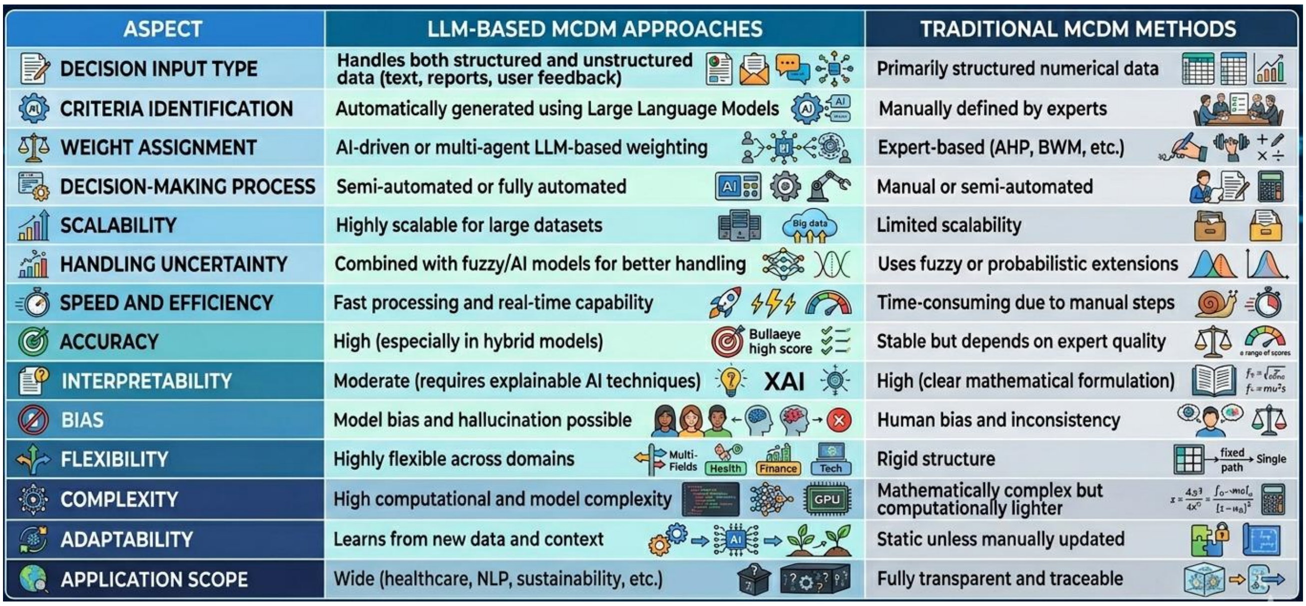
The fast adoption of Large Language Models into MCDM has led to various methodologies, architecture, and fields of application. It is important to compare these approaches to be able to systematically consider them with respect to methods, the role of LLMs, goals, performance, and limitations as it will be discussed in Table 6. This section makes a comparison of representative studies to bring out important trends and differences.

Table 6
Comparative Analysis of LLM-based MCDM Studies

Authors	Method Used	Role of LLM	Objective	Key Results	Limitations
Sun *et al*. [47]	AHP	Weight assigner	Evaluate LLM as virtual expert	High correlation with human experts (r=0.838)	Bias in some criteria
Alabool [59]	Fuzzy AHP	Decision framework	Select best LLM in healthcare	Identified key criteria (reliability highest)	Expert dependency
Meng *et al*. [52]	GNN + LLM	Hybrid model	Improve ranking accuracy	High performance on benchmark datasets	Computational complexity
Phoka *et al*. [49]	LCCC + MCDM	Decision-maker	Improve recommendation systems	Improved precision (56.6%)	Multi-model complexity
Xue *et al*. [50]	TOPSIS	Evaluator	Rank LLM performance	Robust ranking validation	Prompt sensitivity
Qahtan *et al*. [54]	Fuzzy 3WD	Ranking system	Handle uncertainty in evaluation	High robustness and stability	Model complexity
Ilieva [55]	Fuzzy TOPSIS	Evaluator	Evaluate AI chatbots	Accurate ranking under uncertainty	Complex fuzzy modeling
Ahmed *et al*. [53]	CRITIC + MAIRCA	Hybrid evaluator	Blockchain platform selection	Identified optimal platform	Data dependency
Vahidnia [48]	MAS + AHP	Multi-agent system	Collaborative weighting	Improved consistency and consensus	High system complexity
Aghazadeh *et al*. [45]	LLM-based extraction	Criteria generator	Automate criteria selection	Reduced manual effort	Needs validation

7. Critical Discussion

Although the integration of LLMs with MCDM has potential, it needs to be compared and critically evaluated to gain insight into their capabilities, limitations and applicability as presented in Figure 8 and Table 7. In this section, a balanced discussion will be made with references to comparing the approaches based on the LLM with the traditional ones and the fuzzy MCDM.



ASPECT	LLM-BASED MCDM APPROACHES	TRADITIONAL MCDM METHODS
DECISION INPUT TYPE	Handles both structured and unstructured data (text, reports, user feedback)	Primarily structured numerical data
CRITERIA IDENTIFICATION	Automatically generated using Large Language Models	Manually defined by experts
WEIGHT ASSIGNMENT	AI-driven or multi-agent LLM-based weighting	Expert-based (AHP, BWM, etc.)
DECISION-MAKING PROCESS	Semi-automated or fully automated	Manual or semi-automated
SCALABILITY	Highly scalable for large datasets	Limited scalability
HANDLING UNCERTAINTY	Combined with fuzzy/AI models for better handling	Uses fuzzy or probabilistic extensions
SPEED AND EFFICIENCY	Fast processing and real-time capability	Time-consuming due to manual steps
ACCURACY	High (especially in hybrid models)	Stable but depends on expert quality
INTERPRETABILITY	Moderate (requires explainable AI techniques)	High (clear mathematical formulation)
BIAS	Model bias and hallucination possible	Human bias and inconsistency
FLEXIBILITY	Highly flexible across domains	Rigid structure
COMPLEXITY	High computational and model complexity	Mathematically complex but computationally lighter
ADAPTABILITY	Learns from new data and context	Static unless manually updated
APPLICATION SCOPE	Wide (healthcare, NLP, sustainability, etc.)	Fully transparent and traceable

Fig. 8. Comparison between LLM-based Approaches and Traditional MCDM Methods

Table 7
Critical Discussion of LLM-based MCDM

Aspect	Strengths	Limitations	Comparison with Traditional MCDM
Automation	Reduces human effort, fast processing	Over-reliance on prompts	Traditional methods require manual input
Scalability	Handles large datasets & text	Computational cost	Classical methods limited to structured data
Accuracy	High accuracy with hybrid models	Sensitive to input variation	Traditional methods stable but less adaptive
Bias Handling	Can reduce human bias	Introduces model bias & hallucination	Fuzzy MCDM better for uncertainty
Interpretability	Explainable AI possible	Still limited transparency	Classical models more interpretable
Flexibility	Works with unstructured data	Needs domain tuning	Traditional methods rigid
Robustness	Strong with hybrid & fuzzy models	Instability across prompts	Fuzzy MCDM more stable

The analysis demonstrates that the implementation of MCDM with the help of LLM has a high level of automation, scalability, and intelligence, whereas it has certain weaknesses related to bias, instability, and a lack of transparency. Hybrid models of combining LLM with fuzzy MCDM offer the most moderate performance.

8. Future Research Directions

LLM-integrated MCDM is a relatively young field, which is why there is a plethora of innovation opportunities. As per the analysed literature, some of the promising research areas are revealed to improve performance, reliability and applicability as indicated in Figure 9.

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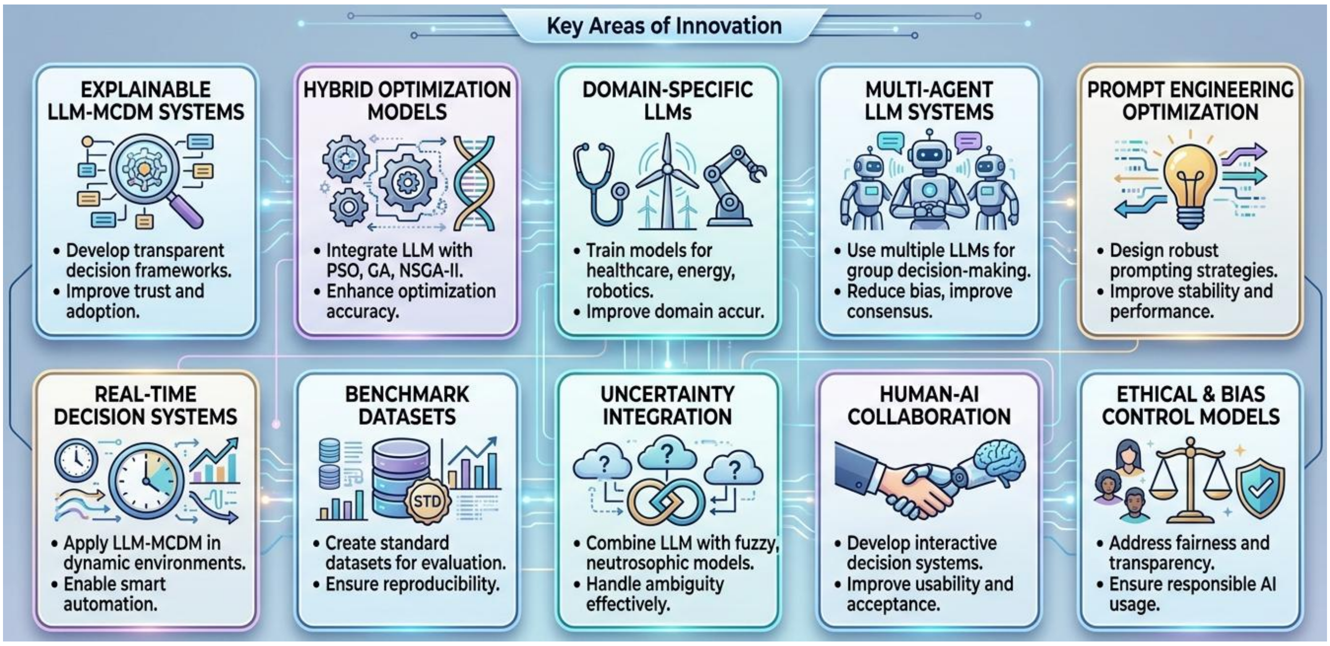

Fig. 9. Future Research Directions

Further studies are needed to build strong, interpretable, and hybrid LLM-MCDM models that will be capable of merging the advantages of artificial intelligence with the accuracy of traditional decision-making systems. The final one is to attain complete independent but reliable intelligent decision systems.

9. Conclusion

This paper provides a data-intensive and thorough study of the combination of Large Language Models and MCDM based on a systematic examination of the literature and bibliometric methodology. Based on the Scopus dataset, a total of 63 research papers were analyzed, revealing that this research domain is highly recent, with no publications recorded between 2020 and 2024, followed by a sharp increase to 40 publications in 2025 and 23 publications in early 2026. This tendency is a clear signal of a swift development and increased scholarly attention to the decision-making structures supported by LLM.

The bibliometric analysis also reveals that the field is geographically well-spread in 37 countries with China (17 publications) and India (6 publications) having the most research publications but countries like Saudi Arabia (20 citations) have high research impact even with less publications. In terms of sources, high-quality journals such as IEEE Robotics and Automation Letters, Scientific Reports, and IEEE Transactions on Fuzzy Systems dominate the field, reflecting strong interdisciplinary contributions across engineering, artificial intelligence, and decision sciences. Nevertheless, institutional analysis and author shows a disjointed research horizons with majority of the authors contributing a single or two articles showing that the research area is at an infantile phase and has yet to have research giants.

The thematic and keyword analysis supports these results, with decision making (39 times), language model (26), and large language model (22) as the prevalent ones, showing the importance of AI-based decision making. The availability of traditional MCDM techniques and the emergence of new technologies, including generative AI and natural language processing, support the fact of a high degree of convergence between the traditional decision science and current AI technologies.

The suggested taxonomy proves that LLMs are mostly applied in the form of decision assistants, criteria generators, and hybrid elements, and are increasingly implemented in the weight assignment and the complete automation of decisions. The comparative analysis shows that the MCDM methods based on the LLM have great benefits in the field of automation, scalability, and unstructured data, but critical drawbacks, such as bias, non-transparency, timely sensitivity, and complexity of calculations, remain.

In general, this paper will conclude that MCDM with the use of LLM is a highly promising, inter-disciplinary, and fast-developing research field, which is at the initial stage of development. Although great strides have been achieved, there is still need to have strong, explainable, and standardized frameworks that would give assurance of reliability and practicality. The observations made in the bibliometric and systematic analysis have a solid background of future studies based on the design of intelligent, adaptive, and human-centric decision-support systems.

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Conflicts of Interest
The authors declare no conflicts of interest.

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