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Advancements of Multi-Criteria Decision-Making Approaches Integrated with Artificial Intelligence and Machine Learning in Sustainable Supply Chain Management

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ABSTRACT

This work examines the application of multi-criteria decision-making (MCDM) techniques in conjunction with artificial intelligence (AI) and machine learning (ML) within sustainable supply chain management (SSCM). Traditional MCDM methods struggle with large datasets and decision-making environments that change dynamically. AI and ML help get around these problems by making it easier to deal with uncertainty and by automating some parts of the analysis. The review discusses new methods, such as Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS), Simple Weight Calculation (SIWEC), and the Aczel Alsina Weighted Assessment (ALWAS). These methods give decision-makers more options for how to look at environmental, social, and economic factors. AI and ML tools can help MCDM methods work better with dynamic data, which improves risk assessment and resource allocation. Combining such methods makes MCDM approaches better able to deal with complicated decision-making situations and gives a more complete picture of how well a sustainable supply chain is doing. The review also offers practical guidance on selecting suitable learning algorithms according to the available data and their intended role in the MCDM process. In addition, it distinguishes between reporting gaps, which can be resolved through more consistent reporting practices, and conceptual gaps, which require the development of new methodological approaches.

1. Introduction

Multi-criteria decision-making (MCDM) methods are analytical tools implemented to evaluate alternatives based on multiple criteria in complex decision-making scenarios [1]. Across these approaches, each alternative is evaluated against multiple criteria, which are typically weighted to

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reflect the decision-maker's strategic objectives and priorities. This enables a more balanced and systematic comparison of the available alternatives [2]. This could be a significant advantage, particularly in highly complex and uncertain situations with numerous variables interacting with one another. Sample applications include project investment selection, supplier selection, product design, urban planning, and environmental impact assessments [3]. This allows us to take both kinds of data into account together, which means that different views can be included. When solving a decision-making problem in a group, it is possible to include all the different views and priorities of different people [4]. MCDM methods include well-known techniques such as the Analytical Hierarchy Process (AHP), Analytical Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VIekriterijumsko KOmpromisno Rangiranje (VIKOR), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and Elimination and Choice Translating Reality (ELECTRE). Each of these approaches has unique pros and cons in certain situations, allowing for flexibility in the decision-making process and delivering adaptable solutions [5].

MCDM is a crucial tool in supply chain management (SCM) because it can effectively handle complex decision-making processes involving multiple conflicting criteria. Applications of MCDM techniques to complex processes, such as supplier selection, achieving sustainability goals, and logistics optimization, have provided significant advantages in operations related to SCM [6]. These techniques have been shown to enhance a bidirectional decision-making process; both strategic and operational methods provide ways to address the complex issues that arise at various stages of the supply chain. To select the best supplier, MCDM techniques are applied to multiple characteristics in the supplier selection and evaluation process, including cost, quality, delivery time, and innovation capability. Additionally, MCDM is utilized in green and sustainable SCM to incorporate social responsibility goals, enhance energy efficiency, and mitigate environmental impacts [7].

MCDM methods contribute to the operational efficiency of SCM by optimizing their economic impact and offering a cost advantage. Additionally, it can make more informed and balanced decisions by considering past performance data and strategic objectives when evaluating supplier performance. Another important point is the ability of MCDM to give flexible and adaptable solutions by considering several criteria altogether, which is of great relevance for rapid adaptation to changing market conditions [8].

In today's complex, competitive business world, the need to ensure operational efficiency, as well as sustainability in supply chains, further reinforces MCDM as a critical tool. Hence, the methods of MCDM will play an indispensable role in the strategic management and improvement processes regarding supply chains. Notably, the post-2020 development in MCDM methods focuses on the increased complexity of decision-making in fields such as sustainability, risk management, healthcare, engineering, and resource management [3]. It considered the values of stakeholders, the application of fuzzy sets and belief function theories to handle imprecise information, and enhancements in techniques to represent human preferences better [9]. Recent trends involve the use of multi-objective techniques, hybrid approaches, and the integration of MCDM with state-of-the-art technologies, such as Artificial Intelligence (AI), big data analytics, and decision support systems, to enhance efficacy [10-16]. It has also drawn attention to the challenges of creating coherent frameworks and confirming new methods, underscoring the need for further research and interdisciplinary collaboration.

The review process was done as follows:

I. *Search Strategy and Data Sources*
   - We searched three major bibliographic databases—Scopus, Web of Science, and Google Scholar—for articles published between January 2020 and December 2024.

- Search terms: ("multi-criteria decision making" OR "MCDM") AND ("sustainable supply chain" OR "SSCM") AND ("machine learning" OR "artificial intelligence") AND ("fuzzy" OR "hybrid").
- Date of Search: Conducted on March 15, 2025.

II. *Inclusion and Exclusion Criteria*
- Inclusion: Peer-reviewed journal articles introducing or substantially extending MCDM methods post-2020.
- Exclusion: Reviews, editorials, methods lacking AI/Machine Learning (ML) integration, or applications unrelated to supply-chain sustainability.

An initial screening based on titles and abstracts identified approximately 143 records. After removing duplicates and non-relevant studies, full-text screening was applied using predefined inclusion and exclusion criteria. Included studies were peer-reviewed journal articles that (*i*) introduced new MCDM methods or substantially extended existing ones, and/or (*ii*) explicitly integrated AI or ML techniques within MCDM frameworks applied to sustainable supply chain contexts. Excluded studies comprised editorials, purely conceptual papers without methodological contribution, traditional MCDM applications lacking AI/ML integration, and studies unrelated to sustainability-oriented supply chain decision-making. Following the screening process, 117 studies were retained for detailed qualitative synthesis. This approach ensures methodological clarity while maintaining the flexibility required to capture emerging and interdisciplinary developments in AI-enhanced MCDM research.

In fact, the study aimed to investigate the pervasiveness of such integrations and the potential role they may play in facilitating better decision-making. It explains the applications of MCDM techniques in sustainable supply chain management (SSCM), highlighting how they are capable of addressing complex problems related to sustainability challenges, such as resource optimization, reduction of environmental impact, and promotion of social accountability.

Unlike earlier reviews that focus on a single MCDM method or a limited set of AI techniques, this study provides a broader account of how recent developments in artificial intelligence are being integrated into MCDM research. It examines emerging objective-weighting methods and the growing roles of ML, reinforcement learning, large language models, and IoT-based systems in decision-making. The review also considers the practical difficulties of applying these approaches in resource-constrained settings, identifies unresolved challenges, and outlines priorities for future research. By connecting established methods with these emerging technologies, the study offers a more comprehensive perspective on the potential of AI-enhanced MCDM, particularly in SSCM and related fields.

The following study will focus on five major research questions (RQs):

RQ1: In which fields are the most advanced MCDM approaches provided?

RQ2: How has the MCDM method changed the scientific literature in recent years?

RQ3: How effectively do MCDM approaches include ML and AI techniques?

RQ4: How may MCDM approaches assist SSCM in addressing issues of ecological, social, and economic sustainability?

RQ5: Which areas of research are recommended for additional study, and what are the primary gaps in the literature regarding the application of MCDM in SSCM?

The subsequent sections of the research encompass the theoretical framework, methodology, recent developments in MCDM methodologies, gaps and future research directions, and conclusions, respectively.

2. Theoretical Framework

In this section, a general framework about MCDM, the integrated use of MCDM methods with AI/ML, and general information about SSCM are given.

2.1 Overview of MCDM

MCDM is a branch of decision theory that provides a systematic and analytical framework for evaluating alternatives involving multiple, often conflicting criteria. The foundational work "Theory of Games and Economic Behavior" also played an important role in shaping the broader field of formal decision analysis [17], where two crucial mathematical disciplines laid the core foundation of utility theory and game theory, utilizing the approach necessary for tackling decision-making problems in a mathematically precise manner.

Modern MCDM originated in the 1950s and 1960s. It was also during this time that goal programming, one of the first methodologies developed for multi-criteria problems, was created. Charnes & Cooper [18] provided an important basis for situations where more than one goal is to be optimized in decision-making processes. Then, the diversification of methods in the field of MCDM accelerated in the late 1960s and the 1970s. For example, one of the early systematic approaches used for evaluating and comparing decision alternatives was the ELECTRE method developed by Roy [19]. Later, created by Thomas L. Saaty in the early 1970s, the AHP became one of the most recognized methods in the field of MCDM. By transforming complex decision problems into a hierarchical structure, AHP allowed decision-makers to evaluate the importance levels between criteria and alternatives in a more systematic way [20]. Currently, MCDM approaches are used in different fields such as engineering, management, agriculture, healthcare, etc.

MCDM has undergone significant evolution from its inception to date, with increasingly complex scenarios involving multiple, mostly conflicting criteria, as shown in Figure 1. TOPSIS [21] is another widely used classical MCDM method. These early approaches generally assume that criterion weights are fixed before the evaluation begins. Subsequent methodological developments gradually relaxed this assumption, allowing weights to vary according to the decision context and available information.

During the following decades, the area expanded with the introduction of fuzzy logic in the 1980s, allowing MCDM to handle uncertainty and imprecision [22]. Further generalizations followed, including Pythagorean fuzzy sets, picture fuzzy sets, and neutrosophic approaches, introduced by Yager [23], Khan *et al.* [24], and Smarandache [25], respectively, which allow for more sophisticated modeling of uncertainty [23,26]. In parallel with these developments, entropy-based methods have emerged since the 1980s for objective weighting, as mentioned by Shannon [27]. Hybrid methodologies, which combine the strengths of multiple approaches, were proposed in the 1990s, such as the one proposed by Shih *et al.* [28]. The integration of ML and big data in the 2000s and dynamic approaches for evolving criteria further enriched the field. Today, MCDM encompasses diverse methodologies that address decision-making challenges across dynamic, stochastic, and group contexts, underscoring its indispensable role in contemporary problem-solving and learning algorithms applied to determine the importance of criteria or classify alternatives. This makes the methods applicable to larger and more complex data sets. AI/ML can be used to predict changing criteria and options in dynamic and real-time decision-making processes. For instance, time series forecasting models support dynamic MCDM methods by forecasting future changes in the values of criteria. At the same time, reinforcement learning (RL) algorithms contribute to the optimization of decision paths. Other benefits that AI provides are in the automation of MCDM processes. In particular, for methods like AHP, automating the process of pairwise comparisons with natural language processing or predicting decision outcomes using ML models can greatly reduce computational time. Today, these integrations are utilized in a wide range of fields, including healthcare, logistics, and finance.

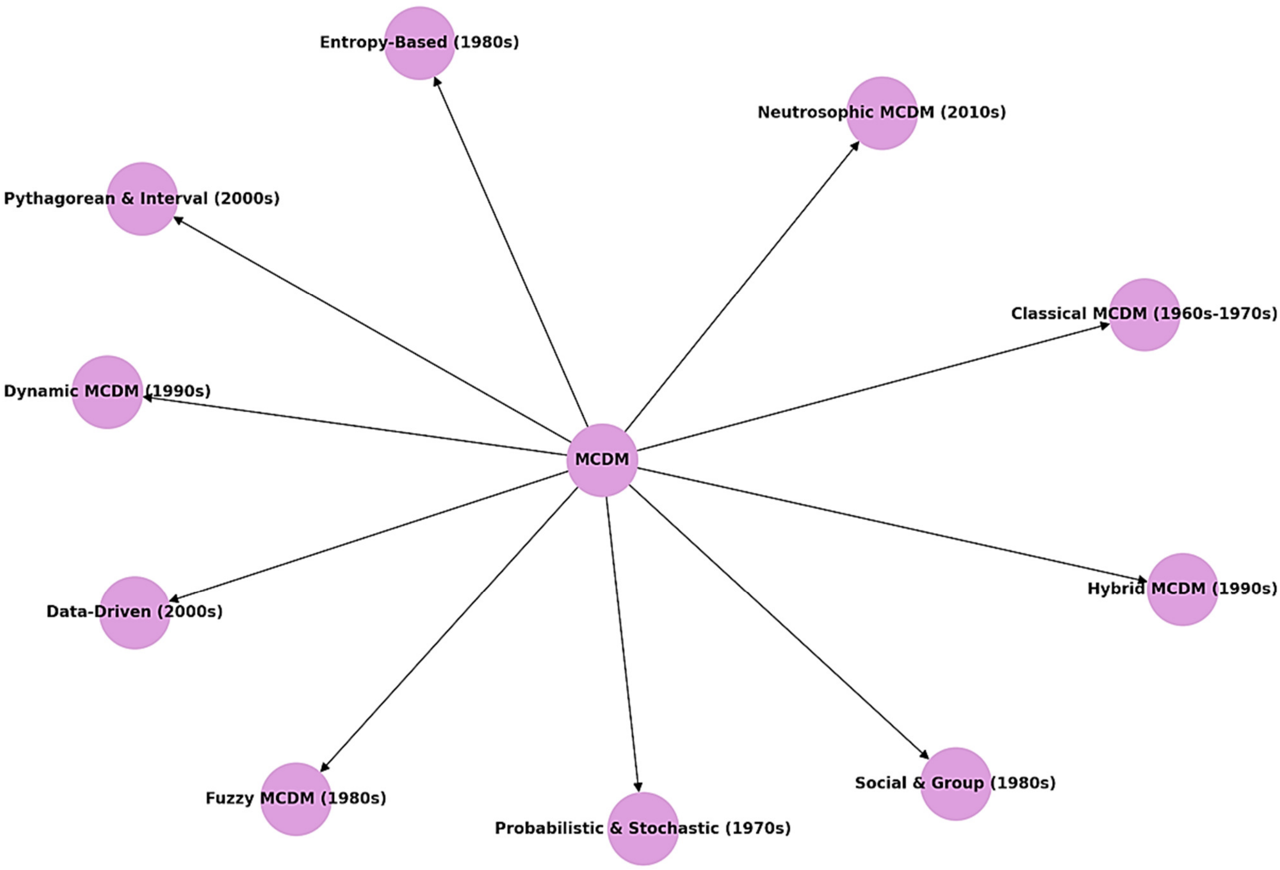

Fig. 1. Historical classification of MCDM methods

2.2 Integration of MCDM with AI/ML

With AI/ML-integrated MCDM, a fairly new field of study in the existing literature, it offers several advantages for solving complex problems in decision-making. Such benefits arise from the features of AI/ML techniques that complement and enhance traditional MCDM by inserting dynamic, data-driven, and adaptive processes. Specific reasons are presented for employing AI/ML methods in many studies found in the literature, such as determining or reducing criteria, classifying data, predicting outcomes between alternatives, verifying the correctness of MCDM methods, and integrating results from multiple MCDM approaches. These capabilities overcome some intrinsic weaknesses of traditional MCDM methods, which are inherently based on static assumptions and manual evaluations, thus enhancing the efficiency and accuracy of the decision-making process. The integration has several critical advantages, including the ability to analyze large volumes of data in a very short time and reveal complex relationships among criteria. ML models excel in discovering hidden patterns in large and multidimensional datasets, enabling decision-makers to identify the most influential factors and derive optimal solutions for multi-criteria problems.

Additionally, AI algorithms may incorporate innovative techniques such as fuzzy logic or genetic algorithms (GAs), which are particularly effective in managing uncertainties and imprecise data. Such integration will enhance the accuracy of MCDM methods in terms of scalability and flexibility, making those solutions more robust and adaptable to a wide range of decision scenarios. Vagueness in decision criteria can be modeled with the help of fuzzy logic; similarly, GAs work to obtain the most optimal solution in highly complex environments with nonlinear variation.

The combination of MCDM and AI/ML helps in conducting sensitivity analyses and scenario planning. AI/ML-driven systems can model changes in criteria weights dynamically by using reinforcement-learning agents, such as deep Q-networks (DQN) that learn weight adjustments through reward feedback [29], or adaptive neuro-fuzzy inference systems (ANFIS) that update membership-function parameters via back-propagation based on decision outcomes [30]. In addition, this feature provides a unique opportunity for decision-makers to assess the strength of their policies and make adjustments to their decisions well in advance, before the situation changes. Additionally, the flexibility of AI/ML techniques used enables these integrated systems to address real-world issues with high variability and uncertainty. This adaptability not only ensures the effectiveness of the decision-making process but also guarantees that the solution remains relevant and actionable over time.

Besides the theoretical insights, the integration of MCDM with AI/ML offers significant practical benefits: it bridges the gap between abstract models of decision-making and real-world applications, thereby providing decision-makers with an effective toolkit for a wide range of problems arising in SCM, energy planning, and healthcare resource allocation. Combining and validating the results from multiple methods enhances the reliability and consistency of decisions. Thus, such a hybrid approach will lay a solid foundation for further advances in academic research and industry practices, ensuring its relevance and applicability to modern decision-making challenges.

2.2.1 Algorithmic characteristics and problem fit of ML techniques in MCDM-based SSCM

The studies reviewed typically combine MCDM with a relatively narrow range of learning algorithms, yet rarely provide a methodological justification for their selection. This choice is particularly important in SSCM applications, where datasets differ considerably in sample size, dimensionality, and measurement scale. Selecting an algorithm that is appropriate for the data is therefore essential to obtaining reliable criterion weights and predictions. This section discusses the conditions under which the two most commonly used learning algorithms are suitable.

The random forest (RF) algorithm constructs an ensemble of decision trees using bootstrap samples and considers a random subset of features at each split. This process reduces the correlation among individual trees, while averaging their predictions generally produces a model with lower variance than a single decision tree [31]. Several characteristics make RF particularly useful in MCDM frameworks. It can accommodate different types of variables within the same model, allowing audit outcomes, binary certification indicators, and numerical performance measures to be analyzed together. It can also capture nonlinear relationships and interactions without requiring them to be specified in advance. Moreover, its feature-importance estimates can be used to derive objective criterion weights or to validate subjective weights obtained through methods such as AHP, BWM, or SWARA. For this purpose, permutation importance is generally preferable to mean decrease in impurity. Nevertheless, these measures should be interpreted carefully. Impurity-based importance tends to favor continuous variables and variables with many possible values [32]. In addition, when criteria are highly correlated, their importance may be distributed among them, causing the contribution of individual criteria to be underestimated.

Support vector machines (SVM) solve a convex maximum-margin optimization problem in a feature space defined by a kernel function, with model complexity controlled primarily through regularization and kernel parameters [33]. This formulation makes SVM particularly useful in high-dimensional, small-sample settings, where the number of criteria may approach or even exceed the number of observations. Such conditions are common in sustainable supplier selection; for example, when a company evaluates 40 suppliers against 30 triple-bottom-line criteria. Support vector regression (SVR) extends this principle by using an epsilon-insensitive loss function that ignores errors within a specified tolerance margin. Because larger errors are penalized linearly rather than quadratically, SVR may also be less sensitive to extreme observations than least-squares regression [34]. However, these advantages come with several limitations. Model performance depends heavily on feature scaling and the joint tuning of the regularization and kernel parameters. Nested resampling is therefore necessary to avoid overly optimistic estimates of predictive accuracy [35]. Training complexity typically ranges from quadratic to cubic in the number of observations, which limits the suitability of SVM for very large stock keeping unit (SKU)-level or raster-based datasets. Furthermore, nonlinear SVM models do not provide a direct measure of feature importance; consequently, criterion selection often requires additional procedures such as recursive feature elimination [36].

These applications suggest a practical basis for selecting an appropriate learning algorithm. When thousands of observations are available, and the dataset contains heterogeneous features, tree-based ensembles are often a suitable choice because they perform well with relatively limited parameter tuning [37]. By contrast, kernel methods may be more appropriate when the dataset contains only a few dozen observations and a similar number of criteria, although feature selection and dimensionality reduction then become central modelling concerns. A different strategy is needed when the outcome of interest is rare, as in cases of supplier default or supply disruption. Under such conditions, both kernel methods and tree ensembles may receive too few minority-class examples to learn reliable patterns. Possible solutions include cost-sensitive learning, resampling techniques such as SMOTE [38], or one-class classification trained primarily on normal observations [39]. Interpretability must also be considered: when audit results need to be communicated to non-technical stakeholders, the limited transparency of kernel-based models can be a significant drawback [40].

A second consideration is the role assigned to the learning algorithm within the MCDM process, as each role requires a different validation strategy. Four recurring functions were identified in the reviewed studies. In criterion reduction, the algorithm removes less informative criteria from the initial set before preference elicitation. In criterion weighting, estimates of feature importance are transformed into criterion weights. In prediction, the algorithm forecasts future criterion values, enabling the development of a dynamic MCDM model. Finally, in validation, a classification model trained on expert judgements is used to examine whether the resulting ranking remains robust under perturbations. Criterion reduction and weighting raise a particularly important concern that is often overlooked. When the same observations are used both to derive the weights and to evaluate the alternatives, information leakage or circularity may occur, potentially overstating the model’s discriminatory ability. Studies employing these functions should therefore clearly report their resampling procedure, hyperparameter search space, and tuning strategy [41,42], and explain how the weight-derivation and alternative-evaluation stages were separated.

2.3 Supply Chain Management

The term “sustainable supply chain” refers to the approaches of SCM that balance environmental, social, and economic factors. This concept is not only related to traditional measures such as cost and efficiency but also to processes aimed at reducing environmental impacts, increasing social responsibility, and ensuring long-term economic sustainability [43]. The concept of SSCM emerged in the 1990s, influenced by developments in environmental management and corporate social responsibility. It gained greater theoretical and practical attention during the 2000s as regulatory pressures increased and stakeholders demanded greater environmental transparency across value chains. Today, it is a strategic priority for companies and their stakeholders, particularly in addressing climate change, carbon emissions, and ethical business practices [44,45].

MCDM is applied increasingly widely within SSCM, and those applications are examined in detail below. The criteria employed across this literature fall into five groups:

i. *Environmental* – SCM has some ecological goals. When conducting operations within the supply chain, it is essential to minimize ecological harm and make decisions that consider their impact. Therefore, some environmental criteria have emerged, and these criteria have been evaluated in decision-making issues within the SCM [46-48].
ii. *Economic* – Since the general purpose of companies is to make a profit (reduce costs) throughout their operations, there are inevitably economic criteria in the decisions taken [46, 49-53].
iii. *Social* – These criteria encompass factors that reveal a company's social status. In all choices made in supply chain operations, whether it is a company or a process, social criteria include issues such as social structure, employee status, and human rights [46,51,54-57].
iv. *Management and organizational* – These criteria aim to understand the management functions of companies and encompass factors such as the sustainability perspective of management, information sharing, and cooperation [58,59].
v. *Technological* – Since the use of technology is mandatory, especially within supply chain functions, factors such as the level of use of technology and the degree of adaptation to innovative technologies are among these criteria in many selection problems [53,60-62]. The requirements in these categories are listed in Table 1.

2.4 Application in SSCM

As SSCM allows for multiple points of view and has many decision variables, the literature in this area is wide. The next chapter presents the application fields where MCDM has been applied based on the amount of literature available.

2.4.1 Supplier selection and evaluation

Supplier selection and evaluation is one of the most widely studied topics in SSCM. The process typically involves defining the decision problem, establishing the evaluation criteria, screening potential suppliers, and selecting the most suitable supplier or group of suppliers [83,84].

As the present study focuses only on MCDM approaches, by reviewing the literature post-2020 and the studies applying MCDM for sustainable supplier selection, one can easily observe that several approaches have been applied [3]. In some studies, sustainable supplier selection and evaluation are addressed using classical MCDM methods, while others employ extended MCDM or new MCDM methods [85-89]. In addition, studies that integrate different solution methods with MCDM methods have become more common recently. In some of these studies, AI/ML methods are applied in determining the criteria [90,91], while in others, the simulation-optimization approach was used for supplier selection or in the same way for determining the criteria after selecting the weights of the criteria [92]. Some of these studies are shown in Table 2.

Table 1
Criteria used in SSCM

Criteria	Specific factor	References
Environmental	Carbon emission reduction, waste management and recycling, reuse applications, reduction of energy consumption, protection of natural resources, pollution controls and prevention, environmental management system, green manufacturing, green design of products, green purchasing, green logistics, green transportation, energy and resource consumption, emission and waste generation, recycling and reverse logistics.	Ali *et al.* [63]; Xu *et al.* [64]; Muchenje [65]; Jemai *et al.* [66]; Dada *et al.* [67]; Kolasani [68]
Economical	Cost optimization, product and service quality, innovation capacity, financial sustainability, supply flexibility, economic welfare and growth, cost reduction activities, products' quality improvement, time and lead time.	Bentalha [69]; Carter & Liane Easton [70]; Igwe *et al.* [71]; Awasthi *et al.* [46]
Social	Health and safety, ethical behavior, human rights protection, fair trading and against corruption, local community influence, diversity and social responsibility, employee rights and job safety, employment practices and job opportunities, community initiatives and stakeholders influence.	Nasseri *et al.* [72]; Yıldızbaşı *et al.* [73]; Igwe *et al.* [71]
Management and organizational	Internal management support for green development, training and education, information and collaboration among supply chain members, green warehousing, reverse logistics.	Stan *et al.* [74]; Fu *et al.* [75]; Li [76]; Baah & Jin [77]; Prasad *et al.* [78]
Technological	Green technologies and innovations, energy efficiency improvement, innovative product design and production technologies.	Pratap *et al.* [79]; Farazi [80]; Cappellesso & Thomé [81]; Singh & Trivedi [82]

2.4.2 Inventory management

Inventory management is one of the most complex and multifaceted problems a company confronts when implementing SCM. This discipline encompasses far-reaching variations in decisions, including strategic ones that differ significantly, requiring specialized analyses that extend from determining the optimal amount of stock to be on hand to determining which replenishment methods are appropriate for managing inventories across multiple locations. At the center of each of these lies the delicate balance of demand, reliable suppliers, and storage house capacity. The complexity increases when these decisions must be integrated into a single, workable strategy that aligns with the overall supply chain objective. Thus, these decisions are of major importance, as they impinge directly on the profitability and operational efficiency of enterprises. Effective inventory management reduces holding and ordering costs, minimizes waste, and therefore increases efficiency. Simultaneously, it ensures that products are available to meet consumer demand, aiming to increase customer satisfaction and loyalty. Furthermore, in modern, competitive, and dynamic markets, effective inventory strategies will continue to support businesses in their efforts to manage disruptions, improve service levels, and maintain a competitive edge. Therefore, inventory management remains one of the most important focus areas in the quest for optimization of supply chain performance.

Table 2
Some studies on supplier selection and evaluation applications

Reference	Application domain	Decision problem	Dataset characteristics	MCDM method	AI or ML technique and role	Validation and evaluation	Key finding and stated limitation
Liou *et al.* [91]	A case study from a Taiwanese electronics company	Criteria reduction and green supplier ranking	Real data; 25 criteria reduced to 13; number of 250 green suppliers	Fuzzy BWM, fuzzy TOPSIS	SVM; criteria reduction role	Not reported	Process pollution control ranked highest
Nguyen *et al.* [98]	Steel production company in Vietnam	Sustainable supplier selection	Real data; mixed qualitative and quantitative criteria	DEA, SF-AHP, SF-WASPAS	None	Not reported	Quality ranked highest among environmental criteria
Saputro *et al.* [92]	Illustrative numerical case study	Supplier selection under uncertainty	Adopted from previous studies	Fuzzy AHP, interval TOPSIS, simulation-optimization	None	Sensitivity analysis of decision-maker weight	Monetary criteria ranked highest
Chai *et al.* [85]	E-bike sharing; recycling services	Sustainable recycling supplier selection	Real data with 15 criteria and four alternatives	Intuitionistic fuzzy sets, interval-valued fuzzy sets, cumulative prospect theory	None	Not reported	Safety and health, and employment practices ranked highest
Thanh & Lan [99]	Food processing; Vietnam	Green supplier selection	Real data	Triple bottom line metrics, fuzzy AHP, CoCoSo	None	Not reported	Process pollution control ranked highest
Singh *et al.* [100]	Illustrative example	Supplier evaluation via decision support system	Implemented in JRank software	Dominance-based rough set analysis, triple bottom line	None	Not reported	Economic sustainability criteria ranked highest
Jain *et al.* [101]	Iron and steel; India	Supplier selection	Real data	Fuzzy AHP, fuzzy TOPSIS, Kano model	Fuzzy inference system	Not reported	Product development ranked highest
Ma & Li [102]	Automotive; large firm	Aggregation of supplier rankings	Real data	TOPSIS, VIKOR, PROMETHEE, MOORA	ML-based aggregation model; aggregation and validation role	Not reported	Supplier quality capacity and supplier risk ranked highest
Stevic *et al.* [89]	Healthcare; private polyclinic; Bosnia and Herzegovina	Supplier selection; introduction of MARCOS	Real data	MARCOS	None	Comparative analysis against existing MCDM methods	Quality ranked highest; MARCOS introduced
Sahu *et al.* [88]	Automotive; India	Agile supplier evaluation	Real data	AHP, DEMATEL, ANP, MOORA, SAW	None	Not reported	Internal communication agility ranked highest

Numerous studies in the literature utilize MCDM methods in the field of inventory management, and some of these studies are listed in Table 3.

Table 3
Some studies on inventory management applications

Reference	Application domain	Decision problem	Dataset charact.	MCDM method	AI or ML technique and role	Validation and evaluation	Key finding and stated limitation
Goswami & Behera [103]	Materials handling equipment	Conveyor, AGV and robot selection	Three separate decision problems	Entropy, COPRAS, ARAS	None	Cross-method comparison of COPRAS and ARAS rankings	Carrying capacity, flexibility and loading capacity ranked highest respectively
Patyk *et al.* [104]	Mining	Deposit evaluation and equipment selection	Real mine site data	ELECTRE III	None	Not reported	Cost, distance to residences and transportation distance ranked highest
Petroutsatou *et al.* [105]	Construction equipment procurement	Review of procurement decision practice	Twenty-five years of published AHP applications	AHP	None	Not reported	Cost and ease of maintenance ranked highest
Sayed *et al.* [96]	Agriculture; tractors; Nile Delta, Egypt	Criteria reduction and equipment selection	Real data; small farms; nine criteria and four tractors	AHP	Agglomerative hierarchical clustering; criteria reduction role	Not reported	Maintenance cost and spare parts ranked highest
Gorski *et al.* [94]	Maintenance services; Brazil	Work order prioritisation	400,512 work orders	TOPSIS	SVM, naive Bayes, decision trees; classification role	Not reported	Technical competence and personnel suitability ranked highest
Dohale *et al.* [93]	Manufacturing; India	Manufacturing strategy and inventory policy	Real company data	Delphi, voting AHP	Bayesian network; probabilistic weighting role	Not reported	Market needs and competitive priorities ranked highest
Vukasovic *et al.* [97]	Inventory policy	Inventory classification and supply optimisation	Real data	Fuzzy FUCOM, fuzzy EDAS, ABC analysis	None	Not reported	Supply cost and demand ranked highest
Kaur *et al.* [106]	Inventory policy; North India	Selection among four inventory policies	Four alternative policies; six criteria	TODIM, Pythagorean fuzzy sets	None	Not reported	JIT selected; inventory cost ranked highest
Negi & Kharde [95]	Potential causes of inventory aggregation	Root cause identification for inventory build-up	Eight potential causes and five crireria	Root cause analysis, TOPSIS	None	Not reported	Forecast error, quality issues and communication gaps identified as principal causes; supports early detection of NMI and SMI

In addition to MCDM methods, different approaches have been integrated into these studies. For example, as in other subjects, ML has been used to control the criteria in the literature in inventory management, Bayesian networks have been used to determine the criteria weights and the selection probabilities of alternatives, different ML methods have been used to determine various inventory policies, root cause analysis has been used to determine the criteria in the field, and ABC method has been used to analyze inventory values [93-97].

2.4.3 Location selection

Location selection in the supply chain is a strategic decision that enables firms to minimize costs, maximize operational efficiency, and enhance customer satisfaction. It primarily concerns determining the most suitable locations for facilities such as warehouses, production facilities, and distribution centers within logistics networks. Besides economic factors, it also considers transportation costs, access to energy, labor costs, and proximity to suppliers, among other environmental sustainability issues and social impacts. Therefore, location selection is crucial not only in terms of operational efficiency but also in minimizing ecological and social impacts. Location decisions are increasingly supported, from a scientific perspective, by modern SCM analytical tools, such as MCDM methods and geographic information systems (GIS) [107-110]. Additionally, this system can manage uncertainties and analyze complex datasets to select the best option among various available alternatives. Fuzzy logic and ML-based approaches can subsequently yield efficient outcomes, particularly in problems with large data sizes and uncertain criteria [107,111-113]. Selecting a location with the best output in supply chains is cost-effective, enhances the resilience of supply chains, and enables businesses to compete more effectively. Some studies on this subject are given in Table 4.

3. Recent Advancements in MCDM Methodologies (Post-2020)

In the realm of MCDM, numerous new methodologies have emerged since 2020, as global supply chains continue to become increasingly complex. These approaches reflect the emerging need for more robust and data-driven methods to underpin the development of decision tools. At the same time, their presence also indicates integration with the use of more advanced AI/ML techniques within traditional frameworks. It attempts to outline the landscape of new MCDM methodologies, considering the necessity for these decision-making aids to evolve to master multifaceted sustainability criteria, combined with the dynamic market conditions characterizing modern supply chains. Furthermore, this section will explain the core novelties that have been developed in recent times, utilizing some of the state-of-the-art methods to outline their applicability within the SSCM environment. A structured approach has been employed to identify the methods introduced or substantially improved since 2020, ensuring this review accurately represents the latest developments in MCDM. The process was initiated by considering the comprehensive pool of literature compiled during the methodology stage, which included studies published between January 2020 and December 2024. Initial screening focused on identifying explicit novelty works, including new theoretical frameworks, the introduction of innovative hybrid models, and the integration of emerging AI/ML techniques with traditional MCDM foundations.

Table 4
Some studies on location selection applications

Reference	Application domain	Decision problem	Dataset charact.	MCDM method	AI or ML technique and role	Validation and evaluation	Key finding and stated limitation
Yilmaz *et al.* [113]	Energy storage; Balikesir, Turkey	Facility location for energy storage	28 wind power plants	TOPSIS, ARAS, EDAS, MOORA, BORDA, interval type-2 fuzzy TOPSIS	K-means and elbow method; clustering role	Cross-method rank comparison via BORDA	Environmental impact and investment cost ranked highest
Eren & Katanalp [109]	Urban mobility; Izmir, Turkey	Bike-sharing station siting	Eight central districts; spatial data	AHP, VIKOR	None; GIS used for spatial analysis	Not reported	Railway transportation and slope ranked highest
Wang *et al.* [114]	Public services; Beijing, China	Facility siting	Four candidate locations	Fuzzy MULTIMOORA, fuzzy DEMATEL	None	Not reported	Haidian district selected; service capacity and equipment purchase cost ranked highest
Kannan *et al.* [115]	Solar energy; South Khorasan, Iran	Solar plant siting	14 candidate locations	BWM, VIKOR, GRA	None	Monte Carlo simulation; robustness testing and cross-method comparison	Initial investment and construction cost ranked highest
Chaibi *et al.* [107]	Onshore wind; Morocco	Wind farm siting	Raster suitability maps	SF-AHP, WASPAS	XGBoost; prediction and map accuracy role	Accuracy of suitability maps assessed	Wind speed and distance to transmission lines ranked highest
Al Awadh & Mallick [116]	Waste management; Abha-Khamis, Saudi Arabia	Landfill siting	Spatial dataset	Fuzzy AHP	Self-organising map, K-means, XAI; clustering and explanation role	Not reported	Drainage density and land use ranked highest
Raad *et al.* [110]	Dry port logistics; Shahid Rajaee Port, Iran	Dry port siting	12 alternatives; spatial criteria	Fuzzy SWARA, fuzzy MULTIMOORA	None; GIS and fuzzy gamma operator	Not reported	Transportation cost and railway access ranked highest
Topaloğlu [117]	Manufacturing; Turkey	Regional siting of production facilities	Six main criteria; regions	AHP, standard scoring method	None	Not reported	Transportation and labor ranked highest
Mondal *et al.* [112]	Waste management	Site selection for waste facilities	Geographic raster data	AHP	RF; classification role	Not reported	Land use and land cover ranked highest
Bojer *et al.* [111]	Land suitability; Adea region, Ethiopia	Spatial suitability and siting	Field survey and raster data	AHP	RF; classification and prediction role	Not reported	Elevation and land use ranked highest

Building on these preliminary indicators, each candidate study was investigated in more detail to distinguish between incremental improvements and genuinely new contributions. This included checks on whether a given method contributed to filling any of the previously identified gaps in decision-making efficiency, complexity handling, uncertainty modeling, or sustainability evaluation. Works that were of particular interest included new algorithmic combinations, new extensions of fuzzy logic, or the introduction of advanced data-driven techniques such as deep learning or evolutionary algorithms to make new state-of-the-art proposals. Additionally, it was observed that the new methodologies were clearly applicable in contexts relevant to SSCM. Preference was given to those approaches that could accommodate MCDM frameworks within environmental, social, or economic sustainability dimensions, or performed better under dynamic and uncertain market conditions. The benchmark with literature before 2020 also confirmed their distinctiveness, ensuring that the methods are genuine improvements, not minor variants of established techniques. Finally, where applicable, insights from contemporary review articles and expert commentaries were leveraged to corroborate the novelty of certain methods. By following this rigorous selection process, the section that follows focuses only on those MCDM methodologies introduced or significantly enhanced after 2020, thereby providing a targeted perspective on the most current directions in sustainable supply chain decision-making research. Table 5 reviews these methodologies based on their core ideas and advantages/disadvantages.

Table 5
Review of the recent MCDM methods

Method	Core idea/Purpose	Main advantages	Main disadvantages	Key reference
RAWEC	Ranks alternatives using predefined criterion weights and deviation from ideal values.	• Simple and transparent ranking process • Easy normalization and interpretation • Suitable for non-technical decision-makers • Uses deviation from ideal (unlike SAW)	• Cannot be applied if decision matrix contains zero values • Requires two normalization steps	Puška *et al.* [118]
MARCOS	Compromise-based ranking using ideal and anti-ideal solutions.	• Considers both best and worst scenarios • Produces balanced compromise solutions • Easy-to-interpret utility indices • Suitable for sensitivity analysis • Stable ranking results	• Sensitive to improperly defined reference points • Interpretation becomes complex with correlated criteria • No pairwise outranking logic • Computational burden for large-scale problems	Stević *et al.* [89]
SIWEC	Determines criterion weights through normalized expert input and dispersion measures.	• Easy to understand and implement • Flexible for diverse criteria • Integrates statistical measures • Can be used without alternative performance data	• Subjective and bias-prone • Sensitive to outliers • Loss of criterion-specific nuance	Puška *et al.* [119]
ABAC	Ranks alternatives through alternative-by-alternative dominance comparisons.	• Simple and computationally light • Effective for ranking similar alternatives • Highlights small differences • Suitable for complex problems	• Ignores criterion interdependencies • Requires normalization • Minor differences may be indistinguishable • Rank reversal-free but limited sensitivity	Biswas *et al.* [120]

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AROMAN	Two-stage normalization (vector + linear) ranking method.	• Easy to apply • Fairer and more consistent ranking • Suitable for cost–quality trade-offs • Robust under extreme values	• Ignores criterion relationships • Weight-dominant outcomes • Limited ranking sensitivity for similar alternatives	Bouraima *et al.* [121]
RAFSI	Functional interval mapping for standardized ranking.	• Novel normalization technique • Resistant to rank reversal	• Requires accurate interval definitions • Sensitive to scale variation • Limited for vague data	Žižović *et al.* [122]
OPA	Rank-based method for deriving criterion weights.	• No pairwise matrices or normalization • Simple expert input • Simultaneous weighting of experts, criteria, alternatives • Avoids numeric judgments	• Subjective bias • Sensitive to boundary changes • Masks magnitude differences • Limited for complex systems	Ataei *et al.* [123]
WENSLO	Derives weights using envelope and slope sensitivity analysis.	• Captures true criterion influence • Identifies sensitive criteria • Reduces subjective bias • Effective for many alternatives	• Data- and computation-intensive • Sensitive to extreme values • Difficult for non-experts • Limited handling of correlated criteria	Pamucar *et al.* [124]

Table 5 (*continued*)

Method	Core idea/Purpose	Main advantages	Main disadvantages	Key reference
ALWAS	Fuzzy weighted aggregation using Aczel-Alsina t-norms.	• Flexible aggregation behavior • Handles uncertainty and partial compliance • Suitable for fuzzy data • Supports strategic weighting	• Requires parameter tuning • Higher computational complexity • Less transparent for non-fuzzy experts • Weight subjectivity	Pamucar *et al.* [124]
ARTASI	Ranking using adaptive standardized intervals.	• Reduces dominance of large-scale criteria • Highlights clusters and outliers • Works with mixed data • Adaptive to new data	• Interval selection critical • Requires sufficient data • Needs frequent updates • Ignores criterion interactions	Pamucar *et al.* [125]
PROMSIS	Hybrid PROMETHEE-TOPSIS ranking method.	• Combines distance-based and outranking logic • Handles quantitative and qualitative data • Mitigates dominance of large-scale criteria • Rich preference insights	• Methodologically complex • Parameter calibration required • Possible result ambiguity • Harder to explain to non-experts	Beheshtinia *et al.* [126]
COBRAC	Converts ranked criteria into consistent numeric weights.	• Structured ranking-to-weight transition • Transparent comparisons • Encourages stakeholder discussion • Compatible with MCDM frameworks	• Cumbersome for many criteria • Oversimplifies subtle priorities • Sensitive to ranking accuracy • Depends on domain expertise	Pamucar *et al.* [125]

Moreover, the comparison of these methods is provided in Table 6 based on several important factors.

Table 6
Comparison of the reviewed MCDM methods based on several important factors

Methods	Ease of Use	Computational Efficiency	Handling Uncertainty	Adaptability	Transparency	Suitability for Big Data	Stakeholder Engagement
RAWEC	Easy	Moderate	Limited	Moderate	High	Low	Moderate
MARCOS	Easy	Moderate	High	High	High	Moderate	Moderate
SIWEC	Very Easy	Very High	Low	Low	Very High	Very Low	High
ABAC	Easy	High	Low	Moderate	High	Low	High
AROMAN	Moderate	Moderate	Moderate	Moderate	High	Low	Moderate
RAFSI	Moderate	Moderate	High	High	Moderate	Moderate	Low
OPA	Very Easy	Very High	Low	Low	Very High	Very Low	Very High
WENSLO	Moderate	Low	High	High	Moderate	High	Low
ALWAS	Easy	Moderate	High	High	Moderate	Moderate	Moderate
ARTASI	Easy	High	Low	High	Moderate	Moderate	Moderate
PROMSIS	Moderate	Low	High	High	Moderate	Moderate	Moderate
COBRAC	Very Easy	Very High	Low	Low	Very High	Low	Very High

A radar chart is also depicted in Figure 2. The qualitative ratings reported in Table 6 and visualized in Figure 2 were developed through a structured comparison of the methodological characteristics of the reviewed MCDM methods. Ease of use was assessed in terms of procedural complexity and the level of mathematical expertise required, while computational efficiency was evaluated based on algorithmic demands and reported scalability. The ability to handle uncertainty was determined by whether a method explicitly incorporated fuzzy, probabilistic, or other uncertainty-modelling mechanisms. Adaptability referred to its capacity to accommodate changing criteria, dynamic data, and hybrid extensions. Transparency was assessed through the interpretability of the results and the clarity of the underlying decision logic. Suitability for big-data applications reflected computational scalability and compatibility with data-driven and AI/ML environments, whereas stakeholder engagement considered the extent to which a method supported intuitive inputs, expert judgement, and group participation. The categories Very High, High, Moderate, and Low therefore indicate relative performance inferred from methodological design, reported applications, and comparisons across the literature rather than from a numerical scoring system. The purpose of this synthesis is to facilitate comparison among the methods, not to establish a definitive ranking.

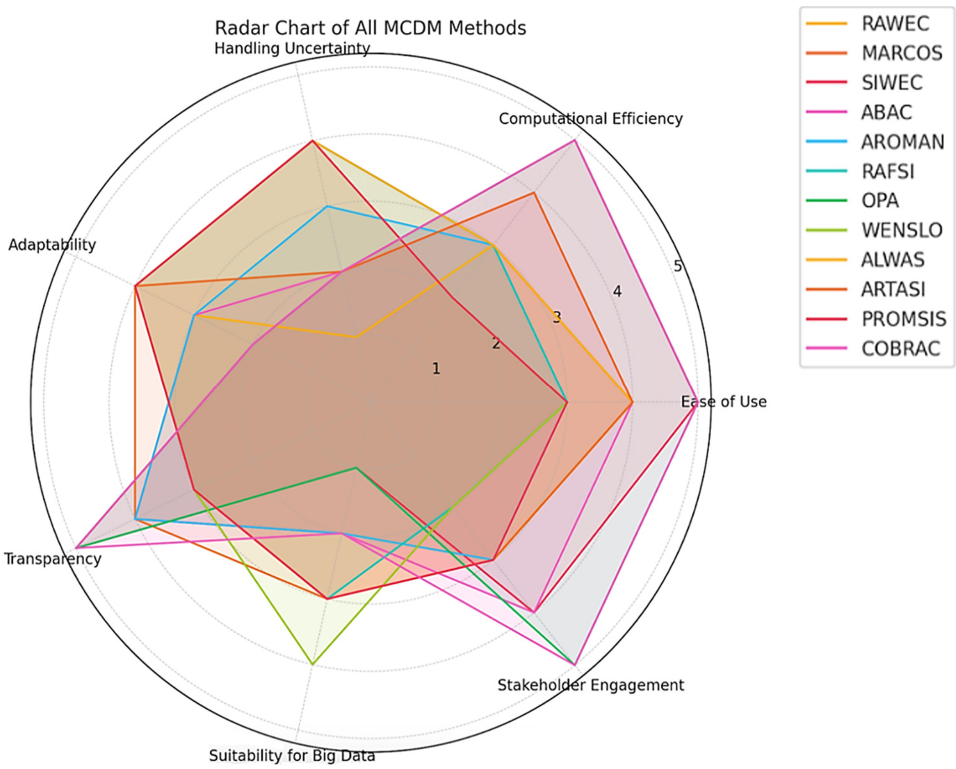

Fig. 2. Radar chart of MCDM methods

4. Gaps and Future Research Directions

In this study, the general framework of MCDM has been provided up to the above sections. Some current MCDM methods that have contributed to the literature in recent years have been mentioned, and some application areas connected to AI/ML integration have been shown by matching these with the studies in SSCM content. This section highlights the gaps in the literature that were identified within the framework of this study, along with recommendations for future research to address these gaps.

4.1 AI/ML Integration in MCDM

The integration of AI and ML into MCDM frameworks has opened new frontiers in tackling complex decision problems. AI/ML enhances the adaptability, scalability, and precision of MCDM methods by availing advanced computational and analytical capabilities. This subsection discusses the role of AI/ML in enhancing MCDM methodologies and presents their transformative potential, which can be manifested across diverse domains.

4.1.1 Enhancing dynamic weighting and criteria selection

AI/ML techniques facilitate the dynamic determination of weights and the selection of criteria, addressing the limitations of static, subjective weight assignments in traditional MCDM methods. Techniques such as:

i. *Neural networks* (NNs) – Learn patterns from historical data to adjust criterion weights based on evolving decision contexts dynamically. For example, a supply chain resilience model might prioritize "lead time" during disruptions but shift focus to "cost efficiency" in stable periods.
ii. *Feature selection algorithms* – Techniques like Recursive Feature Elimination (RFE) identify the most relevant criteria from large datasets, streamlining decision-making and reducing complexity.

Dynamic weighting systems have been effectively employed in real-time decision-making scenarios, such as resource allocation during disaster response and adaptive pricing in e-commerce. Although AI-driven dynamic weighting significantly improves the adaptability of MCDM models, its effectiveness depends heavily on the availability of reliable historical or real-time data. In relatively stable decision environments, the additional computational complexity introduced by dynamic weighting may not always justify its implementation.

4.1.2 Predictive analytics for decision support systems

ML models, including supervised learning and time-series forecasting, empower MCDM methods by providing predictive insights. Predictive AI models provide valuable forecasts that support decision-making; however, they do not directly optimize the decision process itself. Therefore, their effectiveness depends on how accurately prediction outputs are integrated into subsequent MCDM analyses. These predictions can be integrated into MCDM frameworks to assess the likely outcomes of decisions:

i. *Regression models* – Forecast demand or resource requirements to enhance decisions in logistics and inventory management.
ii. *Time-series models* (e.g., ARIMA, LSTMs) – Predict trends in energy consumption or market dynamics, enabling proactive decisions in energy planning and supply chain optimization.

Predictive analytics has been successfully combined with MCDM in demand forecasting for sustainable production planning and supply chain risk assessment.

4.1.3 Improved handling of uncertainty

AI/ML techniques enhance the ability of MCDM methods to manage uncertainty and vagueness, particularly in fuzzy environments:

i. *Fuzzy logic systems* – Enable MCDM methods such as ALWAS and MARCOS to process qualitative and uncertain data effectively.
ii. *Probabilistic models* (e.g., Bayesian networks) – Quantify uncertainty in decision-making, offering probabilistic evaluations of alternatives based on incomplete or uncertain inputs.

Such integrations are pivotal in environmental management, where criteria like "ecological impact" or "social acceptance" are inherently uncertain. While fuzzy and probabilistic AI techniques substantially improve uncertainty management, increased model complexity may reduce transparency and make practical implementation more challenging for decision-makers with limited technical expertise.

4.1.4 Clustering and grouping in complex decision contexts

ML techniques such as unsupervised learning enable the identification of patterns and clusters within large datasets, simplifying decision problems with numerous alternatives or criteria:

i. *K-means clustering* – Groups alternatives with similar performance, reducing computational complexity and aiding in the preliminary screening process.
ii. *Hierarchical clustering* – Identifies relationships among criteria, helping decision-makers understand interdependencies.

Clustering has been employed in supplier segmentation, customer prioritization, and resource allocation in healthcare. Moreover, these techniques effectively reduce the dimensionality of complex decision problems; however, inappropriate clustering structures may overlook important distinctions among alternatives and influence the final ranking results.

4.1.5 Real-time decision support and automation

The advent of real-time data processing has made it possible for MCDM methods to adapt dynamically:

i. *RL* – Automates decision-making by learning optimal policies through trial-and-error, particularly in iterative or real-time contexts.
ii. *Internet of Things (IoT)-driven decision systems* – Incorporate data from IoT devices (e.g., sensors in supply chains) to provide real-time updates to MCDM evaluations.

Real-time decision-making systems have proven effective in fleet management, smart city planning, and disaster response coordination, as well as in optimizing decentralized energy supply chains through blockchain-enhanced frameworks that simultaneously improve transparency, cost efficiency, and sustainability. In AI-supported MCDM frameworks, IoT data can be used not only to update the performance values of alternatives but also to dynamically adjust criterion weights. For instance, changes detected by sensors, such as increased machine downtime, temperature fluctuations, or supply chain disruptions, may automatically increase the importance of reliability, safety, or responsiveness, allowing the decision model to better reflect real-time operating conditions.

4.1.6 Explainability and stakeholder trust

i. Explainable AI (XAI) addresses the “black-box” problem in AI/ML-enhanced MCDM methods by making decisions interpretable;
ii. Shapley additive explanations (SHAP) explain how individual criteria contribute to an alternative’s ranking;
iii. Local Interpretable model-agnostic explanations (LIME) highlight the role of each criterion in influencing specific outcomes.

XAI integration fosters trust in sectors such as healthcare, where transparency in decision-making is crucial. AI techniques integrated into MCDM frameworks should be viewed as serving distinct, and often complementary, purposes rather than as competing alternatives. ML is commonly used for prediction, classification, and feature selection, while reinforcement learning is better suited to sequential decision problems in dynamic environments. IoT technologies supply continuous, real-time data that support adaptive decision-making, whereas explainable AI improves the transparency and credibility of AI-assisted outcomes. The choice of technique should therefore be guided by the nature of the decision problem, the availability and structure of the data, and the intended role of AI within the MCDM framework. No single AI method is universally superior across all applications.

4.2 Identified Gaps

Some of the literature gaps observed within the scope of the study can be expressed in general terms as follows:

i. *Integration of AI/ML techniques in MCDM* – From the evaluation of related studies, it is clear that the literature has integrated AI/ML-MCDM techniques quite poorly. Areas like SSCM, which require the optimization of complex MCDM processes, are particularly affected by this circumstance. Despite the apparent benefits of incorporating AI/ML-based techniques into MCDM, particularly when managing large datasets, simulating complex interconnections, and addressing uncertainty, the connections between these two fields remain a broad and understudied area. Such research is still in its infancy, but the dynamical, multi-dimensional, and occasionally multivariate nature of the criteria utilized in all sustainability-oriented decision processes, for instance, increases the potential of MCDM models backed by AI/ML. This is due to the recent addition of research on incorporating AI/ML approaches into MCDM methodologies to the body of literature. All components, including criteria weights and alternative evaluations, have been manually calculated using traditional MCDM procedures, which are typically based on static assumptions. However, the capacity of AI/ML approaches to learn from dynamic data is superior, enabling them to adjust to changing conditions and circumstances quickly. However, the application examples and theoretical framework that may include these benefits in MCDM models are still in their infancy. More research is specifically required in the area of AI/ML analysis of complex aspects, such as environmental and social criteria, particularly in the context of SSCM, and the incorporation of this data into the MCDM decision-making process. However, this is expected to change soon. AI/ML combined with MCDM is anticipated to be a powerful tool, particularly for business decision-makers seeking to achieve sustainability objectives. The decision-making process will be faster, more accurate, and more flexible when AI/ML is integrated with MCDM. It is anticipated that in the future, MCDM techniques will be integrated with the potent data processing and modeling capabilities of AI/ML to help optimize sustainable supply chains. It is anticipated that more studies in this field will lead to the development and wider adoption of theoretically and practically integrated models.

ii. *Contemporary methods in MCDM* – The development of new MCDM methods post-2020 addresses the growing need for tools that can manage increasingly complex decision-making challenges in dynamic and uncertain environments. These methodologies, such as RAWEC, MARCOS, SIWEC, and PROMSIS, offer innovative solutions to key limitations of traditional approaches while incorporating advanced computational techniques and hybrid frameworks. The implications of these advancements can be summarized as follows:
    - *Enhanced decision accuracy and flexibility* – Recent methods, such as MARCOS and PROMSIS, emphasize adaptability to dynamic conditions by integrating robust mechanisms, including ideal and anti-ideal benchmarks or hybrid pairwise comparison models. These methods ensure higher decision accuracy by capturing subtle performance variations across multiple criteria. Their flexibility allows decision-makers to recalibrate weights and criteria easily, making them highly relevant for industries such as SCM, healthcare, and energy planning.
    - *Improved handling of uncertainty and vagueness* – Methods such as ALWAS and RAFSI, which integrate fuzzy logic and advanced data transformation techniques, excel in scenarios where uncertainty and imprecision dominate decision-making environments. These tools enhance the applicability of MCDM methods to domains requiring nuanced evaluation, such as sustainability, resource management, and social responsibility.
    - *Integration of advanced data techniques* – The introduction of methods like Weights by the Envelope and Slope method (WENSLO) and ARTASI demonstrates the integration of data-driven principles, such as slope-based sensitivity analysis and adaptive interval standardization. These methods bridge the gap between traditional decision-making tools and modern data science techniques, enabling decision-makers to effectively utilize large-scale, heterogeneous datasets.
    - *Streamlined computational efficiency* – Approaches such as SIWEC and AROMAN emphasize efforts to simplify the computational demands of MCDM without compromising decision quality. By employing straightforward normalization and weight calculation techniques, these methods cater to decision-makers with limited technical expertise or computational resources.
    - *Applicability across diverse contexts* – The diversity in design and focus of these new methods ensures their applicability across various sectors. For instance, ABAC and COBRAC are particularly suited for ranking problems in supply chain optimization, while RAWEC and PROMSIS excel in group decision-making and multi-objective optimization problems.
    - *Increased stakeholder involvement* – Methods such as OPA prioritize simplicity and transparency, making them accessible to stakeholders without technical expertise. This inclusivity fosters more collaborative decision-making processes, enabling organizations to align decisions with strategic goals and stakeholder priorities.
    - *Broader implications for the field* – Many of the new methods, such as MARCOS and RAFSI, explicitly address sustainability concerns, making them integral to solving challenges in environmental management, green supply chains, and social

responsibility. The hybrid nature of methods such as PROMSIS and ALWAS encourages collaboration among disciplines, including operations research, data science, and behavioral decision-making. Simplified tools, such as SIWEC and ARTASI, lower the barrier to entry for smaller organizations, thereby fostering the broader adoption of MCDM tools in less resource-intensive settings.

4.2.1 Addressing practical challenges in implementing MCDM

While recent breakthroughs in MCDM methodologies have shown the potential of this area to revolutionize decision-making in nearly all aspects of life, several practical challenges hinder the effective application of these techniques in real-world situations. One of the most significant issues concerns the availability and quality of data. Most decision-making problems involve incomplete, inconsistent, or heterogeneous datasets, which complicate the processes of normalization, weighting, and evaluation inherent in MCDM. For instance, in SCM, the streams of data may originate from various sources, such as IoT devices, manual reports, and third-party databases, which differ in their level of reliability and granularity. Investing in robust data management systems for integration and preprocessing is the key to overcoming this barrier. Equally, automated aids for data cleaning, imputation, and standardization can strengthen the inputs, thereby enhancing reliability and enabling MCDM methods to yield meaningful and actionable insights.

Another critical challenge is related to stakeholder engagement and acceptance. MCDM methods often require active participation from decision-makers in defining the criteria, assigning weights, and interpreting the results. However, these stakeholders may not be in a position to understand somewhat complex methodologies; hence, resistance or misinterpretation of the outcomes may occur. The problem is accentuated when advanced techniques, such as AI/ML integration, are used, as the approaches may seem opaque or overly technical to some individuals. Researchers and practitioners should place a greater emphasis on explainability and transparency when presenting MCDM results. The use of simplified interfaces, visualizations, and clear documentation can demystify the process. Additionally, workshops or training sessions aimed at familiarizing stakeholders with the tools can help build trust and ensure that collaboration on decision-making is both inclusive and effective.

Practical adoption of advanced MCDM methods is often constrained by limited time, computing capacity, and technical expertise. These barriers are particularly significant for SMEs, which may lack the infrastructure and specialized staff needed to implement computationally demanding or iterative MCDM–AI models. Lightweight and scalable models, cloud-based MCDM services, and open-source tools can help lower these barriers and reduce the need for substantial upfront investment. The proposed framework is also intended for strategic decisions, such as major technology investments or adoption choices, rather than routine operational tasks. Because it is applied only when such decisions arise, its overall computational burden remains manageable. In practice, SMEs could implement the framework using accessible software such as Excel, MATLAB, Python, or R, as well as purpose-built decision-support applications. Initial implementation could also be supported through collaboration with universities, technology providers, or external consultants, thereby limiting the need for extensive in-house AI expertise.

Finally, the dynamic and uncertain nature of real-world decision environments poses a significant challenge. Many traditional MCDM methods assume static criteria and weights, which may not reflect rapidly changing conditions. For instance, in SSCM, priorities such as cost efficiency and environmental impact can shift due to economic fluctuations or regulatory changes. Addressing this requires integrating real-time data and adaptive techniques into MCDM frameworks [127]. AI/ML-driven methods, including reinforcement learning and dynamic weighting algorithms, enable decision-makers to better respond to evolving conditions. Moreover, scenario analysis and sensitivity testing should be embedded in each MCDM workflow as a standard component of the study to help organizations prepare for uncertainty and make more robust decisions.

In all, the practical difficulties in implementing MCDM methods must be addressed from multiple angles. Better data management, stakeholder engagement, resource barrier reductions, and adaptability to dynamics are but a few means of ensuring these methodologies realize their full potential when implemented by organizations. Further research is also needed to simplify and scale up MCDM frameworks, thereby bridging the gap between theoretical advances and practical applications.

4.3 Recommendations for Future Research

Although the integration of AI/ML and MCDM methods has high potential in SSCM, it can be observed that this combination has been addressed very scarcely within the existing literature. Traditional MCDM methods are generally based on static assumptions, and their data analysis and evaluation are based entirely on manual processes. On the other hand, the role of AI/ML in dynamic data analysis, processing large datasets, and managing uncertainties itself creates an avenue to improve both the flexibility and accuracy of methods in MCDM. A significant shortcoming of the literature is its incomplete application of theoretical frameworks for integrating sustainability criteria in environmental and social dimensions. While AI/ML-based systems can clearly make a difference in decision-making by rapidly adapting to the ever-changing market conditions and real-time data flows, this aspect is also not studied in sufficient depth.

The gap in the literature is an important one in the context of the complex structure of SSCM: (*i*) scarcity of dynamic and (*ii*) real-time decision-making models. On the other hand, the integration of AI/ML enables MCDM methods to develop systems that can adjust criterion weights over time and dynamically evaluate the performance of alternatives. Equally important will be further consideration of how such models can be applied, particularly with respect to minimizing environmental impacts and promoting social responsibility goals. For instance, AI-based algorithms can provide an optimized approach for sustainability criteria, leading to more informed decision-making. In other words, it is expected that, with the increasing number of studies in this area, hybrid MCDM models for SSCM will gain wider diffusion at both theoretical and practical levels in the years to come, reshaping the practice of decision-making. Future research could develop adaptive MCDM models in which criterion weights are learned using deep Q-networks (DQN) or other ML techniques. Such models could update the relative importance of criteria as new data and feedback on sustainability and cost KPIs become available. This dynamic recalibration would help ensure that the evaluation criteria remain relevant as operating conditions change, thereby supporting more responsive and effective sustainability and cost-management decisions.

5. Concluding Remarks

MCDM methods have been positioned as an important tool, particularly in areas such as SSCM, offering objective and systematic approaches to multi-dimensional and complex decision-making processes [128]. The study has looked at new-generation developments of the MCDM methods, with particular emphasis on those that represent the state-of-the-art approaches: RAWEC, MARCOS, SIWEC, ABAC, AROMAN, RAFSI, OPA, WENSLO, ALWAS, ARTASI, PROMSIS, and COBRAC. The advantages and disadvantages of each method have been thoroughly analyzed. The following approaches have been identified to enhance the flexibility, adaptability, and effectiveness of decision-making processes. However, this potential may be limited by the context of application and the structure of the data. Among the analyzed methods in the context of the research, RAWEC and MARCOS demonstrated an outstanding performance in terms of uncertainty management, making decision-makers more capable even under uncertain and incomplete data sets [89].

Another key advantage of these methods in the context of SSCM is that they can balance vital factors that may be economically costly to a company, as well as those with environmental impact. Methods such as ABAC and AROMAN focus more on sustainability criteria, thereby becoming an attention-grabber for their effective solution tool role in environmentally friendly decision-making processes, as reported by Biswas *et al.* [120] and Bošković *et al.* [129]. However, the ability of methods like SIWEC and RAFSI to handle multi-dimensional criteria sets simultaneously has found a wide application area in group decision-making scenarios [130]. On the other hand, high-computational-power-based approaches, such as PROMSIS and COBRAC methods, may create an applicability problem for small-scale enterprises or decision-makers with limited technical capacity [125]. This research provides a detailed examination of the integration of MCDM methods with AI and ML technologies, as well as the impact of this integration on SSCM.

It has been observed that AI and ML, when combined with big data analytics and automated decision support systems, enhance the accuracy and effectiveness of MCDM methods in decision-making processes [63]. For example, it has been determined that ML algorithms increase the operational efficiency of supply chains and facilitate risk management in processes such as supplier performance evaluation and inventory optimization. On the other hand, AI-supported systems offer an opportunity for more comprehensive analysis for decision-makers, contributing significantly to achieving sustainability and social responsibility performance goals.

The five research questions can now be addressed. Regarding the application areas of recent MCDM approaches (*RQ1*), the literature focuses primarily on supplier selection and evaluation, followed by facility and site selection and inventory management. Energy, waste management, and manufacturing are the most frequently represented sectors. Concerning the evolution of the field (*RQ2*), the approaches introduced since 2020 reflect a broader shift toward objective, ratio-based, and hybrid weighting procedures, together with the growing use of fuzzy representations of hesitation and uncertainty. The findings summarized in Tables 3-5 (*RQ3*) show that the integration of artificial intelligence and ML remains less extensive than the wider literature might suggest. Most of the reviewed applications do not incorporate a learning component, and those that do generally use it for criterion reduction or clustering. With respect to sustainability (*RQ4*), MCDM has proved useful for explicitly evaluating trade-offs among the three dimensions of the triple bottom line. In supplier selection studies, environmental criteria generally receive greater weight, whereas social criteria tend to be less numerous than environmental and economic criteria. Finally, the methodological weaknesses identified in response to *RQ5* are discussed in Section 4.2.

This review makes several specific contributions. First, it provides a comparative synthesis of the twelve MCDM approaches introduced since 2020, examining not only their reported strengths but also their limitations and the conditions under which their performance may deteriorate; issues that are rarely addressed in the original studies. Second, it develops a selection framework that links learning algorithms to decision problems according to both the data context and the role performed by the algorithm within the MCDM process, as described in Section 2.2.1 and Table 2. To the best of our knowledge, previous reviews have not offered guidance at the level of individual learning algorithms. Third, the structured analysis presented in Tables 3-5 provides insight into reporting practices across the field and distinguishes between reporting gaps, which can be addressed through clearer conventions, and conceptual gaps, which require new methodological developments.

The obtained results demonstrate that the application capacity of MCDM methods, integrated with AI and ML, is not limited to SCM alone; rather, it has great potential in a wide range of academic and industrial fields. For example, within healthcare, AI-backed MCDM methods are expected to significantly impact the level of performance in patient management, resource allocation, and treatment scheduling [131]. In the context of energy management, the use of these technologies in sustainability-oriented processes, such as optimizing renewable energy resources, estimating energy consumption, and reducing carbon footprints, offers a new perspective to the sector. In smart city applications, it is evaluated that AI-based MCDM methods can develop innovative solutions in areas such as traffic management, infrastructure optimization, and environmental planning. Additionally, AI- and ML-supported MCDM methods are considered to provide effective resource management and rapid decision-making mechanisms in dynamic and unpredictable processes, such as disaster management [132].

The integration of AI and ML with MCDM methods creates a new paradigm in academic literature, enabling the emergence of innovative research areas across various disciplines. In particular, the combination of big data analytics and deep learning techniques with MCDM methods will allow the development of systems that can adapt to more complex and dynamic decision-making processes in the future [3]. Valuable both theoretically and practically, this volume will discuss in detail the feasibility of applying these technologies to the crucial sectors of health, energy, agriculture, education, and environmental management. More research and interdisciplinary approaches toward issues on the ethics of AI in these key areas will lead to responsible usage and greater efficiency of technology.

The review offers three practical implications. First, method selection should reflect not only technical sophistication but also organizational capacity. The computational demands of methods such as PROMSIS [126] and COBRAC [133] may limit their use among small and medium-sized enterprises, whereas MARCOS [134] and RAWEC [135] may be more practical when computing resources are limited, or data are incomplete. Second, when learning algorithms are incorporated, their selection should be guided by the structure and scale of the data. As indicated in Table 2, supplier evaluation problems often involve only a few dozen alternatives assessed against a similar number of criteria, making kernel methods more suitable than tree-based ensembles. By contrast, the large raster-based datasets commonly used in site-selection problems are generally better suited to tree-based methods. Third, practitioners commissioning MCDM analyses should require clear evidence of the resampling procedure, hyperparameter-tuning strategy, and separation between weight derivation and alternative evaluation. Deriving and applying weights using the same dataset may overstate their ability to discriminate among suppliers, thereby weakening the reliability of the resulting procurement decision.

All in all, these findings suggest that the principal barrier to integrating MCDM with AI is no longer the availability of methods or algorithms. The field now requires greater methodological discipline in how these tools are combined, validated, and reported. Establishing such standards is therefore an urgent research priority and a necessary foundation for the reliable application of AI-enhanced MCDM in practice.

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Conflicts of Interest
The authors declare no conflicts of interest.

Appendix: Nomenclature

ABAC	Alternative by Alternative Comparison method
ABC	Activity-Based Classification
AI	Artificial Intelligence
ALWAS	Aczel–Alsina Weighted Assessment method
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANP	Analytic Network Process
AHP	Analytic Hierarchy Process
ARAS	Additive Ratio Assessment
AROMAN	Alternative Ranking Order Method Accounting for two-step Normalization
ARTASI	Alternative Ranking Technique based on Adaptive Standardized Intervals
BWM	Best–Worst Method
COBRAC	Comparisons Between Ranked Criteria method
CoCoSo	Combined Compromise Solution
COPRAS	Complex Proportional Assessment method
CRITIC	Criteria Importance Through Intercriteria Correlation
DEA	Data Envelopment Analysis
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DQN	Deep Q-Network
EDAS	Evaluation based on Distance from Average Solution
ELECTRE	Elimination and Choice Expressing Reality
GA	Genetic Algorithm
GIS	Geographic Information System
GRA	Grey Relational Analysis
IoT	Internet of Things
JIT	Just-In-Time
KPI	Key Performance Indicator
LIME	Local Interpretable Model-agnostic Explanations
LSS	Lean Six Sigma
MADM	Multiple Attribute Decision-Making
MARCOS	Measurement Alternatives and Ranking according to COmpromise Solution
MCDM	Multi-Criteria Decision-Making
ML	Machine Learning
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis
MULTIMOORA	Multi-objective optimization by ratio analysis plus the full multiplicative form
NIS	Negative Ideal Solution
NMI	Non-Moving Inventory
OPA	Ordinal Priority Approach
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
PROMSIS	PROMETHEE–TOPSIS hybrid method
RAFSI	Ranking of Alternatives through Functional mapping of criterion Sub-intervals into a Single Interval
RAWEC	Ranking Alternatives with Weighted Evaluation Criteria
RF	Random Forest
RFE	Recursive Feature Elimination
RL	Reinforcement Learning
SAW	Simple Additive Weighting
SCM	Supply Chain Management
SF-AHP	Spherical Fuzzy Analytic Hierarchy Process
SHAP	Shapley Additive Explanations
SIWEC	Simple Integrated Weighting Evaluation Criteria
SKU	Stock Keeping Unit
SMI	Slow-Moving Inventory
SSCM	Sustainable Supply Chain Management
SVM	Support Vector Machines
SVR	Support Vector Regression
SWARA	Step-wise Weight Assessment Ratio Analysis

ABAC	Alternative by Alternative Comparison method
TODIM	Interactive and Multi-criteria Decision-Making
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted Aggregated Sum Product Assessment
WENSLO	Weights by the Envelope and Slope method
XAI	Explainable Artificial Intelligence

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