Management Science Advances, Volume 3, Issue 1 (2026) 290-306

Management Science Advances

Journal homepage: www.msa-journal.org
eISSN: 3042-2205

A Systematic Review of MCDM Techniques for Decision-Making in Smart Manufacturing Systems under Industry 4.0

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ARTICLE INFO

Article history:
Received 24 January 2026
Received in revised form 11 March 2026
Accepted 23 April 2026
Available online 27 April 2026

Keywords:
Industry 4.0; Smart manufacturing systems; Decision-making; Multi-criteria decision making; MCDM; Complex systems.

ABSTRACT

The accelerated rate of Industry 4.0 development has turned traditional manufacturing systems into highly networked, smart, and data-driven settings, thus making decision-making processes exceptionally complicated. Smart manufacturing systems are characterized by a number of conflicting criteria, interdependencies, and uncertainty, and thus require powerful and systematic decision-support tools. This paper is a systematic review of the use of multi-criteria decision making (MCDM) in smart manufacturing systems within the Industry 4.0 paradigm. A systematic literature review methodology is followed, which includes database selection, a keyword-based search, and inclusion and exclusion criteria based on the PRISMA framework. The analyzed literature is categorized into major areas of application, such as technology choice, supplier selection, production optimization, sustainability measurement, and risk management. Moreover, a comparative study of the popular application of MCDM techniques, including AHP, ANP, DEMATEL, TOPSIS, and hybrid methods, is conducted to outline their strengths and weaknesses and their applicability to various decision settings. The research points out key research gaps, such as the lack of full integration of artificial intelligence, inadequate treatment of uncertainty, and the absence of real-time decision frameworks. Lastly, possible future research directions are suggested, focusing on the creation of hybrid and AI-enhanced MCDM models for smart manufacturing systems. This review presents important lessons for researchers and practitioners who are interested in adopting effective decision-making models in Industry 4.0 settings.

1. Introduction

The advent of Industry 4.0 has dramatically altered the structural and functional scenery of manufacturing systems by inculcating forward-looking digital technologies like the internet of things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), and big data analytics into production settings [1]. This convergence in technology has been used to ease the process of moving towards smart manufacturing systems where computing intelligence and communication

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https://doi.org/10.31181/msa31202649

networks are well integrated with the physical processes in manufacturing. Consequently, contemporary manufacturing systems are progressively becoming more dynamic in terms of real-time monitoring, adaptive control, predictive and decentralized decision making systems [2]. These characteristics allow making the operations more responsive and efficient, but, at the same time, they add certain level of complexity to the system and uncertainty in decision-making.

Unlike the contexts of classic manufacturing where the variables of the decisions to be made are relatively constant and limited in the range, smart manufacturing environments involve considering numerous and usually conflicting measures in interrelated subsystems [3,4]. The decision-makers have to think through economic considerations of cost and profitability, operations and its aspects of efficiency and productivity and strategic considerations of flexibility, scalability, sustainability and compatibility with the technology. Moreover, the fact that these criteria are interdependent and the Industry 4.0 systems are dynamical and require large amounts of data complicate the decision-making process and require more advanced analytical tools.

Such multi-dimensional situations reveal the weakness of traditional single-criterion or intuitive decision-making methods, which do not represent the trade-offs and interrelationships that are present in more complex manufacturing issues [5]. As a result, MCDM practices have become a formidable group of approaches that can be used to address these issues. MCDM techniques offer an organized approach to organizing decision issues, measuring preferences, and prioritizing options on the basis of several factors. The hierarchical structuring of decision problems can be performed with the help of techniques like the analytic hierarchy process (AHP) and the analytic network process (ANP) that can additionally include interdependencies between criteria. Likewise, decision-making trial and evaluation laboratory (DEMATEL) approach allows the causal relationships of complex systems to be analyzed and order preference by similarity to ideal solution (TOPSIS) method allows the determination of the best alternatives by their relative closeness to ideal solutions [6,7]. The popularity of these approaches in the manufacturing industries points to their success in facilitating the process of making decisions in a structured and transparent way.

Although MCDM techniques have become more and more popular in Industry 4.0 settings, the current literature is still somewhat limited in nature, with research mostly being dedicated to individual uses of MCDM techniques, like the selection of suppliers, introduction of technologies, or optimization of processes [8]. It can be seen that there is a lack of an in-depth and well-structured review to unify these contributions into a larger context of smart manufacturing systems. Additionally, the comparison of various MCDM methods on the basis of their methodological appropriateness, advantages, and weaknesses in the context of solving Industry 4.0-specific decisions have received little focus [5,6]. This gap limits the capability of the researchers and practitioners to choose the right decision-support tools, as well as to discover new research prospects.

To overcome these shortcomings, the current paper will conduct a systematic review on the use of MCDM methods in smart manufacturing systems within the Industry 4.0 paradigm [8,9]. By grouping the existing studies according to application areas, reviewing the methodological trends and assessing the effectiveness of various MCDM methods, the review will strive to offer an integrated approach [10]. Besides this, the study will aim at uncovering key research gaps and suggesting new avenues in future research on how to effectively improve decision-making structures in manufacturing processes that are more complex and data-driven.

The most important findings of this review are four-fold. First, it creates a systematic categorization of MCDM applications in smart manufacturing systems, which allows better seeing how the techniques are applied in the various contexts of decisions. Second, it provides comparative analysis of key MCDM techniques, their relative merits, constraints and applicability [4,5]. Third, it reveals some important research gaps, especially concerning uncertainty modeling, real-time decision-making, and the combination with advanced digital technologies. Lastly, it suggests future research directions to further develop hybrid and intelligent decision-support systems to meet the emerging needs of Industry 4.0.

2. Background Concepts

The fourth industrial revolution, commonly known as Industry 4.0, marks a paradigm shift in the manufacturing sector as a result of the introduction of high-tech digital and communication technologies into the manufacturing process [10,11]. This is not just the automation part and it goes further to the development of smart and intertwined ecosystems where machines, sensors and computational platforms communicate with each other in real time. Smart manufacturing systems are one of the pillars of this paradigm, which employs cyber-physical systems, IoT systems, artificial intelligence, and data analytics to attain high operational intelligence and autonomy [12]. These types of systems can enable constant data collection, predictive maintenance, adaptive control, and decentralized decision-making, improving productivity, minimizing system operational disturbances, and overall responsiveness.

Regardless of these innovations, the decision-making environment of smart manufacturing contexts becomes much more complex [2,3]. The combination of non-homogenous technologies, the interrelation of the parts of the system, present a high level of complexity, when various criteria should be considered at the same time. The decision-makers must strike a balance between technical, economic, environmental, and strategic factors, such as technological feasibility, cost-effectiveness, energy efficiency, sustainability, and system robustness. Additionally, the fact that these criteria have interdependencies implies that alterations in one dimension of the criteria can affect outcomes in other areas, thus requiring a holistic approach to evaluation [9,10]. The Industry 4.0 and its dynamic and data-driven character add a certain degree of uncertainty, ambiguity, and incomplete information, which complicates the decision-making process and restricts the applicability of traditional analytical techniques.

To address these issues, MCDM methods have come up as crucial resources in organizing and solving complicated decision-making problems in intelligent manufacturing systems. These approaches allow systemic consideration of options through the integration of both quantitative and qualitative options, as well as supporting preferences and trade-offs of decision-makers [12,13]. Various categories of MCDM methods can be distinguished on the basis of their methodological basis. The methods based on pairwise comparison, like the AHP and ANP, can be applied to hierarchical and network-structured decision problems, and the benefit of ANP is interdependencies between criteria. Topics such as distance-based methods, such as TOPSIS and VIKOR, are used to rank alternatives in terms of their relative proximity to optimal and anti-optimal solutions, so they are appropriate in selection and prioritization activities [14]. Outranking algorithms (ELECTRE and PROMETHEE) are optimized to address conflicts of criteria and biased preferences, and offer a more adaptable decision-making model. Also, the methods of causal analysis (such as DEMATEL) are especially effective in determining and measuring cause-effect relationships in complex systems, thus facilitating the analysis of potentially interrelated factors.

To offer a more analytical view, Table 1 outlines the main categories of MCDM methods, their main peculiarities, and applicability to smart manufacturing decision situations.

The variety of MCDM methods indicates that there is no universal method which will best suit all decision situations. Rather, the choice of the suitable method is determined by the nature of the problem, the form of criteria, the existence of interdependencies, the degree of uncertainty of the problem [15]. The use of appropriate MCDM frameworks is crucial in improving the quality of decision-making and operational efficiency in the environment of smart manufacturing systems, where the decisions are rather complex, dynamic, and data-intensive.

Table 1
Classification of MCDM techniques for smart manufacturing applications

Category	Representative methods	Key characteristics	Suitability in smart manufacturing
Pairwise comparison methods	AHP, ANP	Structured comparisons; handles qualitative judgments; ANP captures interdependencies	Strategic planning, technology selection
Distance-based methods	TOPSIS, VIKOR	Ranking based on proximity to ideal solutions; computationally efficient	Alternative selection, performance evaluation
Outranking methods	ELECTRE, PROMETHEE	Handles conflicting criteria; allows partial ranking and preference relations	Complex decision scenarios with trade-offs
Causal analysis methods	DEMATEL	Identifies cause–effect relationships; models interdependencies among criteria	System analysis, risk assessment, factor interaction analysis
Hybrid approaches	DANP, Fuzzy MCDM models	Combines strengths of multiple methods; handles uncertainty and complexity	Integrated decision-making in Industry 4.0 environments

3. Research Methodology

This study uses a systematic literature review (SLR) approach to guarantee a rigorous, transparent, and reproducible analysis of the available body of knowledge [16]. The SLR methodology is especially applicable in integrating scattered research results, reducing the selection bias, and offering a systematic basis on how to determine the research trends and gaps. The review protocol to be used in this research is developed based on the PRISMA (preferred reporting items to systematic reviews and meta-analyses) framework that allows conducting a systematic and properly documented literature identification, screening, eligibility check, and ultimate inclusion.

The review procedures start by use of a detailed database selection plan whereby high quality and peer-reviewed academic resources will be targeted in order to guarantee the validity of the results. The selection of major indexing platforms, such as Scopus, Web of Science, ScienceDirect, and IEEE Xplore, is based on the broad coverage of the engineering, manufacturing and decision science literature [17,18]. All these databases offer a multidisciplinary and comprehensive approach, including not only theoretical developments but also practical implementation of MCDM methods in Industry 4.0 settings.

A well-developed search plan is used to locate pertinent publications. The use of the Boolean operators and a combination of keywords is done to maximize coverage and be specific at the same time [12,13]. The main search query is developed by combining the key terms that refer to MCDM and intelligent manufacturing, including: (“MCDM” OR multi-criteria decision making) AND (Industry 4.0 OR smart manufacturing) AND (AHP OR ANP OR DEMATEL OR TOPSIS OR VIKOR) [16]. Further filtering will be done to reduce the list to peer-reviewed journal articles published in the last five years (2015-2025), so that the review reflects modern processes in line with the fast change of the Industry 4.0 technologies.

To increase the level of transparency in methods, the main elements of the search strategy are listed in Table 2.

Table 2
Search strategy and database selection

Component	Description
Databases used	Scopus, Web of Science, ScienceDirect, IEEE Xplore
Time period	2015–2025
Document type	Peer-reviewed journal articles
Language	English
Core keywords	MCDM, Industry 4.0, Smart manufacturing
Method-specific keywords	AHP, ANP, DEMATEL, TOPSIS, VIKOR
Search technique	Boolean operators (AND, OR)

After retrieving initial records, there is a multi-stage screening process to ascertain relevance and quality of the studies selected. The screening process comprises of three steps: (i) title screening, (ii) abstract screening, and (iii) full-text screening. At every step, the studies are evaluated on the basis of predetermined inclusion and exclusion criteria to remove irrelevant or low-quality studies.

The inclusion criteria will be set in a way that only those studies that are directly related to the research objectives will be taken into consideration. In particular, the studies chosen should: (i) use some of the MCDM techniques, (ii) solve a decision-making problem in the context of manufacturing or Industry 4.0, and (iii) have enough methodological information to analyze. On the other hand, the studies are eliminated when they: (i) look at other non-manufacturing areas, (ii) lack a clear methodology, (iii) are conferences papers, reviews or book chapters that provide minimal empirical value and (iv) are duplicated records among databases. Table 3 is a compact presentation of the inclusion and exclusion criteria.

Table 3
Inclusion and exclusion criteria

Criteria type	Inclusion criteria	Exclusion criteria
Relevance	Focus on MCDM applications in Industry 4.0 or smart manufacturing	Unrelated to manufacturing or decision-making
Methodology	Explicit use of MCDM techniques (AHP, ANP, DEMATEL, etc.)	Lack of methodological clarity
Publication type	Peer-reviewed journal articles	Conference papers, books, editorials
Language	English	Non-English publications
Time frame	Published between 2015–2025	خارج the defined time range

In order to make the review even stronger, a quality assessment process is adopted. The evaluation of each chosen study is done according to the criteria, including the rigor of the methods used, the clarity of purpose, the relevance of the MCDM use, and contribution to the field [19]. This measure will help in making sure that the final analysis is only based on high quality studies and thus enhance the reliability of such findings.

The general process of the selection is based on the typical PRISMA flow, consisting of four significant steps: identification, screening, eligibility, and inclusion [20, 21]. Though the graphical PRISMA diagram is not shown here, the process can be illustrated in the following way: an initial pool of articles will be identified by searching databases, duplicates will be eliminated, irrelevant studies will be filtered in the screening phase, and only the rest of the articles will be evaluated to be included in the final set.

Lastly, the chosen literature is systematically reviewed and grouped into domains of application, the methods of MCDM applied, and the methodological features [22]. Such an organized method of work not only makes it easier to synthesize the literature in a comprehensive way but also allows defining the trends in research, gaps in methods, and possible directions of research in the field of smart manufacturing decision-making under Industry 4.0.

4. Classification of MCDM Applications in Smart Manufacturing

The methodological review of the reviewed literature shows that MCDM methods have been widely applied in a wide spectrum of decision-making processes of smart manufacturing systems [21,22]. These applications are indicative of the multi-dimensional nature of Industry 4.0 environments, in which decision problems are defined by conflicting goals and criteria that are interrelated and continually changing operational environments [23]. In order to present a systematic picture, the uses of MCDM in smart manufacturing can be divided into several key areas, such as technology choice, supplier analysis, optimization of production and processes, sustainability analysis, risk and resilience analysis.

The choice of technology is one of the most evident application fields, especially since there is a rapid increase in sophisticated digital solutions related to Industry 4.0. To implement systems like IoT platforms, cloud manufacturing systems, digital twins, and AI-based analytics tools, organizations must assess and embrace these technologies [24]. The decision maker here will have to strike a balance between various factors such as cost of implementation, scalability, interoperability of the systems, security of the data and the long term adaptability. MCDM methods would offer a methodological approach to ranking such technologies considering quantitative measures of performance and the use of qualitative expert judgments to make informed and strategic decisions about the adoption of technology.

Another area of critical concern is supplier selection, particularly in digitally integrated and highly responsive supply chains [25]. Supplier assessment in the context of smart manufacturing is not only limited to the traditional cost, quality and delivery performance criteria but also advanced criteria of digital integration ability, technological advancement, cybersecurity compliance and environmental sustainability. The difficulty of these evaluation criteria has caused the popularity of hybrid MCDM strategies, especially a combination of AHP, TOPSIS, and fuzzy-based models, which allow treating uncertainty and subjectivity preferences more powerfully [21,24]. The approaches enable the identification of the best suppliers who can enable the digital transformation goals of Industry 4.0.

One of the fundamental areas of operation that MCDM methods are utilized to optimize production and processes is the area of manufacturing efficiency and system performance. Problems of decision making in this field involve machine selection, optimization of process parameters, schedule and quality control [25,26]. Such decisions involve the concomitant use of various performance metrics, including productivity, reliability, energy consumption, maintenance needs, and operational flexibility. MCDM techniques will be especially useful here as they can help decision-makers to analyze trade-offs between competing goals and choose the best choices that will be consistent with the overall production objectives.

Sustainability assessment has become more and more significant in recent years as manufacturing organizations struggle to make their operation reflect their environmental and social responsibility objectives [27]. Although technologically advanced, smart manufacturing systems should also be concerned with issues of energy consumption, carbon emissions, waste production, and resource efficiency. MCDM methods are also extensively applied to incorporate these sustainability criteria in decision-making models, enabling companies to assess alternative strategies and technologies according to their environmental and social effects [24,26]. This strategy will facilitate the shift towards a more sustainable and greener manufacturing process which is vital to the long term development of the industry.

Other application areas that are becoming critically important in the era of Industry 4.0 are risk assessment and resilience analysis, especially in the conditions of more system interconnectivity and digital dependence [19,22]. Smart manufacturing systems face multiple risks, such as cybersecurity risks, system failures, and supply chain attacks. The interdependencies between risk factors are studied using MCDM techniques, particularly those that can represent interdependencies like DEMATEL, to determine the drivers of vulnerability in the system [27,28]. This helps the decision-makers to come up with efficient risk reduction measures and a stronger manufacturing system that is resistant to occurrences of disruption.

To offer a unified view, Table 4 shows the key areas of application of MCDM in smart manufacturing, major decision problems, common techniques and decision evaluation criteria.

Table 4
Classification of MCDM applications in smart manufacturing systems

Application domain	Key decision problems	Common MCDM techniques	Typical evaluation criteria
Technology selection	IoT platform selection, AI adoption, cloud systems	AHP, ANP, TOPSIS, VIKOR	Cost, scalability, interoperability, cybersecurity, adaptability
Supplier selection	Vendor evaluation, digital supply chain integration	AHP, TOPSIS, Fuzzy AHP, DEMATEL	Cost, quality, delivery, digital capability, sustainability
Production optimization	Machine selection, scheduling, process optimization	AHP, TOPSIS, VIKOR, ANP	Efficiency, reliability, energy consumption, flexibility
Sustainability assessment	Green manufacturing, energy system evaluation	AHP, Fuzzy TOPSIS, COPRAS	Energy efficiency, emissions, resource utilization, environmental impact
Risk & resilience analysis	Cybersecurity risk, supply chain disruption analysis	DEMATEL, ANP, Fuzzy DEMATEL	Risk severity, likelihood, interdependency, system vulnerability

The classification underscores the fact that the usage of MCDM methods in intelligent manufacturing is widespread and developing. Although the traditional approaches do still maintain a strong presence, there is an evident trend towards hybrid and high-tech approaches that are more capable of tackling the complexity, uncertainty, and interconnectivity of the Industry 4.0 systems [29,30]. Such a systematic classification not only helps to better understand the current research trends, but also a basis to see gaps and prospects in future research.

5. Comparative Analysis of MCDM Techniques

Careful review of the MCDM methods used in smart manufacturing systems shows that all the methods have their unique theoretical bases, computational frameworks, and conditions of their applicability [17,19,20]. In the context of the multi-layered nature of Industry 4.0 environments (interdependent criteria, dynamic flows of data, and uncertainty), no single MCDM method can be deemed an overall best [16]. Rather, the success of a method depends on how well it fits the structural features of the decision problem, including hierarchy, network relationships, causality and presence of ambiguity.

The AHP has been one of the most popular MCDM methods because of its intuitive nature and simplicity to apply. It breaks down the decision problems of complex nature into hierarchical form and uses pair-wise comparisons to come up with relative weights of the criteria and alternatives [22,23]. It is this simplicity that renders AHP very apt in problems with well-defined and independent criteria. Its basic premise of criteria independence, however, makes it less applicable to smart manufacturing systems, where interdependencies and feedback relationships tend to occur. The ANP, on the other hand, builds on the ideas of AHP by including network-based structures that enable interrelationships between criteria and alternatives [19,20]. Even though ANP offers a more realistic model of complex systems, it brings more computational resources and demands more large-scale expert assistance, which can impact its application in practice.

DEMATEL approach provides an alternative view of analysis by emphasizing the identification and measurement of cause-effect relationships between factors of the system [31]. This is especially useful in the analysis of complex and interacting decision environments, like risk assessment and system modeling in Industry 4.0. DEMATEL allows creating influence maps, which differentiate between driving and dependent factors, hence give more insight into the structure of the system [30,31]. Nevertheless, in its pure form, DEMATEL does not offer a direct comparison of alternatives, thus the need to combine it with other MCDM tools to obtain a complete decision support.

To offer a more definite comparative picture, Table 5 presents the main peculiarities, advantages, and shortcomings of the leading MCDM methods when applied to smart manufacturing systems and their appropriateness.

Table 5
Comparative analysis of major MCDM techniques

Method	Key features	Strengths	Limitations	Suitability in smart manufacturing
AHP	Hierarchical structure; pairwise comparisons	Simple, intuitive, easy to implement	Assumes independence among criteria	Suitable for structured and less complex decisions
ANP	Network structure; captures interdependencies	Models feedback and interrelationships	Computationally intensive; requires extensive judgments	Suitable for complex systems with interdependent criteria
DEMATEL	Causal relationship modeling; influence mapping	Identifies cause–effect relationships; visual representation	Does not directly rank alternatives	Suitable for system analysis and risk evaluation
TOPSIS	Distance-based ranking method	Simple computation; clear ranking mechanism	Ignores interdependencies; assumes linear trade-offs	Suitable for selection and ranking problems
VIKOR	Compromise ranking approach	Balances group utility and individual regret	Sensitive to weight assignment	Suitable for conflict resolution in decision-making
ELECTRE	Outranking method	Handles conflicting criteria; partial ranking	Complex computation; less intuitive	Suitable for complex decision environments
Hybrid models (e.g., DEMATEL–ANP–TOPSIS)	Integration of multiple methods	Combines strengths; handles complexity and uncertainty effectively	Higher computational complexity; requires methodological expertise	Highly suitable for Industry 4.0 decision problems

The TOPSIS is another popular technique particularly in the case of ranking and selection issues. It considers the alternatives in terms of their geometrical distance to an ideal and a negative-ideal solution, thus computationally affordable and interpretable [29,30]. In spite of these benefits, TOPSIS does not expressly consider interdependencies between criteria and makes a linear trade-off between attributes, which can simplify the situation of smart manufacturing.

Understanding the weaknesses of each approach, the recent development in research shows that the use of hybrid MCDM approaches and combining various techniques is increasingly popular in an attempt to exploit their complementary advantages [27,28]. As an example, the integration of DEMATEL and ANP (also called DANP) allows considering both causal relationships and interdependencies during the weighting process and the integration of TOPSIS allows ranking of alternatives [31]. These hybrid frameworks are especially useful when dealing with the multidimensional and unpredictable nature of Industry 4.0 decision problems, since they offer greater analytical coverage, strength and precision.

The comparative analysis shows clearly a paradigm shift of standalone MCDM methods to integrated and hybrid frameworks. The rationale behind this change is the necessity to deal with the growing complexity, interconnectivity as well as uncertainty of smart manufacturing systems [32,33]. The more robust nature of the decision-making models as well as a more in-depth insight into the system dynamics that hybrid approaches offer lead to more informed and reliable decision outcomes.

6. Integration of Advanced Approaches

The growing complexity and data volume of intelligent manufacturing systems have led to the shift towards integrating modern computational methods with conventional MCDM methods [34]. Although classical MCDM models can offer formalized decision support models, they tend to be based on clear input data and deterministic assumptions, which might not be sufficiently applicable to the uncertainty, ambiguity, and dynamism of Industry 4.0 contexts [34,35]. In order to overcome these limitations, recent studies have worked on improving MCDM models by integrating fuzzy logic, artificial intelligence (AI), machine learning (ML), and big data analytics, and thus making them more robust, adaptive, and more driven by the data.

One of the most popular extensions is fuzzy MCDM, which is mostly used when there is uncertainty and vagueness in decisions by humans and data in the real world. Decision-makers in smart manufacturing often have to contend with inaccurate data, language variables, and unreliable data [21,26,28,31]. The set of uncertainties can be represented by the use of membership functions, thus converting the subjective evaluation into measurable values through the use of fuzzy set theory. Fuzzy AHP, Fuzzy TOPSIS and Fuzzy DEMATEL are variants that have been widely used to represent ambiguity in criteria weighting, alternative evaluation and causal analysis [36]. These methods improve the realism in decision models by being able to accept the imprecision that comes with expert opinions and dynamic operational conditions.

Simultaneously, the combination of artificial intelligence and machine learning tools and MCDM has been gaining traction, with the creation of intelligent decision-support systems [34,35]. With AI-based models, it becomes possible to engage in predictive analytics and adaptive decision-making because they learn automatically using past and real-time data. Preprocessing of large datasets, discovery of patterns, and derivation of input parameters to the MCDM models can be accomplished by machine learning algorithms, including neural networks, support vector machines, and clustering techniques [36,37]. By integrating, it increases the objectivity and scalability of the decision-making process, especially within the manufacturing context where the environment is complex and where data are high and system conditions keep changing.

Big data analytics also augments MCDM frameworks by offering the ability to process and analyze large amounts of structured and unstructured data produced by smart manufacturing systems [38]. There are sensors, IoT devices, and enterprise systems that are constantly producing data regarding machine performance and energy consumption, supply chain processes, and the quality of production. Combining big data analytics and MCDM, decision-makers will have an opportunity to use real-time and past data to enhance the accuracy of assessments, decrease the reliance on subjective decisions, and facilitate the evidence-based decision-making [39]. This data-driven approach is particularly valuable for applications such as predictive maintenance, process optimization, and demand forecasting.

In order to offer a systematic overview, Table 6 will give a summary of the main advanced methods that are combined with MCDM methods, their functionality and added value to smart manufacturing decision making.

Table 6
Integration of advanced approaches with MCDM techniques

Advanced approach	Key features	Integration with MCDM	Benefits in smart manufacturing
Fuzzy logic	Handles uncertainty using linguistic variables and membership functions	Fuzzy AHP, Fuzzy TOPSIS, Fuzzy DEMATEL	Improved handling of ambiguity and subjective judgments
Artificial intelligence	Intelligent decision-making using rule-based and learning systems	AI-assisted MCDM frameworks	Automation, adaptability, and enhanced decision accuracy
Machine learning	Pattern recognition and predictive modeling	Data preprocessing and parameter estimation for MCDM	Data-driven insights and predictive decision support
Big data analytics	Processing large-scale structured and unstructured data	Integration with MCDM for real-time evaluation	Improved accuracy, scalability, and real-time decision-making
Hybrid intelligent models	Combination of fuzzy, AI, and MCDM techniques	Neuro-fuzzy MCDM, AI-integrated hybrid models	Comprehensive and robust decision-support systems

The combination of these novel methods is a shift to dynamic, intelligent, and adaptive decision models as opposed to static and deterministic decision models [29,30]. These developments are especially essential in Industry 4.0 settings where decision-making should be responsive to real-time data and be able to deal with uncertainty and be in line with the changing system needs [32,33]. Therefore, the intersection of MCDM and innovative computational methods is likely to become a key contributor to the development of next-generation decision-support systems in smart manufacturing.

7. Research Gaps

Despite the fact that the use of MCDM methods in smart manufacturing systems has increased significantly over the recent years, the existing literature indicates that there are a number of serious limitations that preclude the widespread implementation of these methods to Industry 4.0 contexts [40]. The main sources of the gaps are related to the growing complexity, dynamism and data-driven character of modern manufacturing systems that remain to be covered by the current frameworks of decision-making. The systematic review of the studied papers suggests that although the methodologies have been improved, a lot of suggested models are theoretical or semi-empirical and less adaptable to the real-life industrial environment.

Among the most striking gaps, there is the lack of real-time and adaptive decision-making frameworks [38,39]. Majority of the currently existing MCDM models assume that input data and criteria weights do not vary during the process of decision making [33,34]. Nevertheless, smart manufacturing systems are dynamic by their nature, featuring unceasing information creation by IoT devices, swift system states alterations, and shifting operation restrictions [40]. MCDM models lack real time integration, which limits their responsiveness, rendering them less effective in environments where real time and adaptive decision support are needed.

The other relevant research gap is the little merge between artificial intelligence and machine learning and MCDM methods. Although initial research has examined how AI-enhanced MCDM frameworks can be used, their actual application is still in its infancy [29,34,35]. The current models also tend to be based on conventional expert-led assessments as opposed to using data-driven learning processes. This limits the adaptability of decision-support systems, their learning based on historical trends, and their enhancement of the accuracy of decisions in the long term [38]. An open research problem is the creation of fully operational AI and MCDM systems that are able to process large volumes of real-time data.

In order to summarize these observations, Table 7 provides a systematic account of the major gaps in the research, implications, and possible future research directions.

Table 7
Identified research gaps and future opportunities

Research gap	Description	Implications	Future research direction
Lack of real-time frameworks	Static MCDM models unable to adapt to dynamic environments	Reduced responsiveness and decision accuracy	Development of real-time and adaptive MCDM systems
Limited AI integration	Early-stage integration of AI/ML with MCDM	Underutilization of data-driven capabilities	AI-enhanced and learning-based decision models
Inadequate uncertainty modeling	Reliance on deterministic or basic fuzzy approaches	Incomplete representation of real-world variability	Advanced uncertainty methods (probabilistic, interval, rough sets)
Limited empirical validation	Predominance of theoretical or small-scale case studies	Reduced practical applicability	Industrial-scale validation and real-world case studies
Lack of system-level integration	Focus on isolated decision problems	Inability to capture interdependencies across systems	Network-based and integrated decision frameworks
Insufficient sustainability integration	Limited inclusion of environmental and social criteria	Incomplete assessment of long-term impacts	Holistic sustainability and resilience-based MCDM models

Another significant issue in the existing literature is still uncertainty modeling. This is notwithstanding the fact that fuzzy MCDM methods have been developed in order to overcome vagueness and ambiguity but in most cases, research works use deterministic or crisp data sets that do not reflect the inherent variability and stochastic characteristics of the real-life manufacturing systems [33,34]. Additionally, more sophisticated methods of uncertainty modeling, including probabilistic, interval-based, and rough set models, have not been investigated in the Industry 4.0 context yet, so more holistic and hybrid models of uncertainty management are required.

Moreover, we can observe an apparent lack of empirical validation and large-scale application of MCDM models. Much of the current literature relies on hypothetical cases, simulated data, or small case studies, making it challenging to generalize and apply the results in practice [40,41]. The practical implementation of smart factories, which entails the use of real data about the operations and stakeholder responses, is necessary to evaluate the strength, scalability, and usability of suggested decision-making models.

The other area that is facing a crucial gap is the lack of sufficient attention towards interconnectivity and system-level integration. The smart manufacturing systems are networks of networks that incorporate production units, supply chains, information systems, and human operators [31,33,37]. Nevertheless, most MCDM models address specific decision issues in isolation, and do not reflect the system-wide interactions and feedback. This constraint is decreasing the efficacy of decision-making in intricate, networked settings where local choices can have trickle-down effects throughout the system.

Moreover, the concept of sustainability and resilience is not always incorporated in MCDM models. Some studies include environmental requirements but a holistic solution that integrates economic, environmental, and social aspects, as well as the resilience of a system to shocks, is yet to be developed [40,41]. As sustainable and resilient manufacturing gains greater significance, this is a major research prospect in the future.

In sum, these research gaps indicate that there should be a paradigm shift in the traditional, fixed MCDM methods to integrated, intelligent, and adaptive decision-support systems [42]. Overcoming these constraints will be a key to making MCDM techniques more relevant to the emerging highly complex and data-driven environment of smart manufacturing as an Industry 4.0.

8. Future Research Directions

Considering the mentioned limitations and the new technological trends, future studies in the field of smart manufacturing decision-making must be focused on the creation of hybrid and intelligent MCDM frameworks that would be able to deal with the multi-faceted challenges of an Industry 4.0 setting [41,42]. The growing interconnection of manufacturing systems and the access to large-scale data require the combination of traditional MCDM methods with new computational methods, including artificial intelligence, machine learning, big data analytics, and digital twins technologies [39]. This type of integration can greatly improve the flexibility, precision and scalability of decision-support systems.

One of the opportunities is to develop hybrid MCDM models that integrate structured expert judgment and data-driven mechanisms of learning [43]. Specifically, the combination of the Delphi, ANP, and DEMATEL approaches provides an all-encompassing framework of decision-making that can simultaneously solve the issue of uncertainty, interdependencies, and cause-and-effect relationships. Delphi method is useful to build consensus among professionals, ANP is used to describe complex network relations among the criteria, and DEMATEL is used to define cause effect relationships in the system [44]. These approaches can offer a strong analytical basis to tackle the most challenging decision problems in intelligent manufacturing environments when integrated.

The other research direction that is highly important is the creation of real-time and adaptive decision-support systems [45]. As the IoT-enabled devices and sensor networks continue to spread, manufacturing systems constantly produce real-time data regarding the production processes, the work of machinery and the work of the supply chain. Future MCDM systems must be structured to support this streaming data, so that weightings of criteria can be updated dynamically and also rankings of alternatives can be updated dynamically [44,45]. Interactive dashboards and visualization tools can also be further used to improve the decision-making process by offering an easy-to-use and intuitive interface to monitor the performance of a system and review decision scenarios in real-time.

Another important opportunity to advance MCDM applications is the integration of the digital twin technology. Digital twins are virtual models that represent real-world systems, allowing them to simulate and predict manufacturing processes in real-time [46]. Connecting digital twins to the MCDM models, a decision-maker is able to explore various options, analyze possible results, and streamline decisions prior to their implementation in the real-life system. This strategy enhances accuracy of decisions, minimizes operational risks and expenditures.

In addition, the inclusion of sustainability and resilience as essential decision criteria should be given more focus in future research. Although economic and operational aspects have conventionally been prevalent in manufacturing decisions, there is a rising demand to incorporate environmental, social, and resilience-focused aspects into MCDM models [45,46]. These involve assessing the energy efficiency, carbon emissions, resources use, and resilience of systems to disruptions and recoverability. Long-term sustainability of industrial performance, sustainability, and resilience will require the development of multi-dimensional decision frameworks that can address all three aspects simultaneously.

In order to sum up these guidelines, Table 8 presents the main future research topics, their aims, and contributions they are likely to make to smart manufacturing decision-making.

Table 8
Future research directions for MCDM in smart manufacturing

Research direction	Focus area	Expected contribution
Hybrid MCDM frameworks	Integration of AI, big data, and MCDM methods	Enhanced decision accuracy and robustness
Delphi–ANP–DEMATEL integration	Combined handling of uncertainty, interdependence, causality	Comprehensive and realistic decision modeling
Real-time decision systems	Dynamic data integration and adaptive decision-making	Improved responsiveness and real-time optimization
Digital twin integration	Simulation-based decision support	Risk reduction and predictive decision-making
Interactive decision dashboards	Visualization and user-interface development	Improved usability and stakeholder engagement
Sustainability & resilience focus	Inclusion of environmental and disruption-related criteria	Holistic and sustainable manufacturing decision frameworks

In general, the future development of MCDM research in smart manufacturing is the shift to integrated, intelligent, and real-time decision-support systems instead of standalone models [47,48]. Through the use of advanced technologies and hybrid approaches, the complexity, uncertainty, and dynamism of the Industry 4.0 can be more adequately tackled by future frameworks, thus facilitating more effective and sustainable decision-making in smart manufacturing contexts.

9. Conclusion

The present study is a systematic and well-organized review of MCDM methods to solve decision-making problems in smart manufacturing systems in the industry 4.0 paradigm. Combining a broad spectrum of recent research, the review confirms that MCDM approaches are critical to the rising complexity, interconnection, and multi-dimensionality of contemporary manufacturing settings. The shift to smart manufacturing has increased the demands on effective decision-support systems that can combine various criteria, deal with uncertainty, and promote both strategic and operational decisions.

As the analysis shows, the traditional MCDM methods, especially AHP and TOPSIS, remain popular because of their simplicity, transparency, and simplicity of implementation. Nevertheless, their natural weaknesses, including the belief in the independence of criteria and the inability to provide a model of complex interactions in a system, have stimulated the development of more sophisticated and versatile methods. In this regard, ANP and DEMATEL techniques, as well as their combinations, have become prominent due to their capabilities to reflect interdependencies and cause and effect links among the decision variables. The increasing movement to hybrid MCDM frameworks highlights the necessity to have more detailed and versatile models that may successfully tackle the complex decision-scape of Industry 4.0 systems.

Moreover, the review emphasizes the major transition to the incorporation of MCDM methods with sophisticated computational solutions, such as fuzzy logic, artificial intelligence, machine learning, and big data analytics. These integrations improve the ability of decision-making models as they allow to perform data-driven analysis, increase the quality of uncertainty treatment, and support real-time decision-making. Regardless of these developments, there are still a number of key areas of research deficiency such as real-time adaptability, empirical validation, system-level integration, and holistic sustainability evaluation.

To deal with these issues, this paper presents some of the foreseeable future research directions with the focus on the creation of integrated, intelligent, and adaptive systems of decision support. The integration of integrated models like Delphi-ANP-DEMATEL, as well as new technologies like digital twins and real-time data analytics, should go a long way in making MCDM applications more useful in smart manufacturing. Also, the concept of sustainability and resilience as critical decision criteria should be included in the provision of long-term industrial feasibility and compatibility with the global development agenda.

By and large, the results of this review give a cohesive body of knowledge and an analytical monolithic view to both researchers and practitioners. The research will help to develop a better decision-making framework in smart manufacturing systems by providing an elaborate classification of applications, a comparative analysis of methodologies, and a clear outline of gaps in the research. The knowledge provided in the current paper can be used as a valuable source of information in designing and applying the next generation MCDM models to meet the changing needs of Industry 4.0.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was not funded by any grant.

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