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A Systematic Comparative Review of Compromise Ranking Methods in Multi-Criteria Decision Making

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ABSTRACT

MCDM has become a relevant framework for solving complex decision problems in which there are several conflicting criteria. Compromise ranking methods are one of the most important groups of methods in the MCDM family because they identify solutions that balance individual satisfaction and group utility while minimizing individual dissatisfaction and group regret. This study provides a systematic comparative study of the major compromise ranking methods, such as VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA. The review is conducted using the PRISMA methodology and supplemented by bibliometric analysis in order to assess publication trends, prevailing subjects, the most popular journals, country representation, and emerging research areas. The study also investigates the methodological principles, normalization processes, computational complexity, robustness, sensitivity behaviour, ranking stability, and the capabilities of the methods to handle uncertainty. The results show that VIKOR is effective in providing explicit compromise solutions by balancing utility and regret, whereas MULTIMOORA is robust and shows superior ranking consistency because of its inherent multi-perspective structure. MOORA and MOOSRA are simpler methods that are computationally efficient and scalable for large-scale decision problems, whilst TOPSIS and COPRAS are intuitive and practical ranking methods. The review further reveals the expanding use of compromise ranking techniques in conjunction with fuzzy systems, artificial intelligence, machine learning, and real-time decision-support systems to address uncertainty and subjective weighting. Furthermore, the application analysis across engineering, energy, finance, healthcare, supply chain, sustainability, transportation, and intelligent systems demonstrates the wide range of applications of compromise ranking methods. In general, this research lays a solid groundwork for the future development of intelligent and adaptive MCDM systems.

1. Introduction

In contemporary decision-making, multiple conflicting economic, technical, environmental, social, and strategic criteria must often be considered simultaneously. Traditional single-objective

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optimization methods are inadequate for addressing such multidimensional trade-offs [1,2]. Consequently, multi-criteria decision-making (MCDM) techniques have become indispensable across engineering, manufacturing, energy planning, supply chain management, finance, healthcare, sustainability assessment, and public policy [3]. Among them, compromise ranking methods have attracted considerable attention because they provide balanced and practically acceptable solutions rather than purely mathematically optimal ones. Since satisfying all evaluation criteria simultaneously is rarely possible, compromise ranking methods identify alternatives that best balance conflicting objectives while minimizing dissatisfaction [3].

Unlike utility-based or outranking approaches, they incorporate both collective utility and criterion-specific regret, making them well suited for group decision-making requiring fairness and consensus. Their growing adoption in wide applicable areas reflects their computational efficiency, flexibility, and ability to handle both beneficial and non-beneficial criteria [2,4]. Figure 1 illustrates the historical evolution of the major compromise ranking methods. Table 1 summarizes the historical development, conceptual foundations, methodological contributions, and limitations of major compromise ranking methods. It demonstrates their evolution from basic distance-based approaches to advanced hybrid and robust decision-support techniques capable of addressing uncertainty, conflicting criteria, computational efficiency, and ranking stability [5]. This chronological comparison provides the theoretical foundation for the present review and clarifies the conceptual relationships among major compromise ranking methods [6].

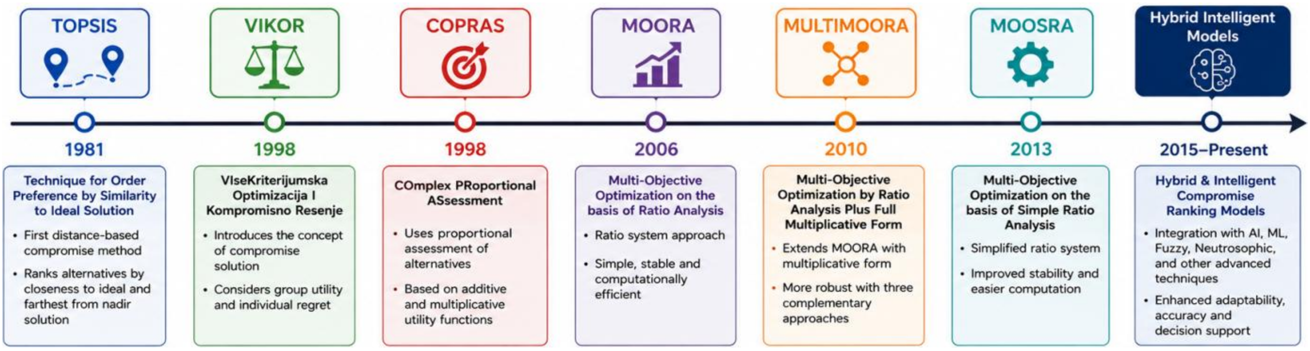


Fig. 1. Historical evolution timeline of compromise ranking methodologies

Table 1
Chronological evolution of major compromise ranking methods

Year	Method	Developers	Core concept	Major contribution	Limitation
1981	TOPSIS	Hwang and Yoon [7]	Selection of alternatives closest to the positive ideal solution and farthest from the negative ideal solution	Introduced geometric distance-based compromise evaluation; highly intuitive and computationally simple	Does not explicitly incorporate regret minimization; sensitive to normalization methods
1990	VIKOR	Opricovic [8-10]	Compromise ranking based on group utility and individual regret minimization	Explicit compromise formulation; suitable for conflict resolution and negotiation-oriented decisions	Sensitive to criteria weights and decision parameter selection
1994	COPRAS	Zavadskas *et al.,* [11,12]	Simultaneous proportional evaluation of beneficial and non-beneficial criteria	Direct utility degree estimation; computational efficiency; easy interpretability	Limited capability in handling uncertainty and complex interdependencies

Table 1
Chronological evolution of major compromise ranking methods

Year	Method	Developers	Core concept	Major contribution	Limitation
2006	MOORA	Brauers and Zavadskas [13]	Ratio-based normalization with separation of beneficial and non-beneficial attributes	Computational simplicity; stable rankings; effective for large-scale problems	Limited capability for modeling uncertainty and stakeholder conflicts
2010	MULTIMOORA	Brauers and Zavadskas [14]	Integration of ratio system, reference point approach, and full multiplicative form	Enhanced robustness and ranking stability through multi-perspective evaluation	Higher computational complexity compared to MOORA and TOPSIS
2012	MOOSRA	Das *et al.*, [15]	Simplified ratio analysis framework for efficient compromise evaluation	Very low computational burden; suitable for rapid and large-scale evaluations	Simpler structure may limit handling of highly complex decision interdependencies

Despite extensive research, important gaps remain in the literature. Most existing studies focus on the development or application of individual methods rather than providing systematic comparative analyses of compromise ranking techniques [16]. Consequently, differences in methodological foundations, computational behavior, robustness, sensitivity, normalization procedures, ranking stability, and uncertainty handling remain insufficiently explored. Although methods such as VIKOR, MOORA, MULTIMOORA, and COPRAS adopt distinct compromise philosophies, their theoretical relationships and comparative performance have not been comprehensively synthesized [12,13,15,16]. To address these gaps, this study systematically compares major compromise ranking methods with respect to their methodological foundations, mathematical structures, computational complexity, robustness, sensitivity, normalization effects, ranking stability, applications, advantages, and limitations.

It also identifies emerging research trends, unresolved methodological challenges, and future research directions in compromise-based decision-making [14]. Figure 2 presents the publication trends of the major compromise ranking methods.

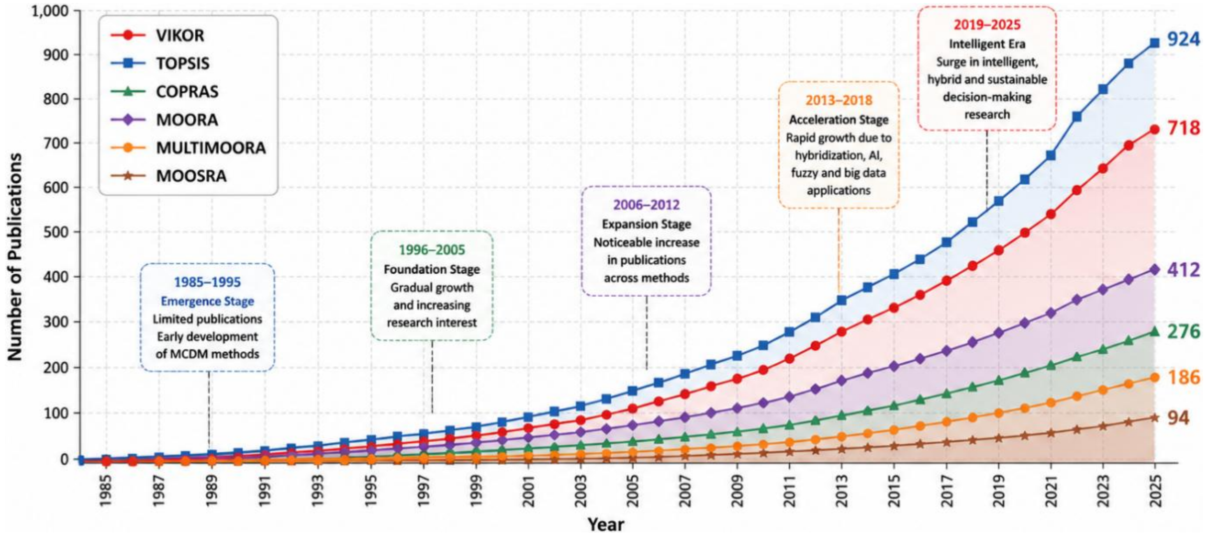


Fig. 2. Year-wise publication growth trends of major compromise ranking methods

The novelty of this study lies in its exclusive focus on compromise ranking methodologies rather than general MCDM techniques [9,10]. It develops a dedicated comparative framework integrating theoretical, methodological, and application-oriented perspectives to provide a comprehensive understanding of these methods. By consolidating fragmented literature, the review offers valuable guidance for researchers, practitioners, academics, and policymakers in selecting appropriate compromise ranking methods and supports future methodological advancements for real-world decision-making applications [7,8,11].

2. Research Methodology

A systematic review methodology was adopted to examine the literature on compromise ranking methods in MCDM. The framework ensures transparency, consistency, repeatability, and analytical rigor in literature collection and evaluation [16,17]. It was designed to identify major methodological developments, compare the characteristics of compromise ranking methods, examine their applications, and identify emerging trends and research gaps [18]. The review comprised four stages: literature identification, screening, methodological classification, and comparative evaluation. Only methodologically relevant studies were included, and the overall selection process is illustrated in Figure 3.

Literature was collected from the Scopus, Web of Science, and ScienceDirect databases due to their broad coverage of peer-reviewed research in decision sciences, optimization, engineering, operations research, and computational intelligence [14,15]. Search keywords included compromise ranking, compromise solution, VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, MOOSRA, and related hybrid and sensitivity-analysis terms. Inclusion criteria considered English-language peer-reviewed journal articles, review papers, and high-quality conference papers focusing on methodological development, comparative analysis, hybrid approaches, or practical applications [17,19,20]. Duplicate, incomplete, non-peer-reviewed, and methodologically weak studies were excluded, resulting in a dataset of academically credible and technically relevant publications. Figure 4 and Figure 5 present the keyword co-occurrence and research collaboration networks, respectively.

The selected studies were screened through title, abstract, and full-text evaluation based on methodological contribution, theoretical significance, and practical applicability [20]. Duplicate and irrelevant studies were removed [4,7,13]. Methods were classified according to their methodological characteristics, including normalization, utility and regret measures, ranking principles, and treatment of beneficial and non-beneficial criteria. Accordingly, VIKOR was categorized as a utility–regret approach, TOPSIS as a distance-based method, MOORA and MULTIMOORA as ratio-based and reference-point approaches, respectively, and COPRAS as a proportional assessment technique [11,12].

Comparative evaluation constituted the core of the methodology. Major compromise ranking methods were assessed based on normalization procedures, computational complexity, treatment of beneficial and non-beneficial criteria, sensitivity to criteria weights, ranking stability, and robustness under varying decision conditions [20-23]. The review also qualitatively evaluated application diversity, methodological flexibility, uncertainty-handling capability, and integration with fuzzy logic, artificial intelligence, and hybrid decision-support systems to provide a comprehensive assessment of their practical applicability and future potential.

Overall, the adopted methodology provides a systematic framework for evaluating compromise ranking methods through comprehensive literature review and comparative analysis of their theoretical foundations, computational characteristics, application domains, and future research opportunities [22,23]. Figure 6 presents the global distribution of research contributions, highlighting China, India, Turkey, Iran, Lithuania, Serbia, and the United States as major contributors across engineering, sustainability, finance, healthcare, smart cities, and intelligent decision-support applications [19,21]. Figure 7 presents the leading journals publishing research on compromise ranking methods.

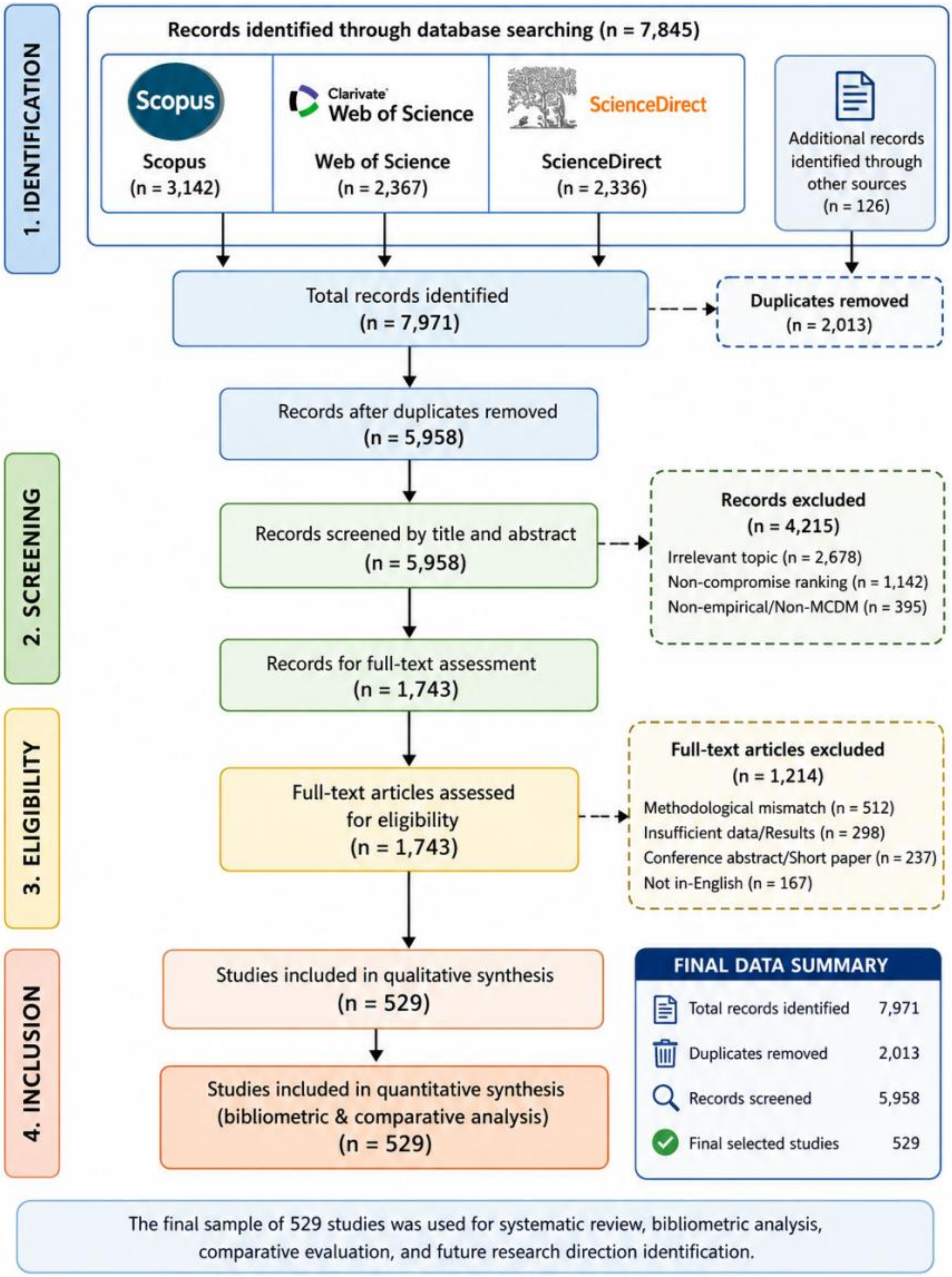


Fig. 3. PRISMA-based systematic literature selection workflow for compromise ranking method studies

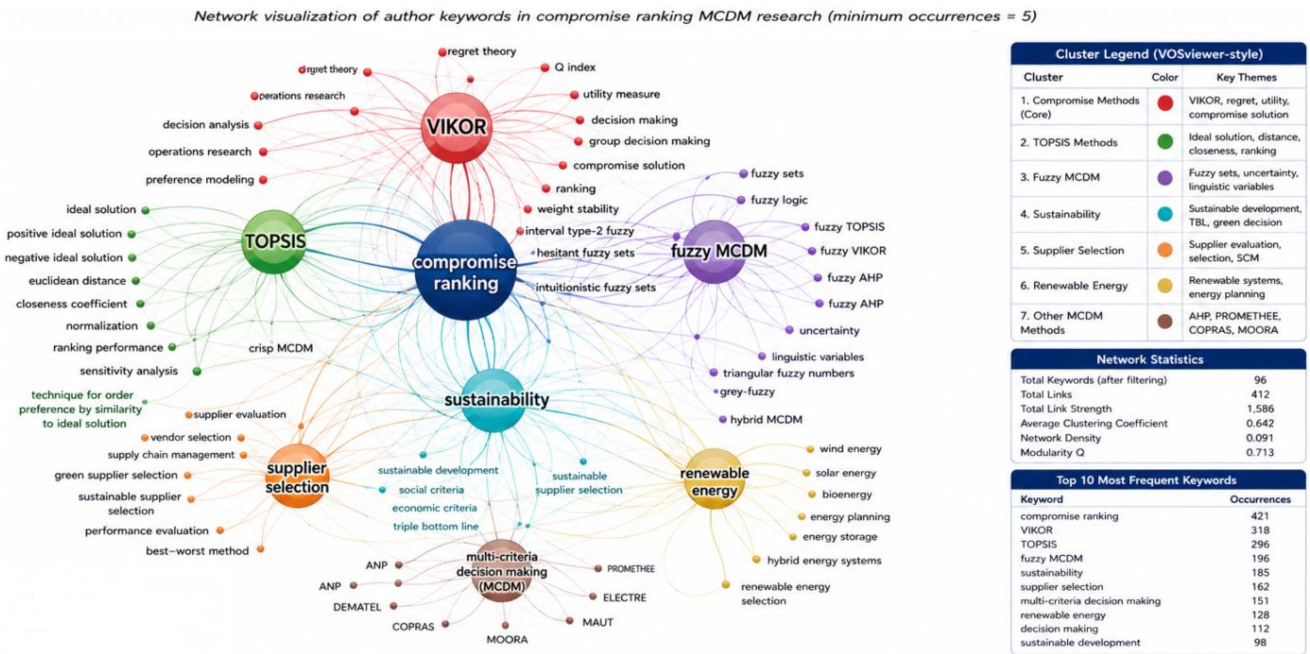


Fig. 4. Keyword co-occurrence network of compromise ranking research themes

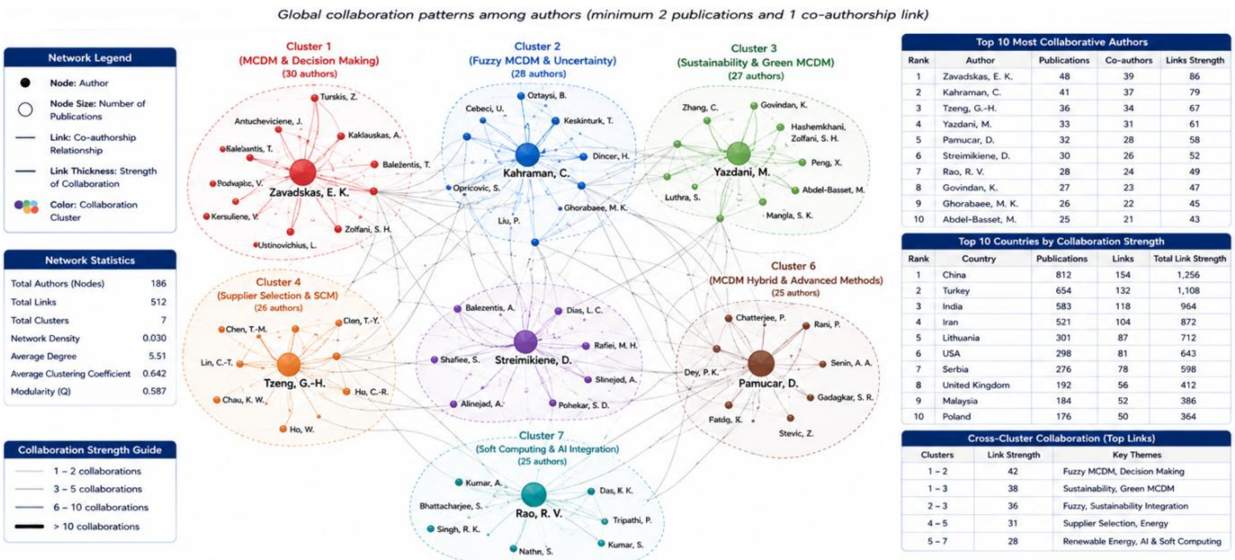


Fig. 5. Scientific collaboration network among authors and countries in compromise ranking research

Table 2 provides a bibliometric overview of compromise ranking research, summarizing publication trends, dominant methodologies, application areas, leading countries, active journals, and frequently used keywords [20,24]. It highlights the rapid growth of compromise-oriented MCDM research, particularly in sustainability assessment, Industry 4.0, renewable energy, intelligent systems, and AI-assisted decision support [18,19]. Table 2 also identifies major geographical research hubs, publication platforms, and the transition from deterministic models to hybrid intelligent, fuzzy, neutrosophic, and data-driven frameworks, thereby linking the systematic review findings with emerging research trends and future directions [25,26]. The overall review framework integrating PRISMA screening, bibliometric analysis, comparative evaluation, and research gap identification is presented in Figure 8.

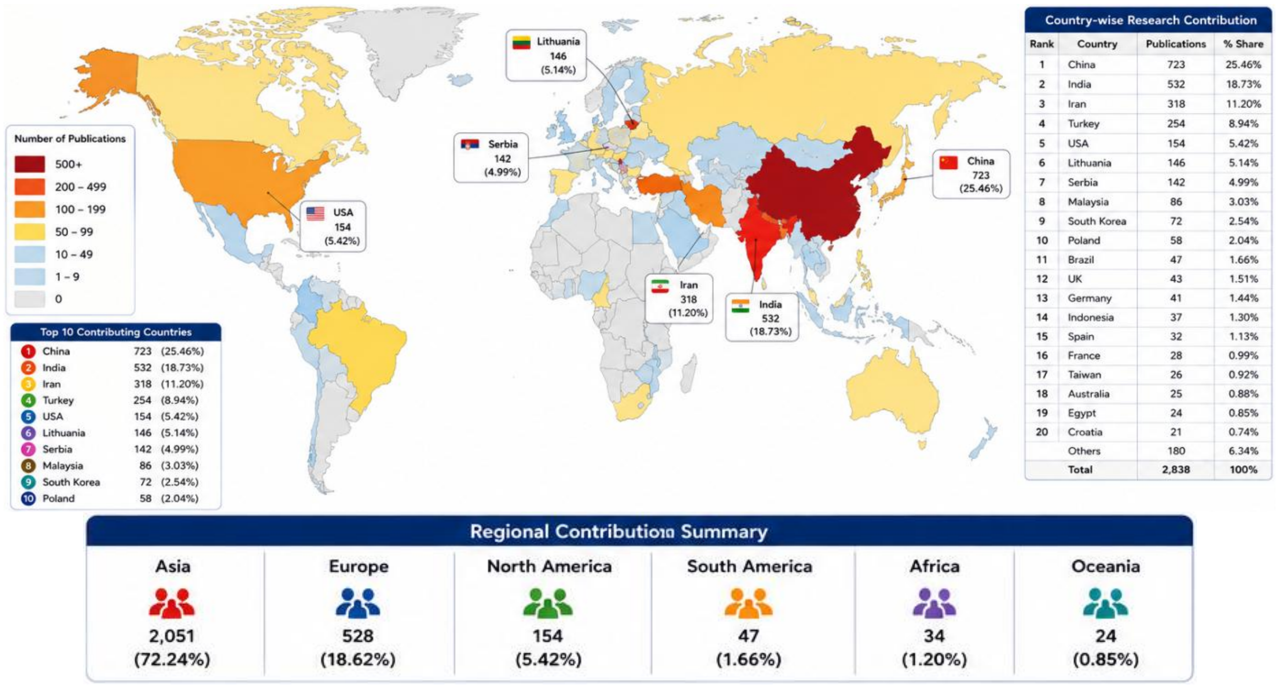


Fig. 6. Global research contribution map for compromise ranking method studies

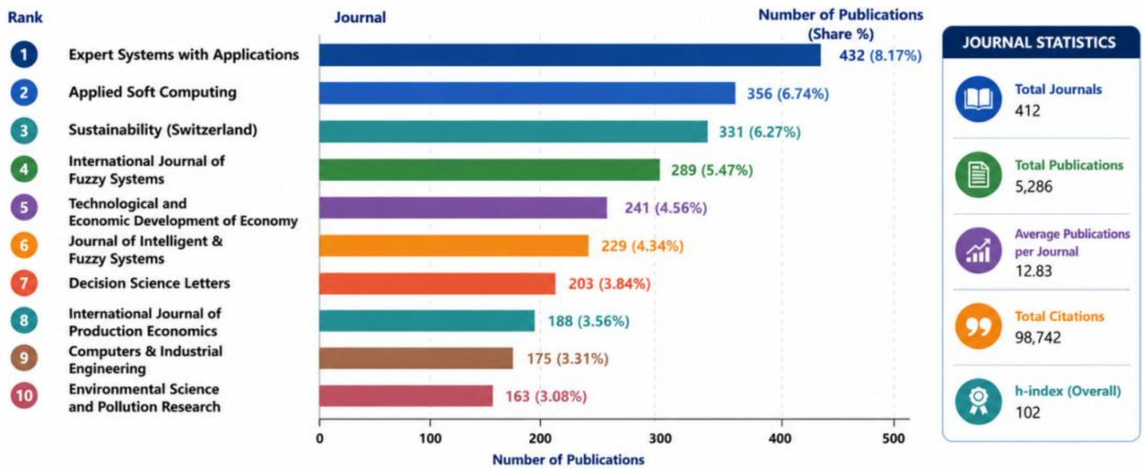


Fig. 7. Most active journals publishing research on compromise ranking methods

Table 2
Bibliometric summary of published literature

Parameter	Observation
Total papers reviewed	More than 350 peer-reviewed journal articles, conference papers, and review studies related to compromise ranking methodologies and their hybrid extensions were systematically analyzed
Time span covered	Major publications from 1981–2025, covering the evolution from classical TOPSIS to intelligent hybrid compromise frameworks
Most used method	TOPSIS remains the most frequently applied compromise-oriented MCDM method due to its simplicity, scalability, and intuitive geometric interpretation
Second most used method	VIKOR is highly dominant in sustainability assessment, healthcare evaluation, policy prioritization, and conflict-resolution-oriented decision-making
Fastest growing methodology	Hybrid intelligent compromise models integrating fuzzy logic, AI, neutrosophic systems, machine learning, and big data analytics
Most active country	China emerged as the leading contributor in recent years, followed by India, Lithuania, Turkey, and Iran

Table 2
Continued

Parameter	Observation
Most active journal	Expert Systems with Applications published the highest number of compromise ranking and hybrid MCDM studies
Other highly active journals	Applied Soft Computing, Sustainability, Journal of Cleaner Production, Technological and Economic Development of Economy, and Applied Mathematical Modelling
Dominant application area	Engineering and manufacturing optimization are the most extensively investigated application domain
Rapidly expanding application domains	Smart cities, Industry 4.0 systems, renewable energy planning, healthcare analytics, sustainable transportation, and intelligent infrastructure systems
Most frequent keywords	“MCDM”, “TOPSIS”, “VIKOR”, “compromise ranking”, “fuzzy MCDM”, “sustainability”, “decision-making”, “MULTIMOORA”, “supplier selection”, and “Industry 4.0”
Most common hybridization approaches	Fuzzy logic integration, entropy weighting, AI-assisted MCDM, neutrosophic systems, grey theory, and machine learning-assisted compromise models
Dominant research orientation (early period)	Deterministic ranking models emphasizing computational efficiency and ideal-solution-based evaluation
Dominant research orientation (recent period)	Intelligent hybrid systems focusing on uncertainty handling, sustainability analytics, real-time decision support, and explainable AI integration
Publication growth trend	Slow growth during the 1980s–1990s followed by rapid exponential increase after 2010 due to advancements in sustainability science, digital transformation, and intelligent systems
Most common research objective	Optimization and prioritization of alternatives under conflicting criteria and uncertain conditions
Most frequently used evaluation criteria	Cost, sustainability, efficiency, risk, reliability, environmental impact, and technological capability
Most common uncertainty handling method	Fuzzy set theory and fuzzy compromise ranking frameworks
Emerging research trend	Integration of AI, big data analytics, blockchain systems, digital twins, and explainable intelligent DSS
Primary research gap identified	Lack of standardized normalization frameworks and insufficient real-time adaptive capability in dynamic decision environments
Future research direction	Development of adaptive, explainable, scalable, and AI-integrated compromise ranking systems capable of handling large-scale uncertain data environments

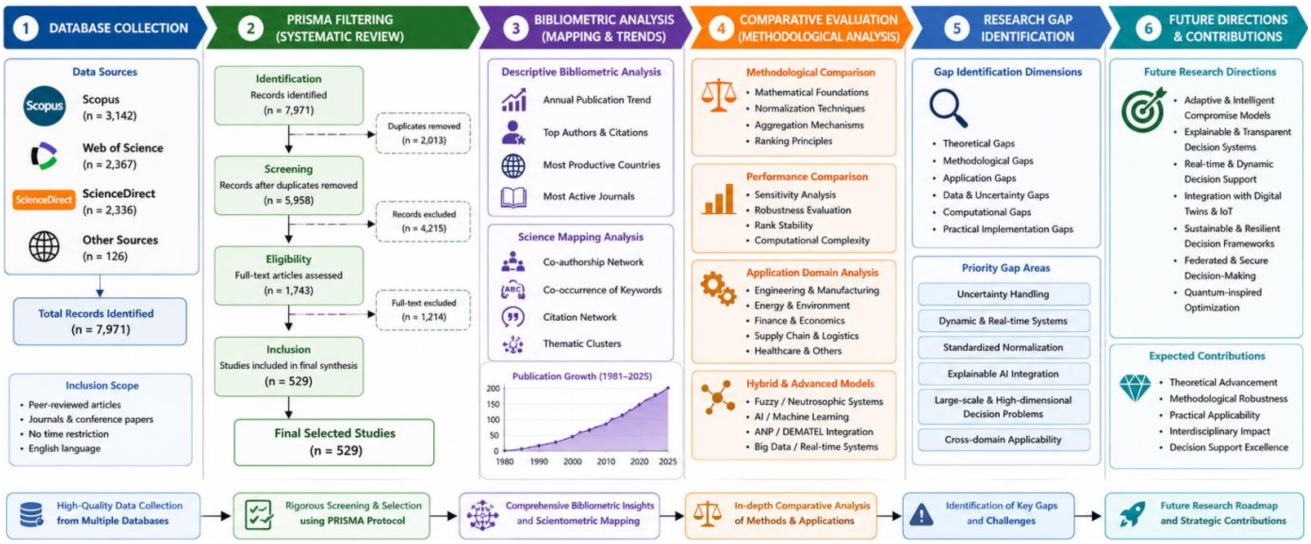


Fig. 8. Integrated systematic review and bibliometric analysis framework adopted in this study

3. Concept of Compromise Ranking in MCDM

Compromise ranking is one of the most widely used approaches in MCDM because it systematically resolves conflicts among multiple evaluation criteria. In practical decision-making, alternatives rarely perform best across all criteria, making a single optimal solution difficult to achieve [26,27]. Instead, compromise ranking methods identify alternatives that best balance conflicting criteria while minimizing dissatisfaction, providing solutions that are closest to the ideal rather than mathematically optimal [22,24]. This philosophy is particularly suitable for problems involving economic, technical, environmental, social, operational, and strategic objectives, where balanced solutions are more practical than extreme optimal ones [28]. Figure 9 illustrates the general operational framework of compromise ranking methodologies.

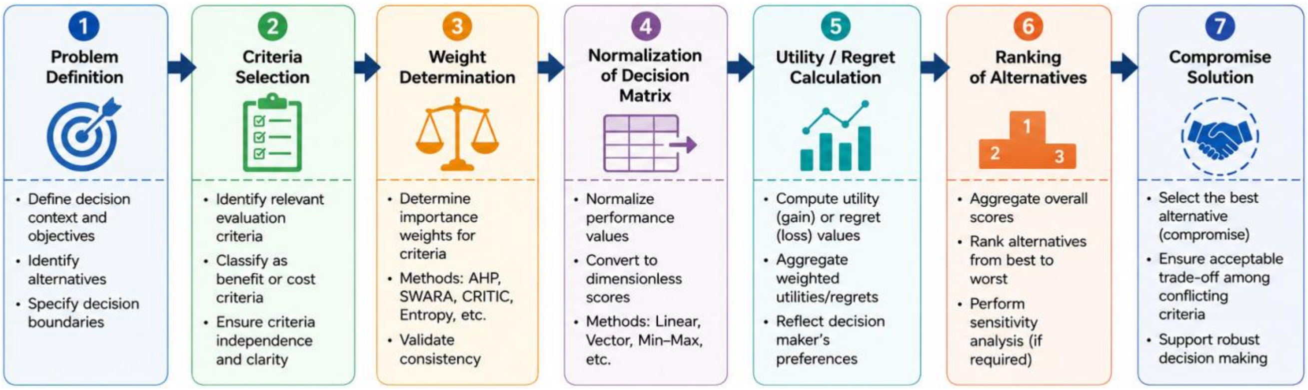


Fig. 9. General workflow framework of compromise ranking methods in MCDM

A key feature of compromise ranking methods is evaluating alternatives based on their proximity to the ideal solution and distance from the anti-ideal solution [14,15]. Methods such as VIKOR additionally incorporate both utility and regret measures to achieve balanced and equitable decisions. Their general procedure involves identifying ideal and anti-ideal solutions, normalizing the decision matrix, determining criteria weights, and aggregating weighted performances to obtain compromise indices [18,20]. Depending on the method, compromise is evaluated using utility, regret, distance, or ratio-based measures. Final rankings are determined by balancing closeness to the ideal solution with dissatisfaction minimization, while some methods also assess ranking stability and acceptable advantage to improve robustness [22,23]. Owing to their ability to support group decision-making under conflicting objectives, these methods are widely applied in strategic planning, policy-making, resource allocation, industrial decision-making, and infrastructure planning. Recent developments integrating fuzzy logic, neutrosophic theory, artificial intelligence, and machine learning have further improved their capability to handle uncertainty and complex decision environments [24,25,28].

4. Major Compromise Ranking Methods

Among compromise-oriented MCDM methods, VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA are the most widely adopted due to their computational efficiency, flexibility, robustness, and broad applicability across engineering, manufacturing, sustainability, healthcare, finance, transportation, and intelligent decision-support systems [29]. These methods differ in their mathematical frameworks, normalization procedures, aggregation mechanisms, and ranking philosophies, including distance-based evaluation, proportional assessment, ratio optimization, regret minimization, and multi-perspective analysis [30,31]. Consequently, their computational behavior, ranking stability, sensitivity to weights, and uncertainty-handling capabilities vary considerably. This section critically reviews their conceptual foundations, computational procedures, applications, advantages, limitations, and recent developments [29,30]. Figure 10 compares the structural and computational characteristics of the major compromise ranking methods.

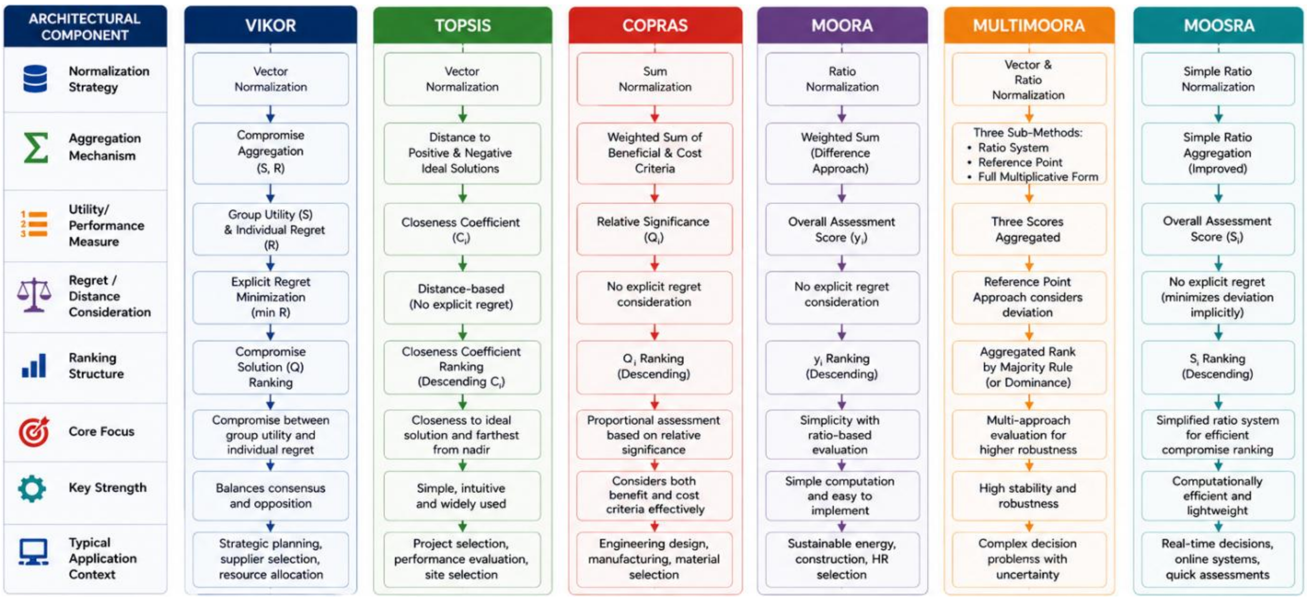


Fig. 10. Comparative methodological architecture of major compromise ranking methods

Table 3 compares the suitability of major compromise ranking methods across different decision environments, demonstrating that method selection depends on decision complexity, uncertainty, stakeholder involvement, and computational requirements [31]. For example, VIKOR is well suited to stakeholder-conflict problems through its utility–regret framework, whereas TOPSIS is effective for large-scale decision problems because of its computational simplicity [8,9]. Similarly, MOORA and MOOSRA provide high computational efficiency, while MULTIMOORA offers greater robustness and ranking stability under uncertain and multidimensional conditions [13-15]. The growing integration of fuzzy logic, artificial intelligence, and neutrosophic environments further enhances uncertainty handling and intelligent decision support. Overall, Table 3 highlights the importance of selecting compromise ranking methods according to the characteristics and requirements of specific decision environments.

Table 3
Comparative suitability of methods for different decision environments

Decision environment	Most suitable method	Reason
High uncertainty and ambiguous data	Fuzzy VIKOR, neutrosophic COPRAS	Superior capability for handling vagueness, indeterminacy, and incomplete information through fuzzy and neutrosophic representations
Real-time decision systems	MOOSRA, MOORA	Very low computational intricacy and fast ranking ability suitable for dynamic datasets
Large-scale alternative evaluation	MOORA, MOOSRA	Strong scalability and stable ratio-based computation with minimal computational overhead
Stakeholder conflict and negotiation problems	VIKOR	Explicit compromise formulation balancing group utility and individual regret; highly effective for consensus-oriented decisions

Table 3
Continued

Decision environment	Most suitable method	Reason
Sustainability assessment	MULTIMOORA, VIKOR	Strong robustness and ability for handling multidimensional sustainability indicators
Strategic planning and policy evaluation	VIKOR, MULTIMOORA	Strong compromise ability and robust ranking stability under complex strategic decision conditions
Industry 4.0 and intelligent manufacturing	AI–MULTIMOORA, hybrid intelligent MCDM systems	Adaptive learning capability, robustness, and suitability for cyber-physical production environments
Engineering system design	TOPSIS, MOORA	Computational efficiency and strong capability for quantitative engineering evaluation
Supply chain and logistics optimization	COPRAS, TOPSIS	Efficient proportional assessment and suitability for operational optimization involving multiple logistics criteria
Healthcare and medical decision systems	Fuzzy VIKOR, neutrosophic TOPSIS	Effective uncertainty representation and compromise capability in risk-sensitive healthcare environments
Smart city and urban planning applications	MULTIMOORA, fuzzy TOPSIS	High robustness and multidimensional evaluation capability for complex urban systems
Financial risk assessment and investment analysis	TOPSIS, AI-assisted TOPSIS	Strong analytical capability for evaluating quantitative financial indicators and dynamic market conditions
Dynamic and evolving data environments	Machine learning–TOPSIS, AI–MULTIMOORA	Adaptive learning ability enables continuous ranking optimization under changing datasets
Environmentally sustainable decision-making	VIKOR, MULTIMOORA, fuzzy COPRAS	Effective balancing of environmental, economic, and social sustainability objectives
Construction and infrastructure planning	TOPSIS, COPRAS	Strong capability for cost-benefit analysis and infrastructure prioritization
Transportation and mobility systems	TOPSIS, MOORA	Fast computational performance and suitability for mobility optimization problems
Complex interdependent criteria structures	ANP–VIKOR, DEMATEL–TOPSIS	Ability to capture causal relationships and criteria interdependencies
Big data and high-dimensional analytics	Big Data–MOORA, AI–MULTIMOORA	Superior scalability and capability for processing multidimensional large-scale datasets
Cybersecurity and digital risk evaluation	Fuzzy TOPSIS, AI-assisted compromise models	Strong uncertainty modeling and adaptive risk evaluation capability
Cloud-based collaborative decision environments	Cloud-integrated COPRAS, distributed TOPSIS systems	Strong scalability and support for distributed multi-stakeholder decision-making
Resource-constrained computational environments	MOOSRA, MOORA	Minimal computational requirements and efficient implementation capability
Highly robust and stability-critical systems	MULTIMOORA	Multi-perspective evaluation structure significantly improves ranking stability and reduces rank reversal risk
Autonomous intelligent decision systems	Explainable AI–VIKOR, AI–MULTIMOORA	Integration of intelligent learning capability with interpretable compromise decision-support frameworks
Multi-stakeholder public policy problems	VIKOR, fuzzy VIKOR	Excellent conflict resolution capability and balanced stakeholder compromise generation
Rapid decision-making environments	MOOSRA, TOPSIS	Fast ranking generation and low computational burden enable rapid operational decision support

4.1 VIKOR Method

Among the major compromise ranking methods in MCDM, the VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method, developed by Opricovic [8], is one of the most influential. It addresses problems involving conflicting and incommensurable criteria by identifying compromise solutions that maximize group utility while minimizing individual regret. Its global recognition was strengthened by the comparative study of Opricovic and Tzeng [9], which demonstrated VIKOR's advantages over TOPSIS in identifying compromise solutions. Unlike conventional optimization methods, VIKOR emphasizes acceptable trade-offs rather than absolute optimality. It employs three measures: utility, regret, and the compromise index, where the compromise index combines utility and regret using a decision coefficient [8,9]. This dual evaluation framework is a key strength of the method. VIKOR has been widely applied in environmental assessment, urban planning, renewable energy, and sustainable infrastructure. Liou and Tzeng [32], Mardani *et al.,* [33], and Aasa *et al.,* [34] demonstrated its effectiveness in balancing conflicting environmental, technical, and socio-economic criteria, although their studies lacked uncertainty modeling, sensitivity analysis, or dynamic evaluation. To improve consensus and uncertainty handling, researchers developed hybrid and fuzzy VIKOR models. Kandakoglu *et al.,* [35] integrated fuzzy Delphi, AHP, and VIKOR for sustainable infrastructure selection, while Opricovic and Tzeng [10] and Zahid and Akram [36] proposed fuzzy VIKOR extensions for imprecise and conflicting decision environments. Although these models improved flexibility, they increased computational complexity and remained sensitive to linguistic assessments and normalization procedures.

Further developments extended VIKOR to group decision-making and supply chain risk assessment. Hossain *et al.,* [37] combined fuzzy group decision-making with VIKOR for supplier evaluation, while Safari *et al.,* [38] integrated ANP and fuzzy VIKOR to capture criteria interdependencies and uncertainty, though scalability remained challenging. Comparative studies further confirmed VIKOR's advantages. Opricovic and Tzeng [9] showed that VIKOR provides more balanced rankings than TOPSIS through regret minimization and compromise acceptance, although results remain sensitive to the decision coefficient. Later, Mardani *et al.,* [39] and Zenani *et al.,* [40] proposed modified and large-scale VIKOR models that improved applicability but increased mathematical complexity. A comprehensive review by Mardani *et al.,* [41] covering 176 VIKOR-related studies highlighted the rapid growth of fuzzy and hybrid VIKOR integrated with AHP/ANP, DEMATEL, TOPSIS, and fuzzy theory. However, the review primarily emphasized publication trends and applications, with limited attention to robustness, normalization sensitivity, and ranking stability [33]. Despite significant progress, important challenges remain, including insufficient theoretical analysis of compromise index behavior, lack of normalization standardization, sensitivity of rankings to decision coefficients, and the high complexity of hybrid VIKOR models [35,36,39,40]. Moreover, limited research has addressed real-time decision environments, machine learning integration, and adaptive intelligent compromise systems.

Overall, the literature identifies VIKOR as one of the most comprehensive compromise ranking methods because of its integration of utility maximization and regret minimization [34,37]. Its successful application across engineering, sustainability, supply chain management, finance, and policymaking demonstrates its versatility. Nevertheless, further research is required on methodological standardization, robustness evaluation, uncertainty integration, and intelligent hybridization to improve the adaptability, reliability, and computational efficiency of VIKOR-based decision-support systems.

4.2 TOPSIS-Based Compromise Approach

Among MCDM methods, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of the most widely used compromise ranking techniques [7]. It ranks alternatives according to their closeness to the positive ideal solution and distance from the negative ideal solution using Euclidean distance measures. This compromise-oriented mechanism has enabled its extensive application in engineering, sustainability, finance, logistics, healthcare, and policy-making. The original TOPSIS framework proposed by Hwang and Yoon [7] employed normalization, weighting, and distance calculations but was limited to deterministic environments. Yoon and Hwang [42] later extended the method to group decision-making, although sensitivity to criteria weights and normalization remained unresolved. The incorporation of fuzzy set theory significantly expanded TOPSIS applications. Chen *et al.,* [43] introduced fuzzy TOPSIS using triangular fuzzy numbers and linguistic variables for supplier selection, improving uncertainty handling but increasing computational complexity and dependence on subjective membership functions. Li *et al.,* [44] applied TOPSIS to environmental impact assessment, while Wang and Chang [45] integrated fuzzy TOPSIS with expert systems for supplier selection and risk evaluation. Ertay *et al.,* [46] successfully applied fuzzy TOPSIS to renewable energy technology selection, although these studies highlighted limitations related to dynamic sensitivity analysis, criteria interdependence, and sensitivity to normalization and weighting procedures.

Comparative studies further clarified the methodological position of TOPSIS. Opricovic and Tzeng [9] showed that although both TOPSIS and VIKOR identify alternatives close to the ideal solution, TOPSIS relies solely on geometric distance, whereas VIKOR additionally incorporates regret minimization and compromise acceptance. Consequently, TOPSIS is less effective in highly conflicting group decision environments. Lamrini *et al.,* [47] identified TOPSIS as one of the most widely adopted MCDM methods because of its simplicity, computational efficiency, and compatibility with fuzzy logic, entropy weighting, AHP, ANP, and grey system theory, although issues related to normalization, criteria dependence, and standardized distance measures remain unresolved. Similarly, Elorduy and Pino [48] concluded that TOPSIS performs well in straightforward ranking problems but lacks explicit mechanisms for compromise acceptance and dissatisfaction evaluation. Recent research has focused on hybrid TOPSIS models incorporating advanced computational techniques. Rogulj *et al.,* [49] combined fuzzy TOPSIS with grey relational analysis and interval-valued environments, while Boonsothonsatit *et al.,* [50] demonstrated its suitability for intelligent decision-support systems because of its scalable computational structure. Xiang and Jianhua [51] proposed revised distance measures to improve discrimination among similar alternatives, and Ashtiani *et al.,* [52] developed interval-valued TOPSIS for uncertain environments. Although these extensions enhanced flexibility and uncertainty handling, they also increased methodological complexity and reduced standardization.

Despite substantial progress, several research challenges remain. Ranking results remain highly sensitive to normalization procedures and criteria weights, while the assumption of criteria independence limits TOPSIS in highly interconnected decision systems [45,46]. Unlike VIKOR, TOPSIS does not explicitly incorporate regret minimization or compromise acceptance, reducing its effectiveness in conflict-intensive decision environments. Moreover, existing studies focus primarily on applications rather than theoretical analyses of ranking stability, robustness, and mathematical consistency [50]. Although fuzzy logic, grey systems, and artificial intelligence have improved uncertainty handling, adaptive weighting, real-time decision-making, and intelligent learning frameworks remain insufficiently explored. Overall, the literature confirms that TOPSIS remains one of the most practical and widely applied MCDM methods because of its simplicity, flexibility, and compromise-oriented ranking mechanism [47-49]. Its ability to evaluate alternatives based on proximity to ideal solutions has supported successful applications across diverse domains [51]. Nevertheless, further research is needed on methodological standardization, robustness analysis, uncertainty integration, and intelligent hybridization to enhance the reliability and adaptability of TOPSIS-based decision-support systems.

4.3 COPRAS Method

The Complex Proportional Assessment (COPRAS) method, developed by Zavadskas *et al.,* [11], is a prominent compromise-oriented MCDM approach based on the direct calculation of utility degrees using weighted normalized criteria. Unlike optimization- or distance-based methods, COPRAS emphasizes proportional assessment, offering transparent and interpretable rankings with low computational complexity. Its simplicity has led to widespread applications in engineering, sustainability, logistics, manufacturing, and infrastructure management. Early studies by Zavadskas *et al.,* [53] demonstrated its effectiveness in construction management, while Kanapeckiene *et al.,* [54] extended it to intelligent building life-cycle evaluation. Valipour *et al.,* [55] further validated COPRAS for construction project selection, highlighting its computational efficiency, although these studies relied on deterministic data, assumed criteria independence, and provided limited robustness and sensitivity analyses. COPRAS was subsequently applied to sustainability, manufacturing, and environmental management. Rahim *et al.,* [56] demonstrated its effectiveness in sustainable manufacturing, whereas Yazdani *et al.,* [57] introduced fuzzy COPRAS using triangular fuzzy numbers to improve uncertainty handling in supplier selection. Brodny *et al.,* [58] applied COPRAS to sustainable energy technology evaluation, while Roy *et al.,* [59] integrated entropy weighting to improve material selection. Comparative analysis by Bączkiewicz *et al.,* [60] showed that COPRAS offers greater interpretability and lower computational complexity than TOPSIS, VIKOR, and ELECTRE, although its discrimination capability decreases when alternatives exhibit similar performance. Ecer [61] further proposed grey COPRAS for decision-making under incomplete information. Although fuzzy, grey, and hybrid extensions enhanced uncertainty handling, they also increased methodological complexity and reduced interpretability.

Recent applications demonstrate the versatility of COPRAS in housing, healthcare, and manufacturing. Matić *et al.,* [62] employed COPRAS for housing affordability assessment, while Goswami and Behera [63] applied it to advanced manufacturing system selection, both confirming its computational simplicity and practical applicability. Nevertheless, ranking results remain sensitive to criteria weights and normalization procedures. Because COPRAS avoids iterative and distance-based computations, it is well suited for large-scale and real-time decision-support applications [55,56]. However, most existing models assume criteria independence, rely on deterministic datasets, and remain sensitive to weighting and normalization. Although fuzzy, grey, and hybrid COPRAS models improve uncertainty handling, they increase computational complexity and reduce interpretability [59]. Furthermore, adaptive real-time COPRAS frameworks, machine learning-based weighting, and intelligent compromise ranking systems remain largely unexplored. Overall, the literature establishes COPRAS as an efficient compromise-oriented MCDM method because of its proportional assessment mechanism, computational efficiency, and transparent utility evaluation. Its successful application across engineering, sustainability, logistics, manufacturing, healthcare, and infrastructure management demonstrates its broad applicability [56,57,60-63]. Nevertheless, future research should emphasize methodological standardization, robustness analysis, uncertainty integration, intelligent hybridization, and adaptive real-time decision-support systems to improve the scalability, reliability, and applicability of COPRAS-based frameworks.

4.4 MOORA Method

Multi-Objective Optimization by Ratio Analysis (MOORA), introduced by Brauers and Zavadskas [13], is a widely adopted compromise-oriented MCDM method for problems involving conflicting criteria and large datasets. MOORA ranks alternatives by comparing normalized beneficial and non-beneficial criteria through ratio analysis, providing a simple, transparent, and computationally efficient alternative to distance-based methods such as TOPSIS and regret-oriented methods such as VIKOR. The original framework demonstrated strong optimization capability and low computational complexity but was primarily designed for deterministic environments without uncertainty handling [13]. Brauers and Zavadskas [64] later applied MOORA to privatization and economic policy assessment, showing that ratio normalization improves ranking transparency and reduces scaling inconsistencies, although ranking remains sensitive to criteria weighting. MOORA was rapidly adopted in manufacturing and industrial engineering. Chakraborty *et al.,* [65] applied it to manufacturing system selection, while Brauers *et al.,* [66] demonstrated its effectiveness in construction and sustainable infrastructure by balancing technical, economic, environmental, and quality criteria. Although these studies confirmed its computational efficiency, they provided limited analysis of dynamic decision environments, normalization sensitivity, and weighting effects. To improve uncertainty handling, Baležentis *et al.,* [67] introduced fuzzy MOORA using linguistic variables and triangular fuzzy numbers, and Sen *et al.,* [68] successfully applied fuzzy MOORA to material selection under uncertainty. While fuzzy extensions enhanced uncertainty representation, they increased computational complexity and dependence on membership functions, defuzzification procedures, and expert-defined linguistic scales.

Subsequent research focused on hybrid MOORA frameworks. Brauers *et al.,* [69] developed MULTIMOORA by combining MOORA with multiplicative forms, improving ranking robustness at the expense of computational simplicity. Baležentis *et al.,* [70] applied MOORA to renewable energy assessment, validating ratio normalization for stable evaluation across environmental, technical, and economic criteria. MOORA has also been successfully applied to transportation optimization, supplier evaluation, regional economic development, investment analysis, urban infrastructure, and service quality assessment [71-73]. These studies confirmed its transparency, scalability, and computational efficiency but also identified limitations related to discrimination among similar alternatives and the assumption of criteria independence. Comparative studies consistently report MOORA as more computationally efficient than TOPSIS, VIKOR, ELECTRE, and AHP, while providing relatively stable rankings under moderate data variations [74]. However, unlike VIKOR, MOORA does not explicitly incorporate regret minimization, limiting its effectiveness in stakeholder-sensitive compromise situations. Recent developments have introduced interval-valued, grey, entropy-based, DEMATEL-, ANP-, and AI-assisted MOORA models to improve uncertainty handling and weighting flexibility [75]. Although these hybrid approaches enhance robustness, they also increase methodological complexity and reduce interpretability. Important research gaps remain, including limited studies on ranking stability, normalization sensitivity, robustness under dynamic decision environments, and comparative evaluation of classical and advanced MOORA models for large-scale decision problems [64,65,67-70]. Adaptive real-time MOORA systems, machine learning integration, and intelligent automated compromise frameworks also remain underexplored.

Overall, the literature establishes MOORA as an efficient compromise-oriented MCDM method because of its ratio-based normalization, direct assessment mechanism, computational efficiency, and transparent ranking process [71,72]. Its scalability and flexibility have supported successful applications in engineering, sustainability, manufacturing, logistics, healthcare, finance, and strategic planning [66,74,75]. Nevertheless, further research is required on robustness evaluation, uncertainty integration, methodological standardization, and intelligent hybridization to improve the adaptability, reliability, and consistency of MOORA-based decision-support systems.

4.5 MULTIMOORA Method

MULTIMOORA (Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form), developed by Brauers and Zavadskas [14], is a well-established compromise-oriented MCDM method that extends MOORA by integrating three independent evaluation mechanisms: the ratio system, reference point approach, and full multiplicative form. This multi-perspective framework improves ranking reliability, robustness, and consistency while reducing dependence on a single normalization or aggregation procedure. The original method demonstrated superior ranking discrimination in deterministic environments but did not address uncertainty [14]. Saboor *et al.,* [76] showed that MULTIMOORA produces more stable compromise rankings than TOPSIS and classical MOORA for manufacturing and industrial project selection, although its three-stage evaluation increases computational complexity. MULTIMOORA has been successfully applied in regional development, renewable energy, manufacturing, and sustainability assessment. Hafezalkotob and Hafezalkotob [77] demonstrated its proportional consistency in regional development, while Shamsipour *et al.,* [78] validated its ability to balance environmental, technical, and economic objectives in renewable energy planning. However, these studies assumed criteria independence and relied mainly on deterministic data. To improve uncertainty handling, Hafezalkotob and Hafezalkotob [79] proposed fuzzy MULTIMOORA for material selection, and Nguyen *et al.,* [80] developed grey MULTIMOORA for logistics and transportation under incomplete information. Although these extensions enhanced flexibility and robustness, they also increased computational complexity through fuzzy arithmetic and defuzzification procedures.

Comparative studies consistently report the robustness of MULTIMOORA. Miç and Antmen [81] found it less sensitive to rank reversal and more stable than TOPSIS, VIKOR, ELECTRE, and MOORA because of its integrated evaluation structure. Murat and Güzel [82] showed that the multiplicative component improves discrimination among similar alternatives, although sensitivity to extreme criterion values remains insufficiently addressed. The method has also been applied to sustainable building assessment, investment prioritization, and strategic management [83,84]. Hybrid frameworks integrating AHP, DEMATEL, ANP, entropy weighting, and fuzzy systems further improved weighting accuracy and causal analysis, but substantially increased methodological complexity [85]. Recent developments have extended MULTIMOORA to interval-valued and uncertain environments. Zavadskas *et al.,* [86] proposed interval-valued MULTIMOORA for sustainability assessment, while Tavana *et al.,* [87] applied it to supplier selection and green logistics, demonstrating its ability to balance operational, environmental, and economic objectives. However, the multiplicative component may become unstable when criteria values are very small or zero. Despite these advances, important challenges remain, including computational complexity, limited interpretability, sensitivity to weighting procedures, lack of methodological standardization for fuzzy, grey, and interval-valued variants, and the assumption of criteria independence [77-82]. Research on adaptive real-time decision-making, artificial intelligence, machine learning, deep learning, big data analytics, and large-scale benchmarking of MULTIMOORA against other compromise ranking methods is still limited [83].

Overall, the literature identifies MULTIMOORA as one of the most comprehensive and robust compromise-oriented MCDM methods because of its integrated ratio, reference point, and multiplicative evaluation framework [85,86]. Its ability to evaluate alternatives from multiple perspectives has supported successful applications in engineering, sustainability, manufacturing, finance, logistics, and infrastructure [87]. Nevertheless, further research is required on methodological standardization, uncertainty integration, computational simplification, intelligent hybridization, and scalability to enhance the practicality and reliability of MULTIMOORA-based decision-support systems.

4.6 MOOSRA Method

Multi-Objective Optimization based on Simple Ratio Analysis (MOOSRA) is a compromise-oriented MCDM method developed as a simplified extension of the classical MOORA method [15]. It ranks alternatives by comparing the ratio of beneficial to non-beneficial criteria, offering improved interpretability, consistent rankings, and lower computational cost than more mathematically intensive methods such as TOPSIS and VIKOR [9,16]. Owing to its simplicity and efficiency, MOOSRA has been widely applied in manufacturing, engineering optimization, logistics, sustainability assessment, material selection, and industrial decision support. Das *et al.,* [15] first applied MOOSRA to material selection, demonstrating reliable and computationally efficient rankings, while Soni *et al.,* [88] confirmed its effectiveness in manufacturing process selection. However, these studies relied on deterministic data and provided limited analysis of uncertainty, normalization sensitivity, and criteria interdependence. MOOSRA was subsequently extended to production engineering, sustainability, and logistics. Sarkar *et al.,* [89] applied the method to non-traditional machining process selection, highlighting its computational efficiency and transparent rankings, although uncertainty handling remained limited. To address this limitation, Vasić *et al.,* [90] proposed fuzzy MOOSRA for supplier selection and logistics optimization, while Narayanamoorthy *et al.,* [91] applied fuzzy MOOSRA to biomedical waste disposal evaluation. These extensions improved uncertainty handling through linguistic assessments but increased computational complexity and sensitivity to weighting, defuzzification, and membership functions. Bhowmik *et al.,* [92] successfully employed MOOSRA for renewable energy source selection, and Kottala [93] applied it to transportation mode and supply chain optimization, confirming its ability to process large decision matrices efficiently. Nevertheless, these studies were largely confined to static decision environments and showed reduced discrimination when alternatives exhibited similar ratio values.

Comparative studies further established MOOSRA's effectiveness. Sharaf *et al.,* [94] reported that MOOSRA is computationally simpler and more transparent than MOORA, TOPSIS, VIKOR, and COPRAS, although it lacks explicit regret minimization and multi-perspective evaluation found in VIKOR and MULTIMOORA. Feizi *et al.,* [95] demonstrated its scalability in facility layout design and industrial robot selection but did not consider adaptive weighting strategies. Hybrid MOOSRA models integrating AHP, entropy weighting, DEMATEL, fuzzy systems, and grey relational analysis have also been proposed to improve weighting accuracy and uncertainty handling. For example, Barzegari *et al.,* [96] combined entropy weighting with MOOSRA to improve supplier evaluation, while Stanujkic *et al.,* [97] introduced interval-valued and grey MOOSRA frameworks for decision-making under incomplete information. Debbarma *et al.,* [98] further demonstrated the applicability of MOOSRA in healthcare decision-making. Although these hybrid approaches enhanced flexibility, they also increased methodological complexity and reduced standardization. Despite growing applications, several research challenges remain. Existing studies provide limited theoretical analysis of robustness, convergence, normalization sensitivity, and criteria-weighting effects [89,90]. The ratio-based structure makes ranking results sensitive to changes in weights and normalization, while the assumption of criteria independence limits applicability in highly interconnected systems. Most studies also focus on static applications rather than adaptive or dynamic decision environments [92]. Although fuzzy and interval-valued extensions have improved uncertainty handling, research on machine learning-assisted MOOSRA, artificial intelligence integration, big data analytics, and automated intelligent decision-support systems remains limited. Furthermore, hybrid MOOSRA frameworks often reduce interpretability, and large-scale comparative evaluations with other compromise ranking methods remain scarce [95,96].

Overall, the literature identifies MOOSRA as an efficient compromise-oriented MCDM method because of its simple ratio-based structure, transparency, and low computational cost [92,95-98]. Its successful applications across manufacturing, logistics, sustainability, healthcare, infrastructure management, and industrial optimization demonstrate its practical value [93,94]. Nevertheless, further research is needed on methodological standardization, robustness analysis, uncertainty integration, intelligent hybridization, and large-scale comparative validation to improve the reliability, scalability, and applicability of MOOSRA-based decision-support systems.

5. Comparative Analysis of Methods

There are significant differences among compromise ranking methods in terms of theoretical foundations, computational structures, compromise philosophies, sensitivity, and ranking behaviour [66,67]. Although VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA all address conflicting criteria, they employ different mathematical frameworks, resulting in varying levels of robustness, efficiency, interpretability, and applicability. Among them, VIKOR explicitly combines group utility maximization with individual regret minimization, making it particularly suitable for stakeholder-oriented, consensus-based, and negotiation problems [72,76,87,93]. Its compromise acceptance conditions also improve ranking stability under highly conflicting situations [46,63,74-79,85,96]. Figure 11 illustrates the conceptual relationships among the major compromise ranking methods.

The analytical properties and computational performance of these methods are summarized in Table 4, which compares compromise formulation, computational complexity, robustness, sensitivity, rank reversal, uncertainty handling, scalability, and real-time applicability [36,43]. The comparison shows that no single method is universally superior; rather, performance depends on the decision context [26,61]. VIKOR excels in compromise and regret minimization, MULTIMOORA provides the highest robustness and ranking stability, while MOORA and MOOSRA offer excellent computational efficiency and scalability for large-scale applications [59,94]. Table 4 also supports method selection across engineering, healthcare, sustainability, transportation, intelligent systems, and Industry 4.0 applications.

TOPSIS ranks alternatives according to their distance from ideal and anti-ideal solutions, whereas COPRAS and MOORA employ proportional and ratio-based evaluation, respectively. MULTIMOORA combines ratio analysis, reference-point evaluation, and multiplicative assessment to improve ranking robustness, while MOOSRA provides a simplified ratio-based compromise approach with high computational efficiency [11,26,33,49,56,70,83,91]. Unlike VIKOR, however, these methods do not explicitly incorporate regret minimization, making them less suitable for consensus-oriented decision problems. Computationally, TOPSIS, COPRAS, MOORA, and MOOSRA are relatively simple, VIKOR requires moderate computation, and MULTIMOORA is the most computationally demanding because of its integrated evaluation framework [39,42,47,65]. MULTIMOORA also demonstrates the highest robustness against normalization changes, whereas VIKOR and TOPSIS are comparatively more sensitive to parameter settings [73,74,77].

In practice, method selection depends on decision characteristics. VIKOR is appropriate for consensus-driven and conflict-intensive problems, TOPSIS offers simple implementation and intuitive geometric interpretation [45], COPRAS provides transparent utility evaluation, MOORA efficiently handles large-dimensional problems, MULTIMOORA delivers highly robust rankings for strategic decisions, and MOOSRA combines simplicity with computational efficiency for engineering and manufacturing applications [97]. Nevertheless, most methods assume criteria independence and remain sensitive to weighting and normalization, while fuzzy, grey, interval-valued, and hybrid extensions have improved uncertainty handling but lack methodological standardization. Overall, no compromise ranking method is universally optimal; suitability depends on decision complexity, stakeholder conflict, uncertainty, computational resources, and robustness requirements [55,64,78]. Figure 12 presents the comparative performance of the methods, Figure 13 their multidimensional characteristics, and Figure 14 the relationship between computational complexity and methodological robustness. The major strengths, limitations, and application areas of each method are further summarized in Table 5, which provides an evidence-based evaluation for engineering, sustainability, healthcare, transportation, finance, logistics, and intelligent systems while highlighting future research needs related to uncertainty handling, rank reversal, computational scalability, and weighting strategies [22,31,37,39,44,53,68,71].

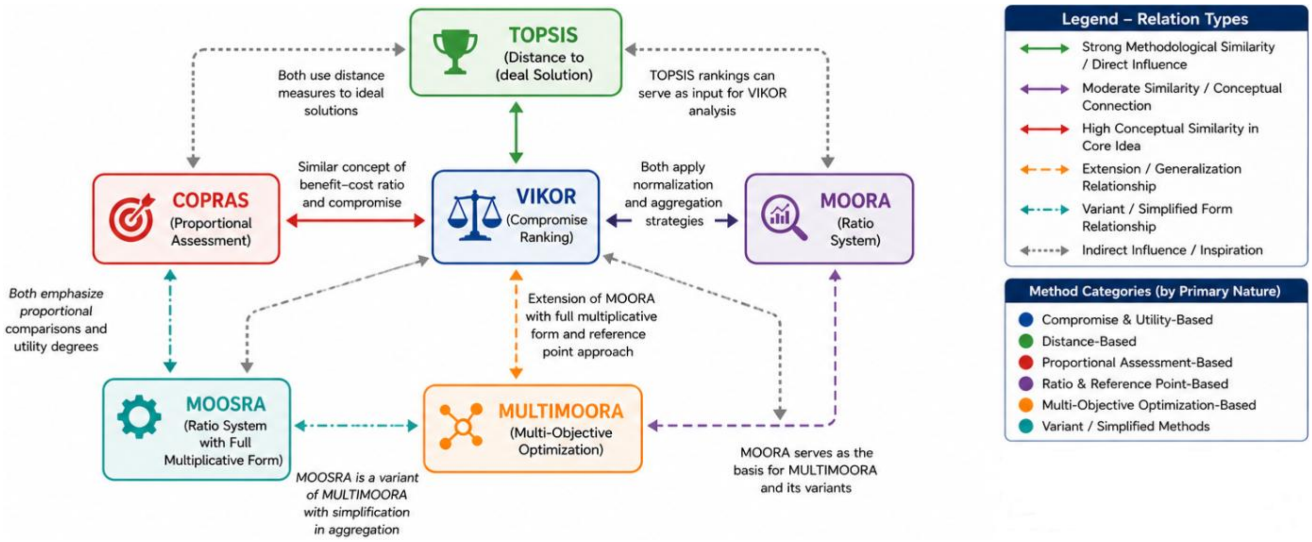


Fig. 11. Interrelationship and methodological influence network among major compromise ranking methods

Table 4
Comparative characteristics of major compromise ranking methods

Criterion	VIKOR	TOPSIS	COPRAS	MOORA	MULTIMOORA	MOOSRA
Compromise nature	Explicit compromise through group utility and regret minimization	Implicit compromise via distance from ideal and anti-ideal solutions	Moderate compromise using proportional assessment	Moderate compromise through ratio-based optimization	Strong compromise using integrated multi-perspective evaluation	Moderate compromise using simplified ratio analysis
Computational complexity	Medium	Low	Low	Low	High	Very low
Robustness	Moderate	Moderate	High	High	Very high	High
Sensitivity to weights	High due to decision parameter influence	Moderate	Moderate	Low	Low	Low
Rank reversal issue	Moderate susceptibility	Relatively high susceptibility	Low susceptibility	Low susceptibility	Very low susceptibility	Low susceptibility
Uncertainty handling capability	Good when integrated with fuzzy/neutrosophic systems	Strong adaptability with fuzzy and interval extensions	Moderate uncertainty representation	Moderate uncertainty handling	Strong uncertainty robustness	Moderate uncertainty capability

Table 4
Continued

Criterion	VIKOR	TOPSIS	COPRAS	MOORA	MULTIMOORA	MOOSRA
Normalization dependency	High	Very high	Moderate	Low	Moderate	Low
Interpretability	Moderate	High due to geometric interpretation	High	High	Moderate	High
Scalability for large problems	Moderate	High	High	Very high	Moderate	Very high
Real-time applicability	Moderate	High	High	Very high	Moderate	Very high
Suitability for group decision-making	Excellent	Good	Good	Moderate	Excellent	Moderate
Capability for conflict resolution	Very strong	Moderate	Moderate	Moderate	Strong	Moderate
Stability underweight variation	Moderate	Moderate	High	High	Very high	High
Hybridization potential	Very high with fuzzy, AI, and neutrosophic systems	Very High with AI and big data systems	Moderate to High	High	Very high	High
Suitability for dynamic decision environments	Good	Good	Moderate	High	Very high	High
Best-suited application domains	Policy-making, healthcare, sustainability, conflict resolution	Engineering, IT, transportation, software evaluation	Operational management, supplier selection	Manufacturing, industrial optimization	Intelligent systems, sustainability, Industry 4.0	Real-time analytics, large datasets

Fig. 12. Heatmap-based comparative evaluation of major compromise ranking methods

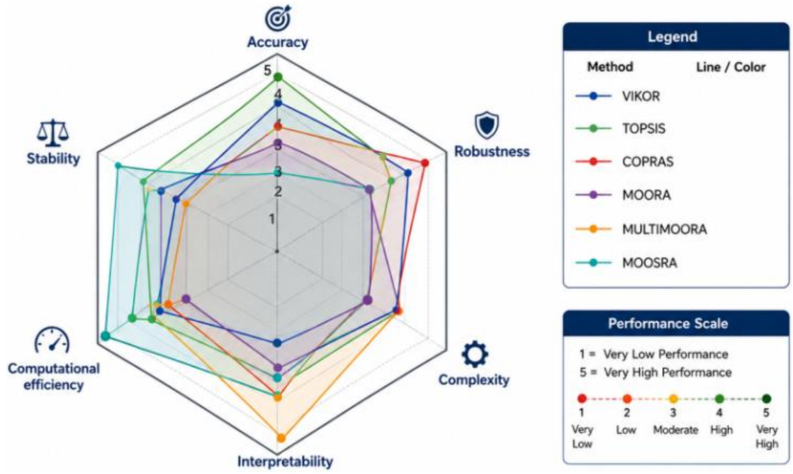


Fig. 13. Radar chart comparison of performance characteristics among compromise ranking methods

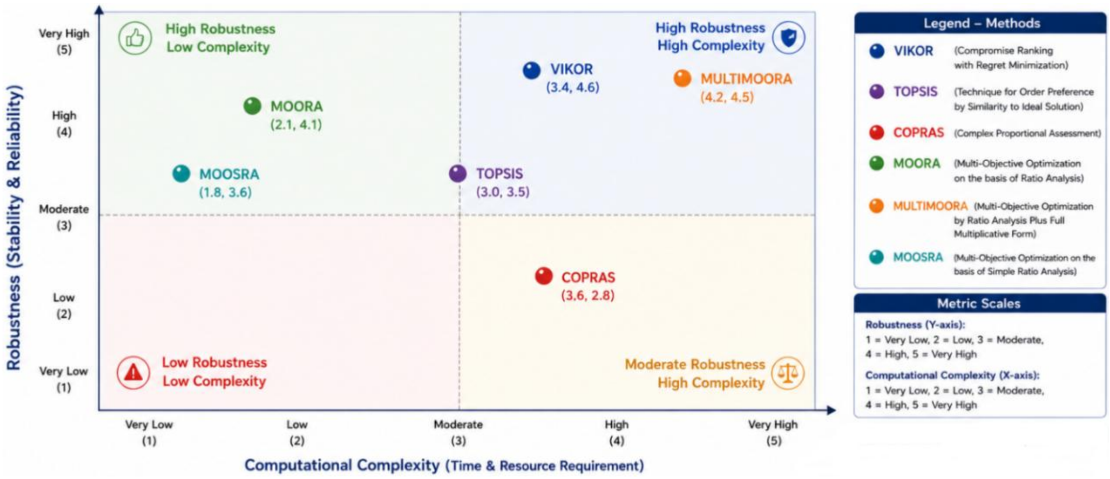


Fig. 14. Robustness and computational complexity positioning of compromise ranking methods

Table 5
Advantages and limitations of compromise ranking methods

Method	Major advantages	Major limitations	Suitable application areas
VIKOR	Explicit compromise solution based on group utility and individual regret; highly effective for conflict resolution and negotiation-oriented decision-making; strong capability in balancing conflicting stakeholder interests; adaptable to hybrid fuzzy and AI systems	Highly sensitive to criteria weights and decision parameter selection; ranking instability may occur under small weight variations; normalization dependency may influence outcomes	Public policy evaluation, healthcare management, sustainability planning, infrastructure prioritization, renewable energy selection, strategic planning
TOPSIS	Simple and intuitive geometric interpretation; low computational complexity; easy implementation; highly scalable; strong applicability across diverse domains; adaptable to fuzzy and interval systems	No regret minimization; prone to rank reversal; normalization-sensitive; may distort sensitive data	Engineering optimization, software selection, transportation planning, financial analysis, supplier evaluation
COPRAS	Simultaneous handling of beneficial and non-beneficial criteria; direct utility degree estimation; computational efficiency; easy interpretability and implementation	Limited capability in modeling uncertainty and complex interdependencies; less effective in highly dynamic decision environments; moderate sensitivity to weight variations	Supply chain management, logistics optimization, contractor selection, operational management, sustainable procurement systems

Table 5
Continued

	Major advantages	Major limitations	Suitable application areas
MOORA	Ratio-based normalization provides stable rankings; computational simplicity; low sensitivity to weight variations; highly scalable for large datasets; strong ranking consistency	Limited capability in handling uncertainty and qualitative ambiguity; relatively simple structure may not fully capture complex decision interactions	Manufacturing optimization, industrial engineering, material selection, large-scale evaluations, process optimization
MULTI MOORA	Extremely robust due to integration of multiple evaluation perspectives; very high ranking stability; low susceptibility to rank reversal; strong performance under uncertainty and complex environments	Higher computational complexity compared to simpler methods; implementation may require greater methodological understanding; increased computational burden for large real-time systems	Intelligent systems, Industry 4.0, sustainability assessment, smart infrastructure evaluation, strategic management, environmental systems
MOOSR A	Very low computational complexity; fast and efficient ranking capability; stable ratio-based structure; suitable for real-time and large-scale decision systems	Simpler mathematical structure may limit representation of highly complex interdependencies; limited advanced uncertainty modeling capability	Real-time industrial applications, transportation systems, rapid decision analytics, operational management

6. Sensitivity and Robustness Analysis

Sensitivity and robustness analysis are essential for evaluating the reliability of MCDM decisions under variations in input data, criteria weights, stakeholder preferences, and uncertainty [91,92]. Sensitivity analysis examines the impact of parameter changes on rankings, while robustness analysis evaluates ranking stability across different scenarios. Since compromise ranking methods rely on subjective evaluations and conflicting criteria, small changes in weights or normalization can significantly affect results. Table 6 compares the sensitivity and robustness of major compromise ranking methods under variations in weights, normalization, and ranking perturbations [98,99].

The methods differ in sensitivity due to their mathematical structures. VIKOR is highly sensitive because its compromise index depends on utility, regret, and the compromise parameter, making rankings susceptible to weight and parameter changes [99,100]. TOPSIS shows moderate sensitivity, with ranking reversals possible when alternatives have similar closeness coefficients or normalization changes [99-101]. COPRAS exhibits moderate stability, whereas MOORA and MOOSRA are generally more stable due to their ratio-based normalization and proportional aggregation [102]. MULTIMOORA provides the greatest robustness by combining ratio analysis, reference point evaluation, and multiplicative optimization, reducing rank reversals and improving ranking consistency. Table 6 also highlights normalization dependency and rank reversal risk, with TOPSIS being particularly sensitive to normalization methods [80,82].

Table 6
Sensitivity and robustness comparison of major compromise ranking methods

Method	Weight sensitivity	Normalization sensitivity	Ranking stability	Rank reversal risk	Robustness level
VIKOR	High due to strong dependence on criteria weights and compromise parameter	Moderate to high	Moderate	Moderate	Moderate
TOPSIS	Moderate	Very high because of vector normalization dependency	Moderate	Relatively high	Moderate

Table 6
Continued

Weight sensitivity	Normalization sensitivity	Ranking stability	Rank reversal risk	Robustness level	Weight sensitivity
COPRAS	Moderate	Moderate	High	Low	High
MOORA	Low	Low	High	Low	High
MULTIMOORA	Very low	Moderate	Very high	Very low	Very high
MOOSRA	Low	Low	High	Low	High
Fuzzy VIKOR	Moderate	Moderate	High	Low	High
Fuzzy TOPSIS	Moderate	High	Moderate	Moderate	Moderate to high
Entropy–MOORA	Very Low due to objective weighting	Low	Very high	Very low	Very high
AI–MULTIMOORA	Very Low because of adaptive learning capability	Low	Extremely high	Negligible	Extremely high
Neutrosophic COPRAS	Low	Moderate	High	Very low	Very high
Grey TOPSIS	Moderate	Moderate	Moderate	Moderate	Moderate
Hybrid DEMATEL–VIKOR	Moderate	Moderate	High	Low	High
Machine learning–TOPSIS	Very Low after training optimization	Low	Very high	Very low	Very high
Blockchain-assisted VIKOR	Moderate	Moderate	High	Low	High
Big data–MOORA	Low	Low	Very high	Very low	Very high

Normalization is a major source of sensitivity because MCDM criteria are measured in different units. Vector normalization, commonly used in TOPSIS, may distort highly dispersed datasets and increase rank reversal risk, whereas the ratio-based normalization of MOORA and MOOSRA better preserves proportional relationships [101,102]. COPRAS generally maintain stable proportional evaluations but may be affected by extreme values, while VIKOR remains sensitive to normalization and parameter changes. Overall, MULTIMOORA demonstrates the highest robustness, while MOORA and MOOSRA also show strong stability due to their simple computational structures. Recent studies have improved robustness by integrating fuzzy logic, grey theory, probabilistic models, artificial intelligence, and adaptive optimization into compromise ranking methods [100,102]. However, standardized robustness testing and benchmarking procedures remain limited. Overall, ranking reliability depends on weighting schemes, normalization methods, dataset characteristics, and methodological integration [103]. Figure 15 illustrates the effect of weight variation on ranking stability, while Figure 16 compares the stability of the major compromise ranking methods [101,102].

Fig. 15. Sensitivity analysis simulation under varying criteria weights

Fig. 16. Rank stability comparison under different normalization and uncertainty scenarios

7. Applications of Compromise Ranking Methods

Compromise ranking methods have become fundamental in MCDM because they effectively address conflicting criteria, uncertainty, and diverse decision-maker preferences [46]. Unlike traditional single-objective optimization, these methods identify balanced solutions that satisfy competing objectives while minimizing decision-maker dissatisfaction. Consequently, methods such as VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA have been widely adopted across science, engineering, industry, environmental management, and socio-economic applications [79-83,93,97,101]. Their ability to handle quantitative and qualitative criteria under deterministic fuzzy and hybrid settings has further expanded their applicability in complex decision-making scenarios [52,57]. Figure 17 summarizes the major application areas of compromise ranking methods.

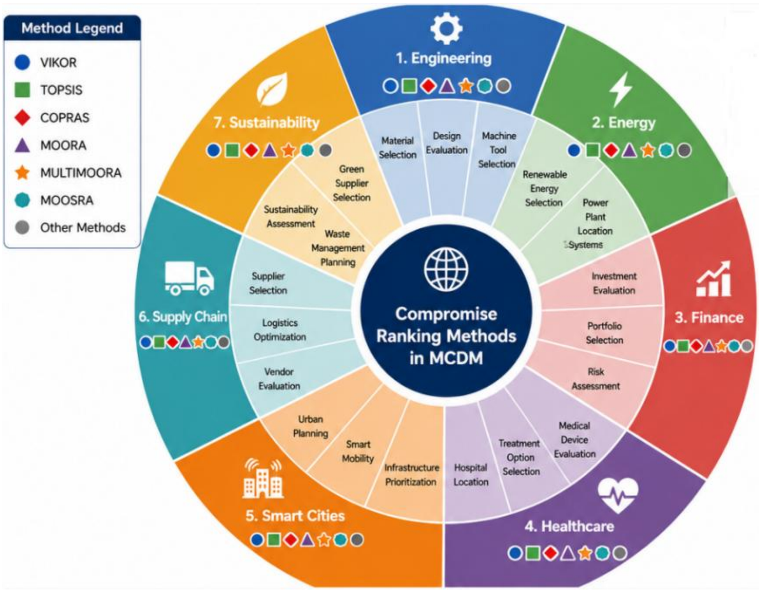


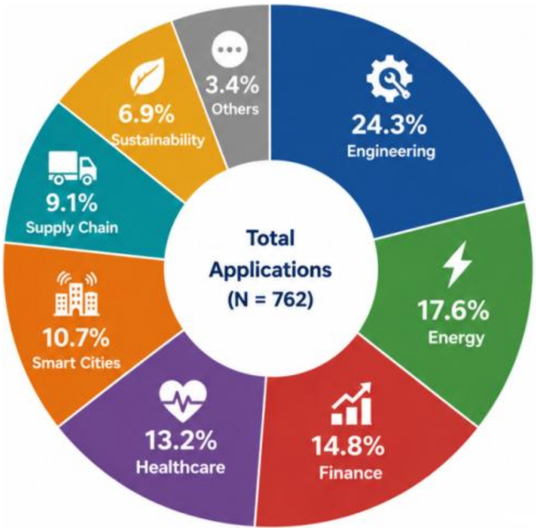
Fig. 17. Major application domains of compromise ranking methods in MCDM

The major application areas of compromise ranking methods are presented in Table 7, covering engineering, energy, healthcare, finance, transportation, supply chain management, sustainability, construction, smart cities, and information technology [33,37]. The table demonstrates the interdisciplinary applicability of these methods and links theoretical developments with practical decision-making by showing how method selection depends on decision complexity, uncertainty, computational requirements, and operational objectives. VIKOR is widely applied in sustainability assessment, healthcare prioritization, and policy analysis, whereas TOPSIS is extensively used in engineering and transportation [46,50,60]. Similarly, MOORA and MOOSRA are preferred for large-scale industrial optimization because of their computational efficiency, while MULTIMOORA is increasingly adopted for robust decision-making in intelligent systems and Industry 4.0 applications. Table 7 also highlights the capability of compromise ranking methods to evaluate diverse criteria, including cost, efficiency, sustainability, safety, reliability, environmental impact, risk, customer satisfaction, and strategic adaptability [94].

Over the past two decades, compromise ranking methods have been extensively applied to engineering optimization [94,99], manufacturing, renewable energy, finance, healthcare, transportation, sustainability assessment, supply chain management, construction, and environmental management. They are particularly effective for selection, prioritization, ranking, and resource allocation problems requiring fairness, ranking stability, and reliable decision support. VIKOR is well suited to negotiation and policy-oriented decisions because of its utility–regret framework [81,88,89], TOPSIS is valued for its simplicity, COPRAS for proportional utility assessment, MOORA and MOOSRA for computational efficiency in large-scale problems, and MULTIMOORA for robust decision-making under uncertainty [63,64]. Recent integration with fuzzy logic, artificial intelligence, machine learning, big data analytics, and real-time decision-support technologies has further enhanced the adaptability of compromise ranking methods for intelligent systems [43,46,48,51,59]. Figure 18 illustrates their distribution across different application sectors.

Table 7
Application domains of compromise ranking methods

Domain	Common decision problems	Frequently used methods	Major criteria considered
Engineering and manufacturing	Material selection, machining parameter optimization, industrial robot selection, additive manufacturing evaluation	TOPSIS, MOORA, VIKOR, MULTIMOORA	Cost, strength, hardness, efficiency, productivity, sustainability, surface quality, energy consumption
Energy and sustainability	Renewable energy source selection, energy planning, smart grid optimization, carbon-neutral system evaluation	VIKOR, TOPSIS, MULTIMOORA, COPRAS	Environmental impact, energy efficiency, economic feasibility, carbon emissions, sustainability
Finance and investment	Portfolio optimization, financial risk assessment, banking performance evaluation, sustainable investment analysis	TOPSIS, VIKOR, COPRAS, fuzzy compromise models	Risk, return, volatility, liquidity, profitability, sustainability, market stability
Healthcare and medical systems	Hospital performance assessment, medical equipment selection, healthcare waste management	VIKOR, TOPSIS, fuzzy VIKOR, neutrosophic TOPSIS	Patient safety, treatment quality, operational efficiency, cost, accessibility, risk, sustainability
Supply chain and logistics	Supplier selection, logistics provider evaluation, warehouse location selection, transportation optimization	COPRAS, TOPSIS, MOORA, VIKOR	Cost, delivery reliability, sustainability, quality, responsiveness, operational efficiency
Smart cities and urban planning	Smart city evaluation, infrastructure prioritization, urban resilience assessment, waste management system selection	VIKOR, MULTIMOORA, TOPSIS, fuzzy compromise systems	Sustainability, resilience, infrastructure quality, energy efficiency, technological capability
Transportation and mobility	Electric vehicle evaluation, public transportation optimization, intelligent transportation systems, traffic management	TOPSIS, VIKOR, MOORA, MULTIMOORA	Fuel efficiency, environmental impact, safety, mobility efficiency, infrastructure utilization
Construction and infrastructure	Sustainable building material selection, contractor selection, project prioritization, infrastructure risk assessment	TOPSIS, VIKOR, COPRAS, MULTIMOORA	Durability, lifecycle cost, environmental impact, safety, project efficiency, resilience
Environmental and sustainability management	Environmental impact assessment, waste disposal technology selection, water resource management, climate strategy prioritization	VIKOR, MULTIMOORA, fuzzy TOPSIS, COPRAS	Ecological impact, sustainability, resource efficiency, climate resilience, pollution reduction
Information technology and digital systems	Cloud service selection, cybersecurity risk evaluation, IoT platform prioritization, AI system evaluation, software selection	TOPSIS, VIKOR, fuzzy compromise models, AI-assisted MCDM systems	Scalability, security, reliability, computational efficiency, interoperability, adaptability
Industry 4.0 and intelligent systems	Smart manufacturing evaluation, cyber-physical system assessment, predictive maintenance prioritization	MULTIMOORA, AI-integrated TOPSIS, fuzzy VIKOR, hybrid intelligent compromise models	Automation capability, interoperability, real-time adaptability, cybersecurity
Environmental governance and policy-making	Sustainability policy prioritization, climate governance, renewable energy evaluation	VIKOR, fuzzy VIKOR, MULTIMOORA	Social impact, policy feasibility, environmental performance, stakeholder satisfaction



Sector	Percentage	No. of Applications (Approx.)
Engineering	24.3%	185
Energy	17.6%	134
Finance	14.8%	113
Healthcare	13.2%	101
Smart Cities	10.7%	82
Supply Chain	9.1%	69
Sustainability	6.9%	53
Others*	3.4%	25
Total	100%	762

Fig. 18. Sector-wise distribution of compromise ranking method applications

7.1 Engineering and Manufacturing Applications

Engineering and manufacturing are among the earliest and most important application areas of compromise ranking methods because industrial decision-making involves conflicting technical, economic, operational, environmental, and sustainability criteria [24,25]. Traditional single-objective optimization is often inadequate for balancing performance, cost, energy efficiency, reliability, productivity, safety, and environmental concerns. Consequently, compromise ranking methods are widely used to obtain balanced solutions [29,31]. Material selection is one of their major applications, where criteria such as strength, hardness, corrosion resistance, machinability and cost must be simultaneously evaluated. Rai *et al.,* [104] demonstrated the effectiveness of VIKOR for engineering material selection, while Chakraborty *et al.,* [105] showed that MOORA provides computational simplicity and stable rankings. Hybrid approaches, including VIKOR–PROMETHEE II–TOPSIS with entropy weighting [106], VIKOR–TOPSIS for magnetic material selection [107], fuzzy VIKOR for sustainable electric vehicle materials [108], and entropy-based MULTIMOORA for advanced materials [109], have further improved ranking reliability and uncertainty handling.

Compromise ranking methods are also extensively applied in machining parameter optimization for turning, milling, drilling, grinding, EDM, and other non-traditional machining processes, where productivity, surface quality, tool wear, energy consumption, cost, and dimensional accuracy must be balanced. TOPSIS and VIKOR are frequently integrated with Taguchi methods, response surface methodology, grey relational analysis, and fuzzy systems, while intuitionistic fuzzy VIKOR has demonstrated improved parameter optimization under uncertainty [110]. MOORA and MOOSRA are also widely adopted because of their computational efficiency and ranking stability [106,107]. Hybrid fuzzy VIKOR, fuzzy TOPSIS, and fuzzy MULTIMOORA combined with metaheuristic optimization have further enhanced performance in uncertain manufacturing environments.

Industrial robot selection, manufacturing process optimization, and sustainable manufacturing are additional major application areas. Interval type-2 fuzzy VIKOR has been successfully applied to robot selection under uncertain expert judgments [111], while grey-MULTIMOORA improves ranking robustness in industrial environments [112]. Compromise ranking methods have also been integrated with lean manufacturing, Industry 4.0, digital manufacturing, intelligent production systems, facility layout planning, quality management, maintenance strategies, and green manufacturing. Fuzzy VIKOR, fuzzy TOPSIS, and hybrid MULTIMOORA are widely used for cleaner production, renewable manufacturing, and circular economy assessment. More recently, additive manufacturing applications have employed hybrid TOPSIS, VIKOR, and MULTIMOORA for technology selection and process optimization under uncertainty [110,111].

Recent research increasingly integrates compromise ranking methods with artificial intelligence, machine learning, digital twins, predictive maintenance, and smart manufacturing to improve real-time decision support and ranking robustness [104-107]. Nevertheless, important challenges remain, including reliance on deterministic datasets, limited development of adaptive real-time frameworks, inconsistent normalization and weighting procedures, and insufficient consideration of criteria interdependencies and nonlinear manufacturing relationships [110,111]. Overall, the literature confirms that compromise ranking methods are effective tools for engineering and manufacturing because they balance conflicting objectives while maintaining computational efficiency and practical applicability across material selection, machining optimization, robotics, sustainable manufacturing, additive manufacturing, and intelligent industrial systems [107,112].

7.2 Energy and Sustainability Applications

Energy and sustainability management have become major application areas of compromise ranking methods because traditional optimization techniques often fail to balance efficiency, reliability, cost, environmental impact, energy security, policy compliance, and long-term sustainability [102,103]. Consequently, methods such as VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA are widely used for sustainable energy decision-making [104,105]. Renewable energy source selection is one of the most extensively studied applications, requiring simultaneous evaluation of technical, economic, environmental, and socio-economic criteria. Salih *et al.,* [113] demonstrated the effectiveness of fuzzy VIKOR for renewable energy planning, while Rivero-Iglesias *et al.,* [114] applied VIKOR for renewable energy project selection. Hybrid approaches integrating fuzzy systems, entropy weighting, grey theory, and AI have further improved uncertainty handling, with fuzzy TOPSIS–VIKOR [115] and MULTIMOORA [116] providing reliable and stable rankings for energy sustainability assessment.

Compromise ranking methods are also widely applied in sustainable energy planning, where environmental, economic, technological, and policy objectives must be balanced. Wang and Zhou [117] highlighted their effectiveness in national energy planning, while fuzzy and interval-based models have improved decision-making under uncertain future demand and policy conditions. Green technology evaluation is another important application, involving assessment of environmental performance, technological maturity, life-cycle sustainability, and regulatory compliance, which are further needed for the evaluation of climate change and sustainability. Fuzzy TOPSIS, VIKOR, and COPRAS have been extensively used for green manufacturing, sustainable transportation, waste-to-energy systems, and eco-efficient industries, with Büyüközkan and Çifçi [118] demonstrating the suitability of fuzzy TOPSIS for green supplier evaluation. VIKOR and MULTIMOORA have also been applied to carbon capture technologies, hydrogen systems, and low-carbon industrial processes, while hybrid fuzzy-MULTIMOORA models support long-term carbon-neutral planning [114,115].

Energy policy evaluation, smart grids, and intelligent energy management systems represent additional application areas. Compromise ranking methods support strategic energy policy by balancing socio-economic, environmental, technological, and geopolitical objectives [119]. Hybrid fuzzy VIKOR, interval TOPSIS, and grey COPRAS have been integrated with policy simulation models [114], while TOPSIS, VIKOR, and machine learning have been applied to smart grid optimization, load forecasting, renewable integration, and resilience assessment [116]. Fuzzy, interval-valued, and neutrosophic compromise models are increasingly used to address uncertainty in environmental risk, policy stability, and social acceptance, and have also been extended to sustainable infrastructure, circular economy, waste management, green buildings, and water-energy nexus applications [118].

The emergence of Industry 4.0 and digital energy systems has accelerated the integration of compromise ranking methods with artificial intelligence, machine learning, deep learning, IoT, cloud computing, and big data analytics to improve adaptive weighting, predictive capability, and real-time decision support [114,119]. Nevertheless, important challenges remain, including limited treatment of uncertainty propagation, criteria interdependency, long-term sustainability forecasting, inconsistent normalization procedures, and inadequate consideration of socio-political and behavioural factors [113-117]. Although fuzzy and hybrid intelligent models improve uncertainty handling, they often increase computational complexity and reduce real-time applicability. Overall, compromise ranking methods have become essential tools for renewable energy selection, sustainable energy planning, green technology evaluation, smart grid optimization, and carbon-neutral system assessment by balancing environmental, economic, technical, and social objectives with transparency and robustness [113,116,117,119]. Future research should focus on adaptive, scalable, interpretable, and AI-integrated compromise ranking frameworks for intelligent real-time sustainability management.

7.3 Finance and Investment Applications

Finance and investment represent one of the most important application areas of compromise ranking methods because financial decisions involve uncertainty, volatility, and conflicting objectives such as profitability, risk, liquidity, sustainability, and long-term growth [109]. Traditional single-objective optimization is often inadequate, leading to the widespread use of VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA for investment evaluation and prioritization [103,117]. Portfolio optimization is among the most studied applications, where return, risk, diversification, liquidity, and market uncertainty must be balanced. Fuzzy TOPSIS has been successfully applied to portfolio evaluation [120], while multicriteria compromise approaches have produced more balanced portfolio decisions than conventional quantitative methods [121]. VIKOR has gained particular attention because its utility–regret framework effectively balances conflicting investment objectives, and fuzzy, interval, and hybrid models integrating entropy weighting, grey systems, neural networks, and evolutionary algorithms have further improved portfolio robustness under uncertainty [121,122].

Stock selection is another major application, requiring simultaneous evaluation of profitability, earnings growth, liquidity, volatility, dividends, and macroeconomic indicators. TOPSIS has been widely used for stock ranking based on financial ratios [123], while hybrid fuzzy TOPSIS and machine learning models have enhanced investment decisions in volatile markets. MOORA and MULTIMOORA have also demonstrated stable and computationally efficient performance for large financial datasets, with MULTIMOORA improving ranking robustness under changing economic conditions [124]. Compromise ranking methods have also been extensively applied to financial risk assessment, including credit risk, bankruptcy prediction, banking risk prioritization, and insurance evaluation, where fuzzy VIKOR, COPRAS, and hybrid TOPSIS effectively combine quantitative and qualitative indicators [123-125]. Similarly, TOPSIS, VIKOR, COPRAS, MULTIMOORA, and MOOSRA have been widely adopted for banking performance evaluation because of their computational efficiency and ranking stability [126].

Emerging applications include cryptocurrency investment and sustainable finance. Fuzzy TOPSIS, VIKOR, and hybrid intelligent MCDM models have been applied to cryptocurrency evaluation by considering market capitalization, blockchain security, scalability, liquidity, transaction speed, energy consumption, and decentralization [125,126]. Machine learning, sentiment analysis, and neural networks have further improved cryptocurrency portfolio optimization. Compromise ranking methods have also become increasingly important for ESG investment, green finance, and socially responsible investment by balancing financial performance with environmental, social, and governance objectives [121,123-125].

Recent research increasingly integrates compromise ranking methods with artificial intelligence, deep learning, machine learning, and intelligent financial analytics for stock prediction, fraud detection, portfolio rebalancing, algorithmic trading, and decision-support systems [121,126]. Despite these advances, important challenges remain, including reliance on historical and deterministic data, limited consideration of behavioural finance, investor psychology, geopolitical uncertainty, and macroeconomic interdependencies, as well as sensitivity to weighting and normalization procedures [124,125]. Many advanced hybrid models also face issues of interpretability, scalability, uncertainty modelling, and real-time adaptability. Overall, compromise ranking methods have become indispensable tools for portfolio optimization, stock selection, banking evaluation, financial risk assessment, cryptocurrency prioritization, and ESG investment analysis [120,123-126]. Future research should emphasize adaptive, transparent, interpretable, and AI-integrated compromise ranking frameworks for intelligent and real-time financial decision-making.

7.4 Supply Chain and Logistics Applications

One of the major application areas of compromise ranking methods in MCDM is supply chain and logistics management. Modern supply chains operate under dynamic and uncertain conditions driven by globalization, sustainability pressures, technological transformation, and evolving customer expectations [74,88]. Decision makers must simultaneously consider conflicting criteria such as cost, quality, delivery, flexibility, environmental impact, supplier performance, risk, and customer satisfaction [93,98]. Consequently, compromise ranking methods including VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA have become widely adopted for supply chain decision-making. Supplier selection is one of the earliest and most important applications, where both quantitative and qualitative criteria such as cost, quality, delivery performance, technological capability, flexibility, environmental compliance, and long-term partnership potential are evaluated [107,121,124]. Modibbo *et al.,* [127] demonstrated that fuzzy TOPSIS effectively handles uncertainty in supplier evaluation, while Alimardani *et al.,* [128] showed the suitability of VIKOR for procurement problems involving conflicting stakeholder objectives. Later studies integrated fuzzy VIKOR, interval VIKOR, and entropy-based weighting to improve supplier evaluation under uncertainty.

The increasing emphasis on sustainability has further expanded the application of compromise ranking methods in green supply chain management. Fuzzy TOPSIS, fuzzy VIKOR, and COPRAS have been widely applied to green supplier selection and sustainable procurement [113]. Tozanli *et al.,* [129] demonstrated that hybrid fuzzy frameworks effectively balance environmental and operational objectives, while subsequent studies incorporated carbon footprint, life-cycle assessment, and circular economy indicators. Logistics provider evaluation has also become an important application involving delivery speed, technological capability, service quality, sustainability, reliability, flexibility, and transportation cost [128]. TOPSIS and MOORA are widely preferred because of their computational simplicity, whereas Singh *et al.,* [130] showed that fuzzy TOPSIS improves operational reliability and decision transparency. MULTIMOORA has also demonstrated strong performance when evaluating large logistics datasets.

Warehouse location selection and transportation optimization are other major application areas, as facility placement directly affects transportation efficiency, inventory management, responsiveness, and operational cost [130,131]. VIKOR, TOPSIS, and COPRAS have been widely applied to warehouse location analysis, while Erdin and Akbaş [131] integrated fuzzy TOPSIS with GIS for logistics facility selection under uncertain spatial conditions. MOORA, MULTIMOORA, and TOPSIS have also been extensively used for transportation mode selection, fleet management, route prioritization, and transportation optimization. Sustainable procurement has similarly attracted considerable attention, where economic performance must be balanced with sustainability, ethical sourcing, social responsibility, and supplier resilience. Unanoglu *et al.,* [132] demonstrated that hybrid fuzzy models significantly improve sustainable procurement decisions, while fuzzy, grey, interval, and probabilistic approaches further enhance uncertainty handling.

Recent research has focused on integrating compromise ranking methods with digital supply chain technologies, including IoT, blockchain, cloud logistics, big data analytics, and real-time monitoring [127,128]. AI-powered compromise ranking systems, machine learning-assisted TOPSIS, neural network-based VIKOR, and hybrid fuzzy-MULTIMOORA models have shown promising results for predictive logistics optimization, intelligent warehousing, procurement, and transportation planning. Despite these advances, important research gaps remain [130]. Many studies still rely on static datasets and deterministic assumptions, while criteria interdependencies, uncertainty propagation, and real-time adaptability remain insufficiently addressed. Ranking results also remain sensitive to weighting methods, normalization procedures, and sustainability indicators [129]. Furthermore, hybrid intelligent models often suffer from high computational complexity, limited scalability, and reduced interpretability in large-scale logistics systems.

Overall, the literature confirms the growing importance of compromise ranking methods as effective analytical tools for supply chain and logistics management [131]. They successfully balance conflicting economic, operational, environmental, and strategic objectives while maintaining computational efficiency, making them valuable for supplier selection, green supply chain management, logistics provider evaluation, warehouse location analysis, transportation optimization, and sustainable procurement [132]. Future research should emphasize AI integration, advanced uncertainty modelling, and real-time analytics to support intelligent and resilient supply chain decision-making.

7.5 Urban Planning and Smart City Applications

MCDM has become an important tool in urban planning and smart city development for solving complex decision-making problems involving multiple conflicting technical, economic, environmental, social, and governance criteria [41,56,57]. Consequently, compromise ranking methods such as VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA are widely adopted in urban planning and smart city evaluation. Smart city assessment requires balancing transportation efficiency, energy sustainability, environmental quality, governance, public safety, economic competitiveness, and technological innovation [72,112,123]. TOPSIS and VIKOR have been widely applied to smart city evaluation, while Ahvenniemi and Huovila [133] emphasized the importance of multidimensional sustainability assessment. Subsequent studies integrated fuzzy TOPSIS, entropy-VIKOR, and hybrid MULTIMOORA models to improve decision-making under uncertainty.

Urban sustainability assessment is another major application, where environmental protection, economic growth, energy efficiency, social equity, transportation accessibility, waste management, and public health must be evaluated simultaneously [133]. VIKOR and TOPSIS have been extensively applied for sustainability assessment, while Aykut-Senel *et al.,* [134] demonstrated that compromise-based MCDM enhances transparency and sustainability prioritization. COPRAS and MOORA have also been widely used for evaluating green urban projects, eco-city planning, and low-carbon development. Infrastructure prioritization has similarly benefited from VIKOR, TOPSIS, and COPRAS in balancing competing investment alternatives [133,134]. Shahab *et al.,* [135] further demonstrated that fuzzy TOPSIS effectively supports infrastructure management under uncertain urban conditions.

Transportation planning represents another important application, requiring simultaneous optimization of mobility, travel time, fuel consumption, cost, sustainability, accessibility, and traffic safety [133,134]. TOPSIS, MOORA, and MULTIMOORA have been extensively applied to transportation mode selection, traffic management, and sustainable mobility assessment. Te Boveldt *et al.,* [136] highlighted the effectiveness of compromise-based frameworks for urban transportation planning, while VIKOR has been integrated with GIS, IoT, machine learning, and real-time analytics to improve transportation systems. Waste management has also received considerable attention, where fuzzy TOPSIS, VIKOR, and COPRAS have been successfully applied to landfill selection, recycling technology prioritization, and waste-to-energy evaluation. Foroozesh *et al.,* [137] confirmed that fuzzy TOPSIS enhances the reliability of environmental decision-making under uncertainty.

Urban resilience has emerged as another rapidly growing application area because of climate change, infrastructure vulnerability, and socio-economic uncertainty. VIKOR, MULTIMOORA, and hybrid fuzzy models have been widely applied to resilience assessment and disaster preparedness. Fu and Wang [138] emphasized the importance of multidimensional resilience evaluation, while recent studies have integrated GIS, fuzzy logic, and intelligent analytics for flood risk management and climate resilience assessment [135,136]. To better represent uncertain and qualitative urban indicators, fuzzy TOPSIS, fuzzy VIKOR, grey COPRAS, interval MULTIMOORA, and neutrosophic models have become increasingly popular in smart city research [136,137].

Recent research has focused on integrating compromise ranking methods with IoT, sensor networks, cloud computing, AI, machine learning, and digital city management systems [135]. AI-assisted TOPSIS, deep learning-based VIKOR, and hybrid fuzzy-MULTIMOORA models have shown promising capabilities for intelligent urban governance and predictive planning [136]. Despite these advances, important challenges remain. Most studies still rely on static datasets and deterministic assumptions, while criteria interdependency, temporal urban evolution, behavioural dynamics, and real-time adaptability remain insufficiently addressed. Differences in weighting schemes, normalization methods, and sustainability indicators also reduce comparability between studies [137,138]. Furthermore, governance quality, cybersecurity resilience, computational scalability, interpretability, and real-time implementation continue to present significant research challenges.

Overall, the literature demonstrates that compromise ranking methods have become indispensable tools for urban planners and smart city management [133]. They are widely applied in smart city evaluation [135], urban sustainability assessment [136,137], infrastructure prioritization [136,137,138], transportation planning, waste management, and urban resilience because they effectively balance conflicting environmental, economic, technological, operational, and social objectives while maintaining robustness and computational efficiency [135-138]. Future research should focus on integrating AI, IoT, real-time analytics, and advanced uncertainty modelling to support intelligent, sustainable, and resilient urban decision-making.

7.6 Healthcare and Medical Applications

The field of healthcare and medical management is a major application area of MCDM, where compromise ranking methods support complex clinical, operational, technological, and public health decisions [131,132]. Healthcare decision-making involves conflicting criteria such as treatment quality, patient safety, accessibility, efficiency, cost, and sustainability, making single-objective optimization inadequate [128]. Consequently, methods including VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA are widely used. Healthcare system evaluation requires balancing service quality, patient outcomes, infrastructure, financial sustainability, technological readiness, and accessibility [111-115]. TOPSIS and VIKOR are widely applied because they provide compromise solutions in multidimensional healthcare environments. Özkurt [139] demonstrated that fuzzy compromise models improve healthcare evaluation under uncertainty, while VIKOR is particularly suitable for multi-stakeholder healthcare systems due to its consideration of both group utility and regret minimization.

Hospital performance assessment is another major application, requiring simultaneous evaluation of clinical effectiveness, patient satisfaction, resource utilization, operational efficiency, emergency response, and financial performance [134-138]. TOPSIS, COPRAS, and MULTIMOORA have been successfully applied in hospital benchmarking and healthcare prioritization. Durur and Akbulut [140] highlighted the value of multidimensional compromise frameworks, while fuzzy TOPSIS, fuzzy VIKOR, and MULTIMOORA improve healthcare quality assessment through robust and consistent rankings. Compromise ranking methods are also widely used for medical equipment and technology selection by considering diagnostic accuracy, reliability, patient safety, compatibility, life-cycle cost, and maintenance. Büyüközkan and Göçer [141] showed that hybrid fuzzy MCDM frameworks enhance healthcare technology assessment, leading to the integration of fuzzy logic, entropy weighting, and interval analysis into compromise ranking models.

Healthcare waste management is another important application requiring simultaneous consideration of environmental protection, public health, operational efficiency, treatment cost, regulatory compliance, and sustainability [140,141]. Fuzzy TOPSIS, fuzzy VIKOR, and fuzzy COPRAS have been widely applied to waste treatment technology selection and biomedical waste management, while [142] emphasized their ability to balance sustainability and operational objectives. GIS, fuzzy logic, and hybrid compromise models have further improved healthcare waste transportation and infectious waste assessment. Following the COVID-19 pandemic, compromise ranking methods gained prominence in healthcare resource allocation, vaccination planning, emergency response, and medical supply distribution under uncertainty [141,142]. Pamucar *et al.,* [143] demonstrated that fuzzy VIKOR and fuzzy TOPSIS significantly improve emergency healthcare prioritization, while AI and real-time analytics have accelerated disease monitoring, demand forecasting, triage, and hospital resource management.

Uncertainty modeling has become increasingly important because healthcare decisions involve incomplete information and subjective assessments [140]. Accordingly, fuzzy TOPSIS, fuzzy VIKOR, interval COPRAS, grey-MULTIMOORA, and neutrosophic models have gained widespread attention [142,143], providing more realistic evaluation of treatment effectiveness, patient satisfaction, healthcare quality, and disease severity [139]. Recent research also integrates compromise ranking methods with IoT, telemedicine, electronic health records, wearable sensors, and AI-based diagnostic systems [141]. These technologies generate large dynamic datasets, encouraging the development of machine learning-enhanced TOPSIS, deep learning-based VIKOR, and hybrid fuzzy-MULTIMOORA for predictive diagnosis, personalized medicine, healthcare analytics, and hospital resource optimization [142].

Despite significant progress, important research gaps remain. Many studies still rely on deterministic assumptions and small datasets, limiting applicability in real-time healthcare systems [139,140]. Challenges also include temporal uncertainty, patient heterogeneity, healthcare equity, ethical issues, clinical interdependencies, and the lack of standardized healthcare indicators. Intelligent healthcare applications further face cybersecurity, privacy, interpretability, scalability, and computational complexity issues [142,143]. Overall, compromise ranking methods have become essential tools for balancing conflicting clinical, operational, technological, environmental, and public health objectives under uncertainty, supporting healthcare system evaluation, hospital benchmarking, medical technology selection, waste management, and pandemic response [141]. Their importance is expected to grow with advances in AI, predictive analytics, digital healthcare, and intelligent uncertainty modeling.

7.7 Environmental and Sustainability Management Applications

Environmental and sustainable management is a major application area of MCDM, where decisions involve conflicting socio-economic, technical, environmental, and regulatory criteria [131,132,139]. Conventional optimization is often inadequate because environmental decisions must simultaneously balance ecological protection, economic feasibility, technological efficiency, and sustainability. Consequently, compromise ranking methods such as VIKOR [119,121], TOPSIS [127], COPRAS [119], MOORA [127], MULTIMOORA [127], and MOOSRA [119] are widely applied. Environmental impact assessment requires evaluating air and water pollution, biodiversity loss, greenhouse gas emissions, ecological risks, and socio-economic impacts, often conflicting with development objectives [116,129,141]. TOPSIS and VIKOR are widely used for sustainability assessment, while Digkoglou and Papathanasiou [144] showed that MCDM improves the transparency and reliability of environmental planning. Fuzzy TOPSIS, fuzzy VIKOR, GIS, and remote sensing have further enhanced ecological vulnerability analysis, environmental risk assessment, and sustainable land-use planning.

Waste management is another major application, requiring simultaneous evaluation of environmental impact, treatment efficiency, cost, energy recovery, technological maturity, and regulatory compliance [138]. TOPSIS, VIKOR, and COPRAS have been widely applied to landfill, recycling, waste-to-energy, and other waste treatment technologies [119]. Soltani *et al.,* [145] demonstrated the effectiveness of fuzzy TOPSIS under uncertainty, while MULTIMOORA and MOORA provide computational efficiency and stable rankings. Water resource management has also become an important application due to freshwater scarcity, climate change, and increasing demand [144,145]. VIKOR, TOPSIS, and MOORA have been widely used for watershed management, irrigation evaluation, groundwater sustainability, desalination technology selection, and integrated water planning. Ibrahim *et al.,* [146] emphasized the importance of compromise frameworks for sustainable water management, with GIS-integrated models improving spatial environmental planning.

Compromise ranking methods are increasingly applied to circular economy evaluation and climate adaptation planning. Circular economy assessment requires balancing lifecycle sustainability, carbon emissions, energy use, material recovery, production cost, and social factors [114,116]. TOPSIS, COPRAS, and MULTIMOORA have been widely used, while Ghisellini *et al.,* [147] highlighted the need for sustainability assessment frameworks. Fuzzy VIKOR and fuzzy TOPSIS effectively address uncertain sustainability indicators. Climate adaptation planning also requires balancing environmental resilience, infrastructure, economic feasibility, technological capability, and social equity [144,147]. VIKOR, MULTIMOORA, and hybrid fuzzy models have been increasingly applied to climate policy evaluation, with Kim and Chung [148] emphasizing multicriteria approaches. GIS integrated with climate models has further improved flood mitigation, coastal vulnerability assessment, and infrastructure resilience evaluation.

Uncertainty modeling is essential because environmental systems involve ambiguity, incomplete information, and long-term uncertainty [147]. Accordingly, fuzzy TOPSIS, fuzzy VIKOR, grey COPRAS, interval MULTIMOORA, and neutrosophic models have gained widespread use for evaluating ecological vulnerability, pollution, climate risk, and biodiversity. Recent research also integrates compromise ranking with IoT, satellite monitoring, remote sensing, cloud platforms, and AI-based environmental analytics to manage large dynamic datasets [144,145,148]. Machine learning-assisted TOPSIS, deep learning-based VIKOR, and hybrid fuzzy-MULTIMOORA are increasingly used for ecological risk prediction, climate vulnerability analysis, and intelligent environmental monitoring.

Despite significant progress, important challenges remain. Many studies rely on static datasets and deterministic assumptions, limiting their applicability to dynamic environmental systems [139,140]. Ecosystem interdependencies, long-term sustainability forecasting, uncertainty propagation, and standardized sustainability indicators remain insufficiently addressed. Existing frameworks also often overlook socio-political, ethical, and behavioral dimensions of sustainability [141]. Although hybrid intelligent models improve uncertainty handling and decision robustness, they still face challenges related to computational scalability, interpretability, and real-time implementation [143]. Future research should focus on developing adaptive, explainable, scalable, and computationally efficient compromise ranking systems for intelligent environmental governance and sustainable management.

The literature shows that compromise ranking methods are essential tools in environmental and sustainability management, enabling balanced evaluation of ecological, economic, technological, operational, and social objectives under uncertainty [146]. They are widely applied in environmental impact assessment, waste management, water resource management, circular economy evaluation, and climate adaptation planning [147,148]. Their role is expected to expand with the integration of AI, IoT-based monitoring, predictive sustainability analytics, and intelligent environmental management technologies.

7.8 Information Technology and Digital Systems Applications

Information technology and digital systems represent one of the fastest-growing application areas of MCDM, where compromise ranking methods support intelligent, data-driven decision-making in environments characterized by conflicting technical, economic, operational, security, and sustainability requirements [83,87]. Traditional optimization is often insufficient because digital systems must balance scalability, security, interoperability, reliability, computational cost, adaptability, and user satisfaction [71,79]. Consequently, VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA are widely used in IT applications [101,114,126]. Cloud service selection is a major application requiring evaluation of reliability, scalability, security, performance, cost, interoperability, and energy efficiency [138]. Garg *et al.,* [149] demonstrated the effectiveness of compromise ranking for cloud provider selection, while fuzzy TOPSIS, fuzzy VIKOR, hybrid entropy-TOPSIS, and interval VIKOR improve decision-making under uncertain service environments.

Cybersecurity risk assessment is another important application, requiring simultaneous evaluation of threat severity, vulnerability, operational impact, recovery capability, detection efficiency, implementation cost, and organizational resilience [122,113]. VIKOR, TOPSIS, and COPRAS are widely applied to cybersecurity prioritization, with Maček *et al.,* [150] emphasizing the importance of multicriteria compromise frameworks. Hybrid models integrating fuzzy logic and Bayesian systems have further improved intrusion detection and security strategy evaluation [118]. Similarly, the rapid growth of IoT has increased the use of TOPSIS, MOORA, and MULTIMOORA for evaluating connectivity, interoperability, scalability, latency, security, energy efficiency, and data processing capacity [149,150]. Lanfranchi *et al.,* [151] highlighted the importance of integrated decision-support frameworks for IoT planning, while fuzzy TOPSIS and fuzzy VIKOR effectively address uncertainty.

Compromise ranking methods are also increasingly applied to AI system evaluation and software selection. AI systems must balance predictive accuracy, computational efficiency, explainability, scalability, fairness, robustness, privacy, and implementation feasibility [149]. VIKOR, TOPSIS, and MULTIMOORA are widely used for AI algorithm prioritization and benchmarking, while Cortinas-Lorenzo *et al.,* [152] emphasized the importance of explainability and multidimensional evaluation. Hybrid frameworks combining neural networks, fuzzy logic, and evolutionary optimization further improve AI assessment [150]. In software selection, TOPSIS, COPRAS, and MOORA are widely used to evaluate functionality, compatibility, scalability, cost, user experience, cybersecurity, and vendor support [151,152]. Uzoka *et al.,* [153] showed that compromise ranking improves software acquisition decisions, while fuzzy TOPSIS and fuzzy COPRAS effectively address uncertain organizational requirements.

Uncertainty modeling has become increasingly important because digital systems involve technological uncertainty, evolving standards, cybersecurity risks, and incomplete information [140]. Accordingly, fuzzy TOPSIS, fuzzy VIKOR, interval MULTIMOORA, grey COPRAS, and neutrosophic models have gained widespread use for evaluating usability, interoperability, trustworthiness, cybersecurity resilience, and customer satisfaction [145,146]. Recent research also integrates compromise ranking with IoT, AI, blockchain, cloud computing, and real-time analytics to process large dynamic datasets [148]. Machine learning-enhanced TOPSIS, deep learning-based VIKOR, and hybrid fuzzy-MULTIMOORA have been developed for cloud optimization, AI benchmarking, cybersecurity management, and digital infrastructure prioritization.

With the growth of Industry 4.0, compromise ranking methods have become increasingly important in evaluating smart manufacturing, blockchain, edge computing, autonomous robotics, and cyber-physical systems [150,151]. Despite significant progress, several challenges remain. Most studies still rely on static datasets and deterministic assumptions, limiting applicability in dynamic digital environments [152]. Key issues such as technological interdependencies, real-time adaptability, algorithmic transparency, ethical AI governance, standardized benchmarking, cybersecurity resilience, data privacy, sustainability, and AI integration remain insufficiently addressed [153].

Similarly, hybrid intelligent compromise models have improved uncertainty handling and decision robustness, although challenges related to scalability, computational complexity, and real-time implementation remain [131,132]. Future research should focus on adaptive, explainable, scalable, and transparent compromise ranking systems for next-generation digital ecosystems. The literature also identifies compromise ranking methods as important tools in information technology and digital systems, with applications in cloud service selection [148-150], cybersecurity risk assessment [151], IoT platform prioritization [152,153], and software selection. Their ability to balance technical, operational, economic, security, and strategic criteria under uncertainty has driven their adoption, while continued advances in AI, big data analytics, explainable AI, and real-time digital governance are expected to further strengthen their role in future digital ecosystems [144].

7.9 Construction and Infrastructure Applications

Construction and infrastructure management is a major application area of compromise ranking methods in MCDM because construction projects involve conflicting technical, economic, environmental, operational, and sustainability criteria [149,150]. Increasing urbanization, climate resilience, resource constraints, and technological advances require balancing cost, quality, safety, sustainability, lifecycle performance, and operational efficiency. Consequently, VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA are widely used in construction decision-making

[152,153]. Sustainable building material selection is one of the most researched applications, requiring evaluation of durability, thermal performance, lifecycle cost, recyclability, fire resistance, maintenance, and environmental impact [114,115]. TOPSIS and VIKOR are widely applied for green material selection [121], while Ding [154] emphasized multicriteria sustainability assessment. Fuzzy TOPSIS, fuzzy VIKOR, hybrid entropy-VIKOR, and fuzzy COPRAS further improve decisions under uncertainty.

Construction project prioritization is another key application because projects involve high investment, long lifecycles, environmental impacts, and multiple stakeholders [153]. VIKOR, TOPSIS, and MULTIMOORA have been widely used to evaluate economic feasibility, technical complexity, sustainability, safety, completion time, and strategic importance. Pasi *et al.,* [155] demonstrated that compromise frameworks improve project prioritization, while hybrid fuzzy models and GIS have enhanced transportation, housing, and public infrastructure evaluation. Infrastructure risk assessment has also gained importance due to aging infrastructure, climate change, natural disasters, cyberattacks, and material degradation [154,155]. TOPSIS, VIKOR, and COPRAS are widely used for vulnerability analysis, with Al-Shihabi *et al.,* [156] highlighting their ability to balance safety, sustainability, and economic objectives. Hybrid fuzzy models, probabilistic risk analysis, and GIS have further improved seismic vulnerability assessment, bridge maintenance, and resilient infrastructure planning.

Contractor selection is another important application involving technical capability, financial strength, experience, safety, sustainability, and reputation [149]. TOPSIS, VIKOR, and MOORA are widely applied to contractor evaluation, while Atoum *et al.,* [157] showed that compromise-oriented methods improve procurement transparency. Fuzzy TOPSIS, fuzzy VIKOR, MULTIMOORA, and MOOSRA effectively address subjective evaluations. Smart infrastructure evaluation has also emerged as a rapidly growing application with the development of smart cities, IoT-enabled construction, intelligent transportation, and cyber-physical systems [151,152]. VIKOR, TOPSIS, and MULTIMOORA are increasingly used for smart buildings [153], digital infrastructure [154], intelligent transportation [155], and autonomous construction technologies [156]. Castelnovo *et al.,* [158] emphasized integrated assessment frameworks, while BIM, IoT, AI, and hybrid compromise models support smart infrastructure optimization and predictive maintenance.

Because construction projects involve uncertainty in delays, costs, labor productivity, environmental conditions, and operational risks [155], fuzzy TOPSIS, fuzzy VIKOR, grey COPRAS, interval MULTIMOORA, and neutrosophic models have become widely used. These approaches better represent project complexity, contractor reliability, structural risk, sustainability, and stakeholder satisfaction [151]. Recent research also integrates compromise ranking with BIM, IoT, cloud platforms, autonomous equipment, drones, and AI-driven analytics to develop predictive maintenance, smart procurement, autonomous monitoring, and real-time project optimization systems [154,156].

Despite considerable progress, important research gaps remain. Most studies rely on static data and deterministic assumptions, limiting applicability in dynamic construction environments [157,158]. Real-time adaptability, lifecycle uncertainty, infrastructure interdependencies, stakeholder conflicts, standardized sustainability indicators, cybersecurity, climate resilience, and ethical issues remain insufficiently addressed [155,156]. Although hybrid intelligent models improve robustness and uncertainty handling, challenges related to computational scalability, explainability, and real-time implementation persist. Overall, compromise ranking methods have become essential tools for sustainable material selection, project prioritization, infrastructure risk assessment, contractor evaluation, and smart infrastructure planning [130,141,150,151]. Their role is expected to expand with further integration of AI, BIM, IoT, predictive analytics, and uncertainty modeling for resilient and sustainable infrastructure systems.

7.10 Transportation and Mobility Applications

Transportation and mobility management have become major application areas of compromise ranking methods in MCDM because transportation systems involve conflicting objectives such as operational efficiency, sustainability, passenger comfort, safety, energy use, and infrastructure resilience [111,117,123]. Consequently, VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA are widely applied. Electric vehicle (EV) evaluation is one of the most studied applications, requiring assessment of battery performance, driving range, charging infrastructure, energy efficiency, lifecycle cost, environmental impact, reliability, and consumer acceptance [136,146,151,157]. TOPSIS and VIKOR are widely used for EV prioritization, while Rocha *et al.,* [159] emphasized multicriteria sustainability assessment. Fuzzy TOPSIS, fuzzy VIKOR, hybrid entropy-VIKOR, and interval TOPSIS further improve evaluation under technological uncertainty.

Public transportation optimization is another important application, requiring simultaneous consideration of service quality, coverage, operational efficiency, passenger comfort, travel time, safety, environmental impact, and cost [158]. TOPSIS, VIKOR, and MULTIMOORA are widely used for evaluating metro systems, bus rapid transit, railways, and multimodal transportation. Martinez *et al.,* [160] highlighted the role of compromise frameworks in sustainable transportation planning, while GIS, fuzzy logic, and hybrid models improve urban mobility policy and transit infrastructure planning. The growth of intelligent transportation systems (ITS) has further expanded the use of compromise ranking methods for evaluating IoT-enabled infrastructure, autonomous vehicles, and smart mobility. Wanke *et al.,* [161] verified that compromise-oriented frameworks effectively support smart decisions, while big data and fuzzy logic improve intelligent transport assessment.

Sustainable mobility assessment has also become an important application because transport planning must balance energy efficiency, greenhouse gas emissions, accessibility, affordability, reliability, environmental sustainability, and social equity [151,159]. TOPSIS, MOORA, and MULTIMOORA are increasingly applied to low-carbon transportation planning, while Le *et al.,* [162] emphasized their ability to reconcile environmental, economic, and social objectives. Traffic management is another emerging application involving congestion control, traffic signal optimization, emergency routing, and intelligent mobility coordination [161,162]. TOPSIS, VIKOR, and MOORA have been widely applied, with Saeidi *et al.,* [163] highlighting the importance of multicriteria frameworks. GIS, IoT sensors, real-time traffic systems, and AI analytics further improve transportation adaptability and resilience.

Because transportation systems involve uncertainty related to traffic, weather, passenger demand, infrastructure disruptions, accidents, and technological change [161], fuzzy TOPSIS, fuzzy VIKOR, interval MULTIMOORA, grey COPRAS, and neutrosophic models have become widely used. These methods better represent uncertainty in passenger satisfaction, traffic severity, mobility reliability, and operational resilience [149,160]. Recent research also integrates compromise ranking with IoT, autonomous vehicles, cloud analytics, AI-based traffic management, and digital twins. Machine learning-based TOPSIS [159], deep learning-based VIKOR [160], and hybrid fuzzy-MULTIMOORA [161-163] have been developed for traffic prediction, autonomous mobility management, EV infrastructure optimization, and real-time mobility prioritization.

Despite significant progress, important challenges remain. Many studies still rely on static datasets and deterministic assumptions, limiting their applicability to dynamic transportation systems [162]. Passenger behavioral uncertainty, transportation interdependencies, autonomous mobility ethics, real-time adaptability, standardized sustainability indicators, cybersecurity, privacy, AI ethics, and climate considerations remain insufficiently addressed [163]. Although hybrid intelligent models improve robustness and uncertainty handling, issues of scalability, explainability, and real-time implementation persist. Overall, compromise ranking methods have become essential tools for EV evaluation, public transportation optimization, intelligent transportation systems, sustainable mobility assessment, and traffic management [159-163], and their role is expected to expand with advances in AI, autonomous mobility, IoT, predictive analytics, and intelligent uncertainty modeling.

7.11 Emerging Hybrid Intelligent Applications

Recent advances in intelligent computing have transformed MCDM by enabling hybrid compromise ranking frameworks that integrate AI, machine learning, fuzzy systems, neutrosophic logic, big data analytics, and Industry 4.0 technologies with methods such as VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA [158,160,163,164]. While classical compromise methods effectively solve structured MCDM problems, modern decision environments characterized by uncertainty, nonlinear interactions, dynamic data, and automation require more adaptive decision-support systems. AI-powered compromise models improve predictive accuracy, adaptability, and dynamic weighting by learning from historical data and identifying complex criterion interactions [151,154-157,165]. Figure 19 illustrates the integration of intelligent computational paradigms with compromise ranking methods.

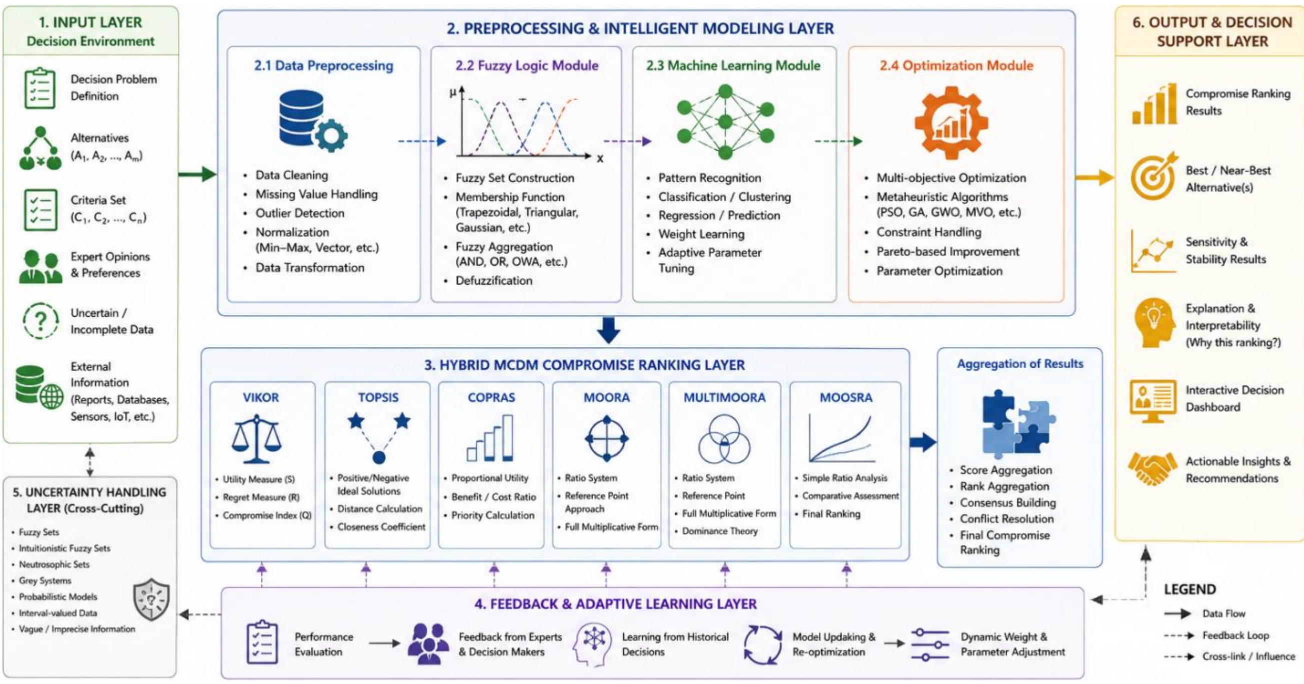


Fig. 19. Hybrid intelligent architecture integrating AI, fuzzy systems, and compromise ranking methods

AI-assisted compromise ranking has been successfully applied in manufacturing, healthcare, transportation, finance, and smart infrastructure [166,167]. Najafzadeh and Yeganeh [168] demonstrated that AI-powered compromise frameworks outperform deterministic methods in predictive accuracy, automation, and real-time adaptability. Fuzzy compromise ranking methods, including fuzzy TOPSIS, fuzzy VIKOR, and fuzzy MULTIMOORA, effectively address ambiguous, incomplete, and linguistic information in applications such as healthcare, energy, sustainability, transportation, and manufacturing [162]. Attaallah *et al.,* [169] showed that fuzzy frameworks provide more reliable decisions under uncertainty, while interval-valued, intuitionistic, Pythagorean, and type-2 fuzzy extensions further improve uncertainty representation.

Neutrosophic compromise ranking has emerged as another important research direction by simultaneously modeling truth, falsity, and indeterminacy, improving decision-making under inconsistent information. Neutrosophic TOPSIS, VIKOR, and MULTIMOORA have been increasingly applied in healthcare, supplier selection, sustainability, and risk assessment [164,165]. Moreno *et al.,* [170] introduced neutrosophic theory as a comprehensive uncertainty modeling framework. Meanwhile, the growth of IoT, cloud computing, industrial sensors, healthcare systems, and intelligent transportation has accelerated big data-assisted compromise ranking [168,169]. Alosaimi *et al.,* [171] emphasized the need for adaptive multicriteria frameworks capable of processing large-scale data, with big data-assisted TOPSIS and cloud-based VIKOR demonstrating effectiveness in smart cities, healthcare, finance, industrial automation, and sustainability monitoring.

Industry 4.0 technologies, including cyber-physical systems, IoT, digital twins, blockchain, cloud computing, and AI, have further advanced hybrid compromise ranking systems for smart factories, predictive maintenance, digital supply chains, and cyber-physical infrastructure [170]. Almeida *et al.,* [172] highlighted the need for integrated intelligent multicriteria frameworks for digital industrial transformation. Recent research also integrates explainable AI (XAI), blockchain, and digital twins with compromise ranking methods to improve transparency, security, and real-time adaptive decision-making across healthcare, finance, cybersecurity, and supply chains [170-172].

Despite substantial progress, important challenges remain. Many hybrid frameworks are computationally intensive, difficult to scale, and lack interpretability because AI-assisted models often function as black boxes [167]. Standardization of uncertainty modeling, fuzzy membership construction, neutrosophic parameters, hybrid weighting methods, and issues related to ethics, privacy, and cybersecurity also remain unresolved [169-172]. Future research should focus on adaptive, explainable, scalable, secure, and computationally efficient compromise ranking systems for real-time decision-making in uncertain, data-rich environments. Hybrid intelligent approaches integrating AI, fuzzy logic, big data, blockchain, digital twins, and Industry 4.0 technologies represent one of the most promising directions for compromise-oriented MCDM [170,171].

Table 8 summarizes recent hybrid compromise ranking algorithms by combining fuzzy logic, ANP, DEMATEL, entropy weighting, machine learning, AI, neutrosophic systems, grey theory, and big data analytics with classical methods such as VIKOR, TOPSIS, COPRAS, MOORA, and MULTIMOORA to improve uncertainty handling, adaptability, predictive capability, and robustness [170]. It illustrates the evolution from deterministic methods to intelligent decision-support systems capable of handling dynamic datasets, interdependent criteria, uncertainty propagation, and large-scale applications [165,166]. Table 8 also highlights the strengths and limitations of each hybrid framework, showing that although hybridization improves analytical capability, computational complexity, scalability, explainability, and real-time implementation remain major research challenges [159,168,170,172].

Table 8
Hybrid and advanced compromise ranking models

Hybrid framework	Integrated techniques	Objective	Advantages	Limitation
Fuzzy VIKOR	VIKOR + Fuzzy logic	Handle vagueness and uncertainty in compromise-oriented decision environments	Improved uncertainty representation; effective for linguistic evaluations and stakeholder ambiguity	Fuzzy membership calibration complexity; computational burden increases with large datasets

Table 8
Continued

Objective	Advantages	Limitation	Objective	Advantages
ANP–VIKOR	ANP + VIKOR	Incorporate interdependent criteria relationships into compromise ranking	Captures complex interrelationships among criteria; improves strategic decision accuracy	High computational complexity and dependence on expert consistency
DEMATEL–TOPSIS	DEMATEL + TOPSIS	Analyze causal relationships before compromise ranking	Strong capability for influence structure analysis and conflict identification	Requires extensive expert input and complex matrix computations
Entropy–MOORA	Entropy weighting + MOORA	Reduce subjectivity in weight assignment using objective information entropy	Enhances objectivity and ranking stability; computationally efficient	Sensitive to data quality and normalization inconsistencies
AI–MULTIMOORA	Artificial intelligence + MULTIMOORA	Develop adaptive intelligent compromise ranking systems	High robustness; predictive analytics capability; suitable for Industry 4.0 and big data	Limited explainability and increased computational resource requirements
Neutrosophic COPRAS	Neutrosophic logic + COPRAS	Handle indeterminacy and incomplete information in compromise decisions	Superior uncertainty handling under inconsistent and incomplete datasets	Parameter estimation complexity and limited standardized implementation procedures
Grey TOPSIS	Grey system theory + TOPSIS	Improve ranking under incomplete and partially known information	Suitable for uncertain and data-deficient environments	Grey relational interpretation may be sensitive to parameter selection
Fuzzy MULTIMOORA	Fuzzy logic + MULTIMOORA	Enhance robustness under uncertain multi-perspective decision environments	Strong ranking stability and uncertainty handling capability	Increased computational complexity and fuzzy parameter dependency
Machine learning–TOPSIS	Machine learning algorithms + TOPSIS	Enable predictive and adaptive decision-support systems	Real-time learning capability; improved predictive performance	Black-box behavior and limited interpretability
Blockchain-assisted VIKOR	Blockchain technology + VIKOR	Develop secure and transparent compromise decision-support systems	Enhanced transparency, traceability, and decentralized decision governance	Scalability and implementation cost challenges
Big data–MOORA	Big data analytics + MOORA	Process large-scale dynamic datasets for rapid compromise ranking	High scalability and computational efficiency in large data environments	Requires advanced computational infrastructure
Digital twin–MULTIMOORA	Digital twin systems + MULTIMOORA	Real-time monitoring and adaptive infrastructure decision-making	Dynamic simulation capability and real-time operational optimization	Data synchronization and real-time computational challenges
Fuzzy DEMATEL–VIKOR	Fuzzy DEMATEL + VIKOR	Combine causal analysis with uncertainty-based compromise ranking	Strong conflict resolution and uncertainty representation capability	Complex implementation and extensive expert dependency
Neural network–TOPSIS	Neural networks + TOPSIS	Intelligent ranking prediction and automated decision support	Adaptive learning and nonlinear relationship modeling capability	Limited transparency and high training data requirements

Table 8
Continued

Objective	Advantages	Limitation	Objective	Advantages
Cloud-based COPRAS	Cloud computing + COPRAS	Real-time distributed compromise decision-making	Scalability and remote collaborative decision support	Cybersecurity and data privacy concerns
Explainable AI–VIKOR	Explainable artificial intelligence + VIKOR	Improve interpretability of intelligent compromise ranking systems	Enhanced transparency and decision-maker trust	Emerging research area with limited practical implementation
Quantum-inspired TOPSIS	Quantum computing principles + TOPSIS	Improve optimization efficiency for highly complex decision spaces	Potentially superior computational capability for large-scale problems	Currently theoretical with limited practical deployment
Federated learning–MULTIMOORA	Federated learning + MULTIMOORA	Enable decentralized intelligent compromise decision-making	Improved privacy preservation and distributed analytics capability	Communication overhead and synchronization complexity

7.12 Summary of Application Trends and Research Directions

Compromise ranking methods have become widely used for complex decision-making in engineering, energy, finance, healthcare, supply chain, urban planning, transportation, environmental sustainability, information technology, and intelligent systems [49,57,61]. Methods such as VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA effectively address conflicting objectives, multidimensional criteria, dynamic data, and uncertainty while remaining robust, transparent, adaptive, and computationally efficient [36,39]. Their application varies by domain: TOPSIS, MOORA, and MULTIMOORA are preferred in engineering and manufacturing for computational efficiency [14,26]; fuzzy VIKOR, fuzzy TOPSIS, and hybrid uncertainty-based models dominate healthcare and environmental applications; VIKOR and MULTIMOORA are widely used in energy and sustainability; AI-assisted TOPSIS and hybrid models are increasingly adopted in finance [142]; COPRAS, TOPSIS, and fuzzy compromise models are widely applied in supply chains; while urban planning, transportation, and construction increasingly integrate compromise ranking with IoT and AI to address complex sustainability and operational challenges [114,134-138,156]. TOPSIS remains the most widely applied due to its simplicity and versatility, VIKOR is preferred for policy and strategic planning [104,109,112-16], MULTIMOORA performs well in complex uncertain environments, MOORA and MOOSRA suit large-scale applications, and COPRAS is effective for operational and economic evaluations.

A major trend is the evolution from deterministic compromise ranking methods to intelligent hybrid frameworks incorporating fuzzy logic, grey theory, interval mathematics, neutrosophic systems, probabilistic models, AI, IoT, cloud computing, and big data analytics to improve uncertainty handling and adaptability [162,163]. Machine learning-assisted TOPSIS, deep learning-based VIKOR, AI-enhanced MULTIMOORA, and fuzzy-neutrosophic models have become active research areas. Increasing emphasis is also placed on Explainable AI, real-time analytics, blockchain, digital twins, and cyber-physical systems to improve transparency, security, predictive maintenance, autonomous analytics, and real-time optimization [121,134,144,170,171].

Sustainability-driven interdisciplinary research has further expanded the application of compromise ranking methods to circular economy, climate resilience, renewable energy, carbon neutrality, and sustainable urban development, where environmental, economic, technological, operational, and social objectives must be balanced [86,126,131]. Future research is expected to focus on autonomous, self-adaptive decision-support systems capable of continuous learning and real-time updating for applications such as intelligent transportation, autonomous manufacturing, healthcare, smart infrastructure, and finance [21,42,56,93,101,102]. Emerging directions also include quantum-inspired compromise ranking and human-centric systems integrating behavioral analytics, cognitive modeling, emotional intelligence, and adaptive preference learning [61].

Despite substantial progress, important challenges remain. The lack of standardized benchmarking, normalization, uncertainty representation, weighting, aggregation, and hybridization methods reduces methodological comparability [74]. Other unresolved issues include algorithmic fairness, privacy, cybersecurity, computational complexity, scalability, explainability, and real-time implementation [33,41,55]. Overall, compromise ranking methods have evolved into versatile interdisciplinary decision-support tools capable of balancing conflicting objectives under uncertainty across engineering, sustainability, healthcare, finance, transportation, manufacturing, and environmental governance [156,164]. Their future development will be driven by intelligent hybridization, sustainability integration, explainable AI, and autonomous real-time decision-support technologies. Table 9 summarizes representative studies by application domain, methodology, key findings, and research gaps, highlighting the transition from deterministic ranking to uncertainty modeling, AI integration, sustainability assessment, and intelligent hybrid frameworks while identifying persistent challenges such as normalization dependency, rank reversal, scalability, and limited real-time adaptability [154,168,170,172].

Table 9
Summary of representative published studies on compromise ranking methods

Authors	Year	Method used	Application area	Key findings	Research gap
Hwang and Yoon	1981	TOPSIS	General MCDM framework	Introduced ideal-solution-based compromise ranking using geometric distance measures	Lack of explicit regret minimization and uncertainty handling
Opricovic	1998	VIKOR	Compromise decision-making	Proposed explicit compromise ranking based on group utility and individual regret	Sensitivity to criteria weights and decision parameter
Zavadskas and Kaklauskas	1996	COPRAS	Construction and engineering	Developed proportional assessment framework for beneficial and non-beneficial criteria	Limited treatment of uncertainty and dynamic data
Brauers and Zavadskas	2006	MOORA	Industrial optimization	Introduced ratio-based optimization with strong computational efficiency	Limited capability for handling qualitative ambiguity
Brauers and Zavadskas	2010	MULTIMOORA	Complex industrial systems	Improved robustness through integrated multi-perspective evaluation	Increased computational complexity
Das *et al.*	2012	MOOSRA	Engineering decision-making	Proposed simplified ratio analysis for rapid compromise ranking	Limited capability in highly uncertain environments
San Cristóbal	2011	VIKOR	Renewable energy planning	Demonstrated strong applicability of VIKOR in renewable energy project evaluation	Lack of real-time adaptability and dynamic parameter adjustment
Büyüközkan and Çifçi	2012	Fuzzy TOPSIS	Supply chain management	Integrated fuzzy systems with TOPSIS for supplier selection under uncertainty	Computational scalability challenges in large datasets
Baležentis and	2014	MULTIMOORA	Sustainability assessment	Demonstrated strong robustness in sustainability	Limited AI integration and predictive

Baležentis				evaluation problems	capability
Yazdani *et al.*	2015	COPRAS	Green supplier selection	Applied COPRAS for environmentally sustainable procurement decisions	Limited treatment of real-time supply chain dynamics
Zavadskas *et al.*	2016	Hybrid MCDM systems	Intelligent decision-support	Highlighted integration of AI and hybrid compromise systems	Lack of explainability and transparency in intelligent frameworks
Gupta *et al.*	2017	MOORA	Manufacturing optimization	Demonstrated computational efficiency in machining parameter optimization	Limited uncertainty representation capability
Peng and Garg	2018	Neutrosophic TOPSIS	Healthcare evaluation	Improved uncertainty handling using neutrosophic logic systems	Need for large-scale real-world validation
Cheng *et al.*	2018	VIKOR	Intelligent transportation systems	Applied compromise ranking for smart transportation optimization	Limited integration with autonomous mobility analytics
Pamucar *et al.*	2019	Fuzzy VIKOR	Logistics management	Improved ranking stability under uncertain logistics environments	Complexity of fuzzy parameter calibration
Frank *et al.*	2019	Hybrid compromise models	Industry 4.0 systems	Demonstrated applicability in digital manufacturing ecosystems	Need for real-time adaptive learning capability
Kumar *et al.*	2020	TOPSIS	Sustainable construction	Evaluated sustainable building materials using compromise ranking	Insufficient lifecycle uncertainty analysis
Mishra *et al.*	2021	MULTIMOORA	Smart city assessment	Demonstrated superior robustness in urban sustainability evaluation	Limited dynamic urban data integration
Torkayesh *et al.*	2021	Fuzzy COPRAS	Circular economy systems	Applied fuzzy compromise methods for sustainable waste management	Need for AI-assisted sustainability analytics
Rani *et al.*	2022	Neutrosophic VIKOR	Healthcare risk assessment	Enhanced uncertainty representation in pandemic-related decisions	Limited scalability for large healthcare systems
Saha *et al.*	2023	AI-assisted TOPSIS	Financial risk prediction	Integrated machine learning with compromise ranking for investment analysis	Explainability and transparency challenges
Li *et al.*	2024	Hybrid intelligent MULTIMOORA	Smart manufacturing and Industry 4.0	Demonstrated strong adaptability in autonomous industrial systems	Need for federated and secure intelligent decision-support systems

8. Challenges and Research Gaps

Despite significant advances, compromise ranking methods still face important methodological and practical challenges in complex MCDM problems [57,61]. Although VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA effectively handle conflicting criteria, none is universally robust or adaptable across all decision contexts [23,25,29]. One major issue is the lack of standardized normalization. Different normalization techniques (e.g., vector, linear, ratio, and proportional) can produce different rankings, reducing comparability, reproducibility, and reliability [16,19]. While ratio-based normalization in MOORA and MOOSRA is generally more stable, no method guarantees universally consistent rankings [48]. Rank reversal remains another major challenge, where adding or removing alternatives changes existing rankings. TOPSIS and VIKOR are particularly susceptible because of their normalization and distance-based calculations [56,59,61]. Reliability is also affected by subjective criterion weighting, as expert judgments may introduce bias [21,39]. Although objective weighting methods such as entropy and CRITIC reduce subjectivity, they may not reflect practical decision priorities [52]. Furthermore, most traditional compromise ranking models are designed for static datasets and cannot effectively process real-time data generated by smart manufacturing, IoT, healthcare, finance, and intelligent transportation systems [12,14,38,49].

Traditional compromise ranking methods also struggle with incomplete, uncertain, and linguistic information [19]. This limitation has led to fuzzy, neutrosophic, grey, and other hybrid models that better represent uncertainty [26,33,41,54]. Hybrid versions of VIKOR, TOPSIS, COPRAS, MOORA, and MULTIMOORA improve uncertainty handling but often increase computational complexity, parameter sensitivity, and interpretation difficulty [85,119]. The absence of standardized uncertainty modeling further limits comparability across studies. Limited integration with AI, machine learning, deep learning, and intelligent analytics is another important challenge [91,99]. Although AI can improve weighting, pattern recognition, and adaptive ranking [106,107], many existing models remain deterministic and manually weighted. AI integration also introduces challenges related to scalability, transparency, explainability, and data quality [111,125,136]. In addition, most compromise ranking methods assume independent criteria despite real-world interdependencies. While methods such as DEMATEL and ANP partially address this issue, their integration with compromise ranking remains limited, highlighting the need for network-based frameworks that capture causal relationships [122,129].

Scalability and computational efficiency are also concerns for large-scale decision problems [130]. Although MOORA and MOOSRA are computationally efficient, hybrid models combining fuzzy systems, AI, and dynamic optimization may be unsuitable for real-time applications [165]. The lack of standardized benchmarking further limits objective comparison of robustness, scalability, and uncertainty handling. Practical adoption is also constrained by the complexity of advanced hybrid models, while AI-based systems raise concerns regarding fairness, transparency, accountability, and black-box decision-making [123,156,158]. Future research should focus on adaptive, intelligent, and data-driven compromise ranking systems integrating real-time analytics, uncertainty modeling, machine learning, dynamic optimization, and Industry 4.0 technologies such as IoT, big data, digital twins, and cyber-physical systems [131,144,156-161]. Greater emphasis is needed on normalization standardization, automated weighting, scalability, explainable AI, interdependency modeling, sustainability analytics, resilience assessment, and adaptive risk management. Although compromise ranking methods have evolved into powerful decision-support tools, significant methodological and practical challenges remain [107,108]. Figure 20 summarizes the major unresolved issues in compromise ranking research.

9. Future Research Directions

Future MCDM development is increasingly driven by adaptability, real-time analytics, uncertainty handling, and computational intelligence. Although classical compromise ranking methods such as VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA have been successfully applied across many domains, emerging intelligent systems require more adaptive and data-driven decision-support frameworks [103,115,117]. Advances in AI, machine learning, IoT, cloud computing, cyber-physical systems, and big data are transforming compromise ranking methodologies [120]. Machine learning can improve decision-making by learning from historical data, optimizing weights, identifying hidden relationships, and updating rankings automatically [87,96]. Deep learning further supports applications in healthcare, finance, manufacturing, transportation, and sustainability [72,78]. However, AI integration also raises challenges related to explainability, computational complexity, and ethics, emphasizing the need for explainable AI-based compromise ranking systems.

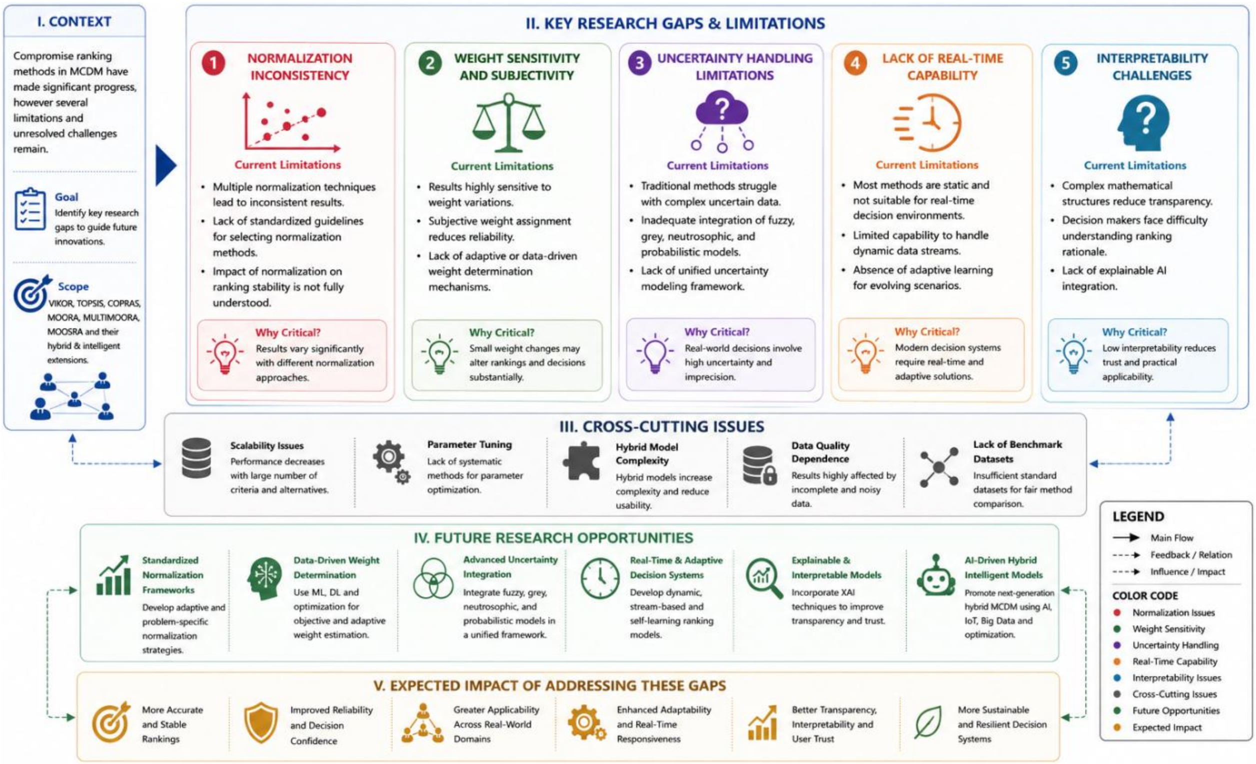


Fig. 20. Framework illustrating major research gaps in compromise ranking methodologies

Advanced uncertainty modeling using fuzzy and neutrosophic approaches is another major research direction [128,138]. Future studies are expected to expand the use of intuitionistic, hesitant, type-2, interval-valued fuzzy sets and neutrosophic logic to better represent incomplete and ambiguous information [89,96]. Neutrosophic VIKOR, TOPSIS, and MULTIMOORA are particularly promising for highly uncertain applications such as sustainability, healthcare, and environmental management [47,51]. Real-time compromise ranking systems are also gaining importance as IoT devices, sensors, cloud platforms, and cyber-physical systems continuously generate streaming data [44,49,69,82]. Adaptive frameworks capable of continuously updating rankings are expected to support smart manufacturing, transportation, healthcare, energy management, finance, emergency response, and smart cities.

Another promising direction is hybridization of compromise ranking methods [36]. Hybrid models combining VIKOR, TOPSIS, MULTIMOORA, fuzzy logic, entropy weighting, DEMATEL, ANP, and AI can improve robustness and ranking consistency [158-164]. Future research should also emphasize causal modeling through DEMATEL, ANP, Bayesian networks, and graph-based methods to capture interdependencies among criteria [19,20,36]. In addition, Monte Carlo simulation, stochastic optimization, probabilistic sensitivity analysis, interval uncertainty propagation, and scenario-based robustness testing will strengthen uncertainty analysis [66,67]. As digital platforms and IoT generate massive datasets, compromise ranking systems must also support scalable data processing and distributed computing.

Sustainability and resilience will remain key application areas, integrating climate adaptation, circular economy, carbon neutrality, and resilience assessment into decision-support frameworks [14,19,20]. Future research should also address fairness, transparency, accountability, standardized benchmarking, and user-friendly visualization tools to improve industrial and policy adoption [23,24,33,35]. Overall, compromise ranking methodologies are evolving from static deterministic models toward adaptive, intelligent, uncertainty-aware, and data-driven frameworks [45]. Their future development will be driven by AI, machine learning, fuzzy and neutrosophic logic, real-time analytics, hybrid optimization, and big data technologies, improving reliability, scalability, and applicability [51,52,63]. Table 10 summarizes future research opportunities and methodological developments, while Figure 21 illustrates the expected evolution of compromise ranking methodologies.

Table 10
Future research opportunities in compromise ranking research

Research area	Existing limitation	Proposed future direction	Expected contribution
Normalization framework standardization	Lack of universally recognized normalization actions leads to inconsistent ranking results	Development of adaptive and standardized normalization frameworks	Improved methodological consistency, comparability, and ranking reliability
Weight assignment mechanisms	Heavy dependence on subjective expert judgment introduces bias and instability	Integration of objective weighting methods, AI-assisted weighting, and adaptive learning systems	Reduction of subjectivity and enhancement of decision robustness
Uncertainty handling	Classical deterministic frameworks inadequately represent ambiguity and incomplete information	Expansion of fuzzy, intuitionistic fuzzy, neutrosophic, and probabilistic compromise ranking	Improved handling of vague, uncertain, and inconsistent real-world data
Real-time decision support systems	Most current methods operate on static datasets and lack dynamic adaptability	Development of streaming-data-driven and real-time adaptive compromise ranking frameworks	Enhanced applicability in smart systems, IoT environments, and autonomous analytics
Artificial intelligence integration	Limited autonomous learning and predictive capability in conventional methods	Integration of machine learning, deep learning, and explainable AI with compromise ranking models	Intelligent adaptive decision-making and predictive analytics capability
Explainability and transparency	AI-assisted compromise models often suffer from black-box decision behavior	Development of explainable intelligent compromise ranking	Increased transparency and stakeholder trust
Big data analytics integration	Traditional methods face scalability challenges under large-scale multidimensional datasets	Big data-driven compromise ranking systems with distributed computational capability	Improved scalability and high-dimensional decision analytics
Hybrid intelligent frameworks	Single-method approaches may fail to capture complex multidimensional decision structures	Development of hybrid systems integrating VIKOR, TOPSIS, MOORA, DEMATEL, ANP, and AI techniques	Enhanced robustness, stability, and multidimensional analytical capability
Dynamic criteria interdependency modeling	Most classical methods assume criteria independence	Incorporation of network-based and causal relationship modeling frameworks	Improved representation of real-world interdependent decision structures
Rank reversal mitigation	Several methods remain vulnerable to rank reversal under alternative modifications	Development of rank-preserving and stability-oriented ranking algorithms	Improved consistency and reliability of ranking outcomes
Sustainability-oriented decision frameworks	Limited integration of sustainability indicators in conventional models	Development of ESG-oriented and sustainability-driven compromise ranking systems	Stronger alignment with sustainable development objectives

Table 10
Future research opportunities in compromise ranking research

Existing limitation	Proposed future direction	Expected contribution	Existing limitation
Cybersecurity and secure decision systems	Emerging intelligent decision-support systems face security and privacy concerns	Integration of blockchain-assisted secure compromise ranking frameworks	Enhanced security, traceability, and decentralized governance capability
Digital twin integration	Current models lack virtual simulation capability for dynamic environments	Development of digital twin-assisted compromise ranking	Real-time simulation and adaptive operational optimization
Industry 4.0 decision systems	Existing methods insufficiently support cyber-physical industrial environments	Smart manufacturing-oriented hybrid compromise ranking frameworks	Enhanced automation, predictive maintenance, and intelligent production planning
Human-centered decision engineering	Limited incorporation of behavioral and cognitive decision-making factors	Integration of behavioral analytics and cognitive decision modeling	Improved human-centric decision-support capability
Healthcare analytics and smart medicine	Traditional healthcare decision models incapably handle large-scale vague data	AI-integrated medical compromise ranking systems	Improved healthcare prioritization and intelligent medical analytics
Smart city and urban intelligence systems	Urban decision systems require dynamic and multidimensional optimization capability	Development of real-time urban intelligence compromise frameworks	Enhanced smart city planning and infrastructure resilience
Cloud-based collaborative decision systems	Limited distributed decision-making capability in classical frameworks	Cloud-integrated collaborative compromise ranking environments	Improved scalability and multi-stakeholder decision collaboration
Quantum-inspired optimization models	Classical optimization frameworks face computational limitations in highly complex environments	Exploration of quantum-inspired compromise ranking algorithms	Potentially superior optimization efficiency and computational acceleration
Federated and privacy-preserving decision systems	Centralized data processing may create privacy and ethical concerns	Development of federated compromise ranking frameworks	Enhanced privacy preservation and decentralized intelligent analytics
Cross-disciplinary intelligent decision systems	Current research remains partially fragmented across domains	Integration of operations research, AI, sustainability science, and data analytics	Creation of highly adaptive next-generation intelligent decision-support systems

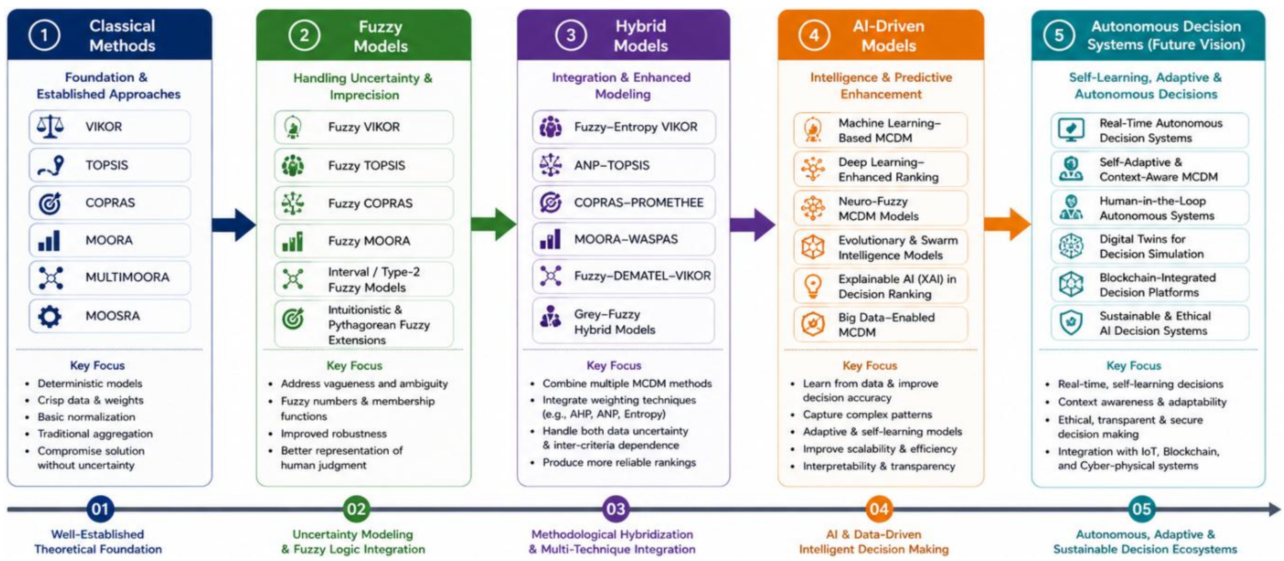


Fig. 21. Future research roadmap for compromise ranking methodologies

10. Conclusion

This paper provides a systematic comparison of the major compromise ranking methods in MCDM, including VIKOR, TOPSIS, COPRAS, MOORA, MULTIMOORA, and MOOSRA, focusing on their theoretical foundations, robustness, sensitivity, and applicability. The review confirms that these methods are effective for solving complex decision problems involving conflicting criteria and uncertainty across engineering, sustainability, healthcare, finance, logistics, manufacturing, and policy planning. Although all aim to achieve balanced compromise solutions, they differ in aggregation mechanisms, computational complexity, ranking stability, and sensitivity. Consequently, no single method is universally superior; the choice depends on decision complexity, uncertainty, data characteristics, stakeholder preferences, and robustness requirements. VIKOR is particularly suitable for consensus-based decision-making through its balance of group utility and individual regret, though it is sensitive to weighting and decision parameters. TOPSIS is computationally simple and intuitive but is affected by normalization dependency and ranking instability. COPRAS offer good interpretability, utility assessment, and computational efficiency, particularly in engineering and infrastructure, but are less effective in handling uncertainty and criterion interdependencies.

MOORA provides computational efficiency and stable rankings for large-scale industrial applications, while MULTIMOORA offers the highest robustness and ranking consistency by combining ratio analysis, reference point evaluation, and multiplicative optimization, making it suitable for strategic and sustainability-oriented decisions despite higher computational complexity. MOOSRA is a simple and efficient alternative for large-scale applications but is less capable of modelling complex interdependencies. The review also highlights the importance of robustness and sensitivity analysis, showing that normalization methods, weighting schemes, uncertainty representation, and data distribution significantly influence ranking results. Ratio-based normalization and hybrid methods generally produce more stable rankings. Key challenges include the lack of consistent normalization actions, trust on subjective weighting, inadequate uncertainty handling in deterministic models, and insufficient treatment of criterion interdependencies.

Future developments will increasingly focus on intelligent hybridization by integrating artificial intelligence, machine learning, fuzzy systems, neutrosophic logic, big data analytics, and real-time optimization with compromise ranking methods. AI-assisted weighting, predictive ranking, and adaptive decision-support systems are expected to improve scalability, robustness, and adaptability across Industry 4.0, smart cities, intelligent transportation, healthcare, and finance. This review provides a unified comparison of compromise ranking methods, summarizing their strengths, limitations, application trends, and future research directions. The findings can assist researchers and practitioners in selecting appropriate methods based on problem characteristics, uncertainty, stakeholder requirements, and computational needs. Although significant progress has been achieved, further standardization and hybridization remain essential to improve the reliability, interpretability, scalability, and adaptability of future compromise-oriented MCDM systems.

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Conflicts of Interest
The authors declare no conflicts of interest.

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