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Review

Multi-Criteria Decision Making in Production Fields: A Structured Content Analysis and Implications for Practice

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Abstract: As the complexity of decision-making problems and the competitiveness in which companies find themselves carrying out their activities increase, the need to use tools that can help Decision-Makers (DM) make more informed and more effective choices increases. Multi-Criteria Decision Making (MCDM) represents a valid decision support tool capable of simplifying the process of choosing, ranking or sorting the alternatives that characterize the problem. This work aims to investigate with a structured content analysis if MCDMs are used in an extremely complex and competitive sector such as the automotive sector. The work also aims to describe and explore in the existing literature the role that entrepreneurs (our decision-makers) play in the construction of MCDM methods. The results show that MCDMs are widely used in different application areas in the domain of interest and that the decision maker is involved in several phases of construction of the MCDM methods.

Keywords: multi-criteria decision making; decision-making process; automotive sector; production; entrepreneur behaviors; MADM; MODM

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1. Introduction

The considerable increase in the complexity of the decisions that companies must make to survive and achieve their competitive objectives has significantly impacted decision-making processes (Dias and Mousseau 2018). A plurality of objectives declared to be prevalent by companies that explode into a multitude of criteria and alternatives represent the usual scenario in which Decision-Makers (DMs) find themselves making choices (Toloie-Eshlaghy and Homayonfar 2011). The process of choosing DMs has therefore become more articulate. In this context, the DM can no longer rely only on intuition or on an approximate analysis of the alternatives but needs to look for new approaches and methodologies that facilitate and support them in the decision-making process (Greco et al. 2016). In recent years, Multi-Criteria Decision Making (MCDM) has been used to support the DM in the process of defining and solving choice, ranking and sorting problems. MCDM aims to provide support to the DM to reach an acceptable compromise between the various objectives pursued (Guzman 2001). These methodologies allow comparisons of several criteria with the aim of contributing to the development of a learning process that feeds the decision-making process. Indeed, MCDM can be used to manage complexity, stimulate the participation of DMs and facilitate communication between the parties involved (Figueira et al. 2005).

According to several authors, MCDM really supports the decision-maker in the decision-making process, helping them to better frame the decision-making problem, the alternatives and the criteria useful for achieving the set objectives (see, e.g., Ishizaka and Nemery 2013; Doumpos et al. 2019; Zavadskas and Turskis 2011). They also help the DM make more accurate decisions (Karbassi Yazdi et al. 2022). In order to demonstrate that

MCDM is really useful to DMs, several authors have conducted comparative studies that demonstrate the usefulness of MCDM for solving problems in a real context. For example, Ishizaka and Siraj (2018) conducted an experiment on real data with respect to incentive mechanisms using three MCDM methods with the aim of verifying whether multicriteria methods really helped DMs and which tool they found most useful (see also Mulliner et al. 2016; Opricovic and Tzeng 2004). Experiments have also been carried out to test the coherence of several models of MCDM (Cavallo and Brunelli 2018; Cavallo et al. 2019).

Bisdorff et al. (2015) identified several case studies in the real world and highlighted how MCDM methods can support the achievement of the goal. In fact, the use of MCDM methods is widely adopted in different fields of interest (e.g., Mulliner et al. 2016; Basílio et al. 2022). Their use is motivated, on the one hand, by the high complexity of decision-making problems (Xu et al. 2012; Toloie-Eshlaghy and Homayonfar 2011) and, on the other hand, by solving problems using advanced techniques (Montmain et al. 2015). This is especially necessary when the sector is particularly competitive (Stoycheva et al. 2018). One of the particularly complex sectors is the automotive one.

The automotive sector represents one of the main production sectors in the world, both for production volumes and for the revenues achieved. Suffice it to say that the cars produced in the world have almost doubled, increasing from about 39.7 million in 2001 to 73.3 million in 2017, numbers that have continued to grow in recent years (Traub-Merz 2017).

The transformation and evolution of the automotive industry have led the sector to be hit by a series of pressures to change rapidly with respect to the needs of the market. It should be remembered that the greatest impulse to change in the automotive industry is attributable to the introduction of Lean Production in companies (Womack and Jones 1997; Jacobides et al. 2016) intended as a modern orientation to design and business management, aimed at pursuing efficiency, by eliminating waste and sources of variability, and effectiveness, understood as the creation of value for the customer (Bhamu and Sangwan 2014).

In this direction, on the operational level, companies are constantly experimenting with methodologies to support the increasingly sophisticated control and Performance Management functions (Ferreira and Otley 2009) such as Total Productive Maintenance, Total Quality Control, Just in Time, Total Industrial engineering (Yamashina et al. 2013), which aim to integrate principles of Lean Production. Yahya et al. (2016) highlighted that these production logics have considerably increased the complexity of the problems and the role of DMs in decision-making processes who have increasingly relied on the use of decision support systems such as MCDM even just for the choice of tools best suited to the objectives of Lean Production (see also, Alhuraish et al. 2016).

The aim of this work is to classify, describe and explore if MCDM methods are used for solving problems in a particularly complex sector such as the automotive one and its areas of application. We also intend to verify if and how the DM intervenes in the construction of an MCDM method.

The paper is organized as follows: Section 2 defines the materials and methods; Section 3 reports the main results; Section 4 concludes the paper.

2. Materials and Methods

This literature review aims to provide an extensive theoretical background on the use of MCDMs—including organizational and managerial consequences—in complex organizations in the automotive sector. For this reason, the study highlights the evolution of related concepts by implementing a qualitative (Bell et al. 2005; Andrade 2009) and exploratory nature (Alcácer et al. 2016). The choice to carry out a systematic review of the literature on this topic allows for an understanding of the current state of the scientific panorama on the topic and to understand the evolution of future research, taking into account the studies already carried out.

2.1. Sources and Search Protocol

In this study, the academic literature analyzed are scientific documents contained in the SCOPUS and Web of Sciences (WoS) databases with a particular focus on MCDM methods in the automotive sector. These data collection channels contain a large number of scientific documents (scientific journals, books and peer-reviewed conference proceedings) routinely used by researchers from all over the world. The papers were extracted and retrieved in July 2022. No time constraints have been applied. The work considered only peer-reviewed journal articles in the English language. According to Tranfield et al. (2003), the following were excluded from the collection of documents: books, chapters/book reviews, professional articles, conference proceedings, working papers, reports, and unpublished works.

To the articles identified with the databases, a further 39 articles were added, considered relevant for the systematic literature review.

2.2. Selection of Scientific Documents

The PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analyzes) guidelines (Moher et al. 2015) were followed to describe all the phases of the data analysis and selection process, as well as the screening process. These guidelines guarantee transparency in the entire systemic literature review process (Liberati et al. 2009).

Figure 1 shows the process of selecting scientific articles to be used in the analysis of the literature. The final database on which the literature review will be made is composed of 167 relevant documents without duplicate articles. The articles have been read to understand their real contribution to the objective of this review and used in the analysis phase of the collected data and the main contributions.

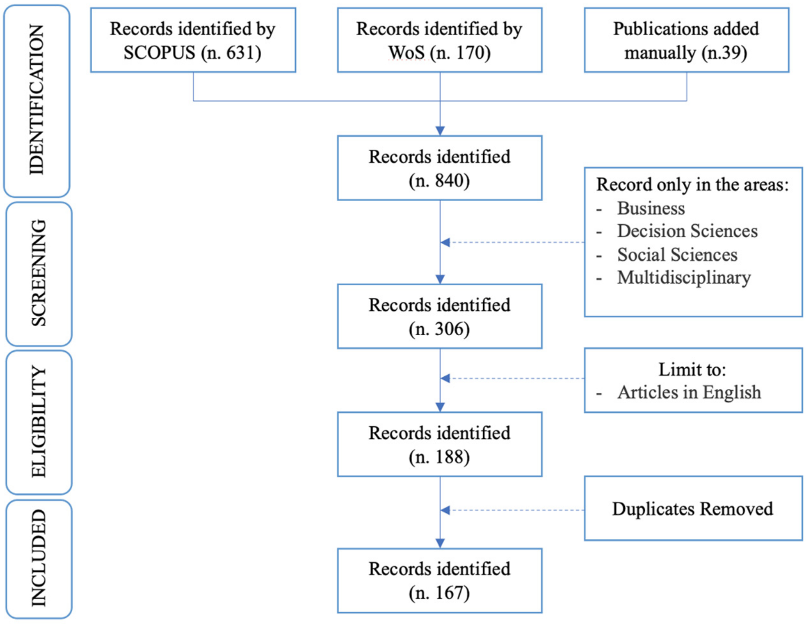

Figure 1. PRISMA guidelines. Source: our elaboration.

2.3. Database Preparation and Pre-Processing

The bibliographic data were exported in CSV (Comma Separated Values) format and ranked by author in alphabetical order. A check was made to make sure that all fields in the document were valid. In addition, useless or duplicate entries were removed from the file. The data were then exported to an Excel worksheet and pre-processed with Excel functions to provide graphs and tables. In order to identify the connection between the works, the keywords used by the authors in the selected papers were analyzed. In this sense, the VOSviewer software (Van Eck and Waltman 2007; Van Eck et al. 2010) was used to analyze the database. Each selected article has been included in the database highlighting: author/s, year, type of articles, setting, methods, analysis methods, main finding and new or renewed property/explained assumption.

3. Results

This section is divided into two areas of analysis. The first analyzes the collection of papers by analyzing the connections that exist between them through an analysis of the scientific landscape. The scientific landscape is made up of the relationships that keywords have with each other. The study of the scientific landscape allows us to understand how the various authors investigated the phenomenon under observation. Furthermore, this section analyzes the scientific production of the research object developed over the years. The second area analyzes the papers, highlighting the results and contributions made to the scientific community on the topic and analyzes the role of the DM in the construction of MCDMs in the domain of interest.

3.1. Data Analysis

In the analysis of the literature, of particular importance is the understanding of the scientific landscape in which the subject of study is placed. In this sense, the database composed of the final articles was analyzed using the VOSviewer software (Van Eck et al. 2010). The analysis provides the mapping of the relationships between the different keywords of the scientific articles highlighting all the connections existing between the articles considered.

Figure 2 shows the scientific landscape composed of the keywords of the selected articles. In particular, the scientific landscape is made up of 766 keywords. The keywords written differently but which had the same meaning have been standardized, i.e., we changed multicriteria to multi-criteria. The filter for the minimum number of relationships that each keyword must have was imposed as equal to 4. With the application of this filter, 60 nodes that make up the network were identified.

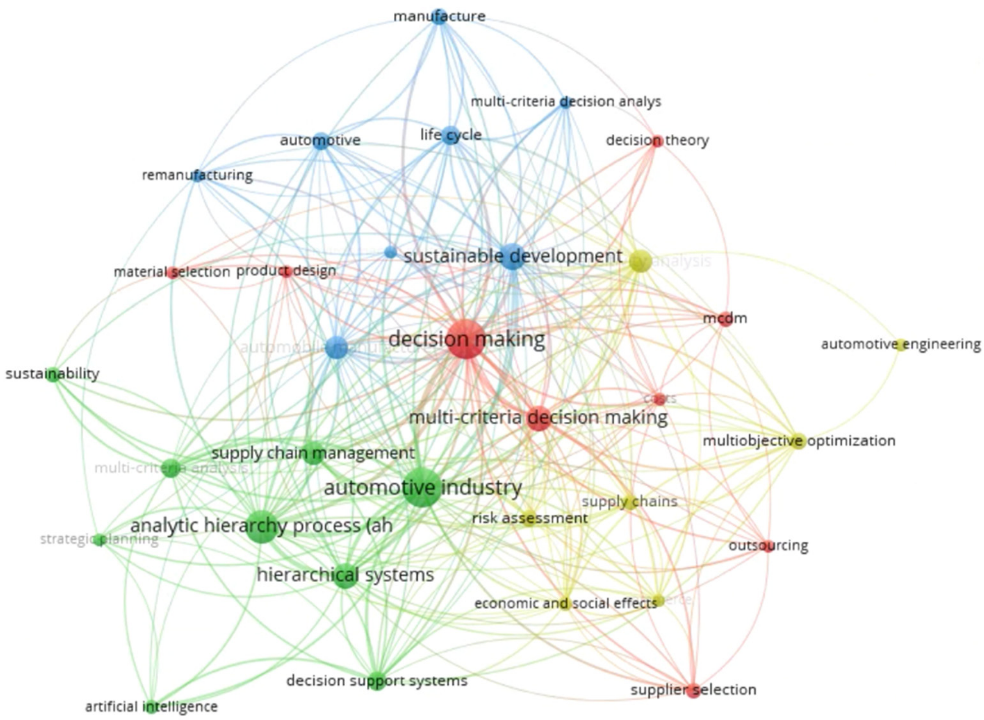

Figure 2. Scientific landscape of keywords. Source: our elaboration with VOSviewer software.

The scientific landscape can be analyzed based on the characteristics of: density, diameter and centralization. The density of the scientific landscape highlights the quantity of documents and the intensity of the relationships between keywords of selected scientific papers. Density can be broken down into cohesion and redundancy. Table 1 shows the characteristics of the relationship.

Table 1. Characteristics of the scientific landscape.

Density	Cohesion	The literature examined is very cohesive. The cohesion of the scientific landscape is represented by the focus on the keywords "*decision making*", "*automotive industry*", "*analytic hierarchy process*" and "*sustainable development*".
	Redundancy	In order to avoid redundancy of information, double or similar keywords have been excluded (e.g., multicriteria/multi-criteria/multi-criteria technique; automobile/automotive; analytic hierarchical process/analytic hierarchy process).
Diameter	Number of Reports/Information decay	The relationships in the literature appear strong and information degradation is minimal.
Centralization	Subgroup Peripherals/Structural Center	The academic literature observed is focused on the theme of decision making. Despite this, it is possible to identify growing subgroups linked to the keywords "*automotive industry*", "*multi-criteria decision making*", "*sustainable development*" and "*decision making*"

Source: our elaboration.

The VOSviewer software devised the nodes into 4 clusters based on their relationships between keywords (Table 2).

Table 2. Cluster and items in the network.

	Cluster 1—Red	**Cluster 2—Green**	**Cluster 3—Blue**	**Cluster 4—Yellow**
Keywords	Costs	Analytic Hierarchy Process (AHP)	Automobile manufacturing	Automotive engineering
	Decision making	Artificial intelligence	Automotive	Multiobjective optimization
	Decision theory	Automotive industry	Environmental protection	Risk assessment
	Material selection	Decision support system	Life cycle	Sensitivity analysis
	MCDM	Hierarchical system	Manufacture	Supply chains
	Outsourcing	Multi-criteria Analysis	Multi-criteria decision analysis	
	Product design	Strategic planning	Remanufacturing	
	Supplier selection	Supply chain management	Sustainable development	
		Sustainability		

Source: our elaboration.

Table 2 shows the division of keywords into clusters. The number of clusters and the breakdown are based on the relationships between the different keywords. Clusters 1 (red) and 3 (blue) have the same number of elements equal to eight. Cluster 2 (green) is the most numerous and has nine elements; cluster 4 (yellow) is the least numerous with five elements. The network shown in Figure 1 and the division into clusters represent the basis for analyzing the phenomenon of interest. The aim of this literature review is to provide a theoretical framework for the use of MCDM methods in companies in the automotive sector. To pursue this objective, data analysis will have the automotive sector as its main focus. In this sense, for the analysis of the cluster-based literature, the relationships between clusters are shown in Figure 2. The main node is therefore the automotive industry, which is linked to different keywords of the clusters shown in Table 2. In this sense, the "automotive industry" was chosen as the main node. By selecting this node, as shown in Figure 2, all the words interconnected with it are identified. As shown in Figure 2, the analysis cluster is composed of keywords belonging to different clusters shown in Table 2. This allows us to make the first consideration. Research relating to the automotive sector is certainly linked to decision-making processes (see the links with the red nodes) relating to the sector and certainly uses hierarchical decision support systems (see the links with the green nodes).

From a first analysis, it also appears that the use of MCDM has different fields of application, such as sustainability, supply chains, risk assessment and so on.

The scientific landscape shown in Figure 3, which has the automotive industry as its main node, can be analyzed by taking into account three parameters: Centralization, Diameter and Density of the network. Network centralization identifies central areas and peripheral areas of the network. Looking at Figure 3, in addition to the automotive industry, it is possible to identify at least four main nuclei: decision making, sustainable development, hierarchical system and Analytic Hierarchy Process (AHP) (Saaty 1988). The main centers revolve around the main node for us and, at the same time, are close to each other. This means that there are few peripheral areas. The analysis parameter is the diameter. The diameter defines the number of relationships present in the network. A large number of relationships lead to information loss. The network under consideration has a limited diameter, and this means that all the present nodes make a contribution to the theme without any dispersion of information. A further parameter of analysis is the density of the network, which makes it possible to identify the research areas with the greatest number of contributions. Density allows us to understand the cohesion or redundancy of information. This criterion brings out two aspects of the network: information cohesion and redundancy. The closer the research themes are, the more cohesion there will be between the various nodes considered. However, if the nodes create a single agglomeration, the information available will be redundant. In Figure 4, the density of the observed phenomenon is shown. It is possible to state that the information available does not appear to be redundant.

Of particular interest is to understand how and when the academic debate on the phenomenon under analysis began. In Figure 5, it should be noted that work on the use of MCDM methods in the automotive sector is a young research field. In particular, in Figure 5, it is shown that the first articles date back to 2004, with an increase in the same types of articles over time. The analyzed data show, in particular, that future research trends have a growing interest in this new area of research.

In particular, from the analysis of Figure 5, some keywords have recently been used by authors to analyze the phenomenon. The network analysis shows a strong link between the automotive and MCDM methods with particular reference to hierarchical systems. It seems interesting that in recent years the automotive sector has also had multi-objective optimization connections.

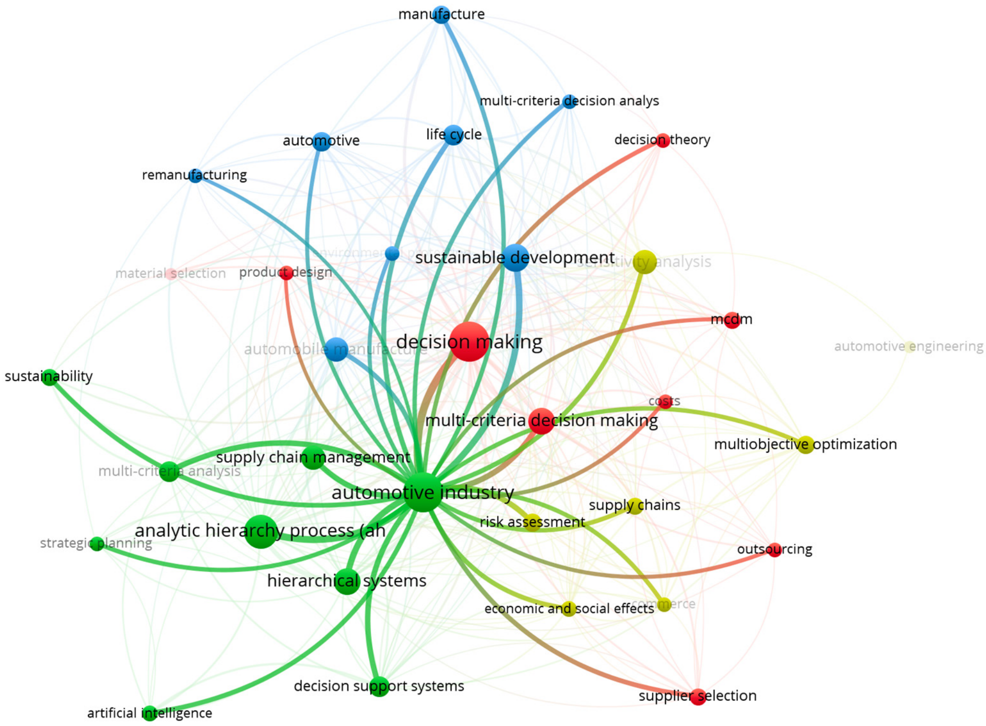

Figure 3. Scientific landscape with a focus on the automotive industry node. Source: our elaboration with VOSviewer software.

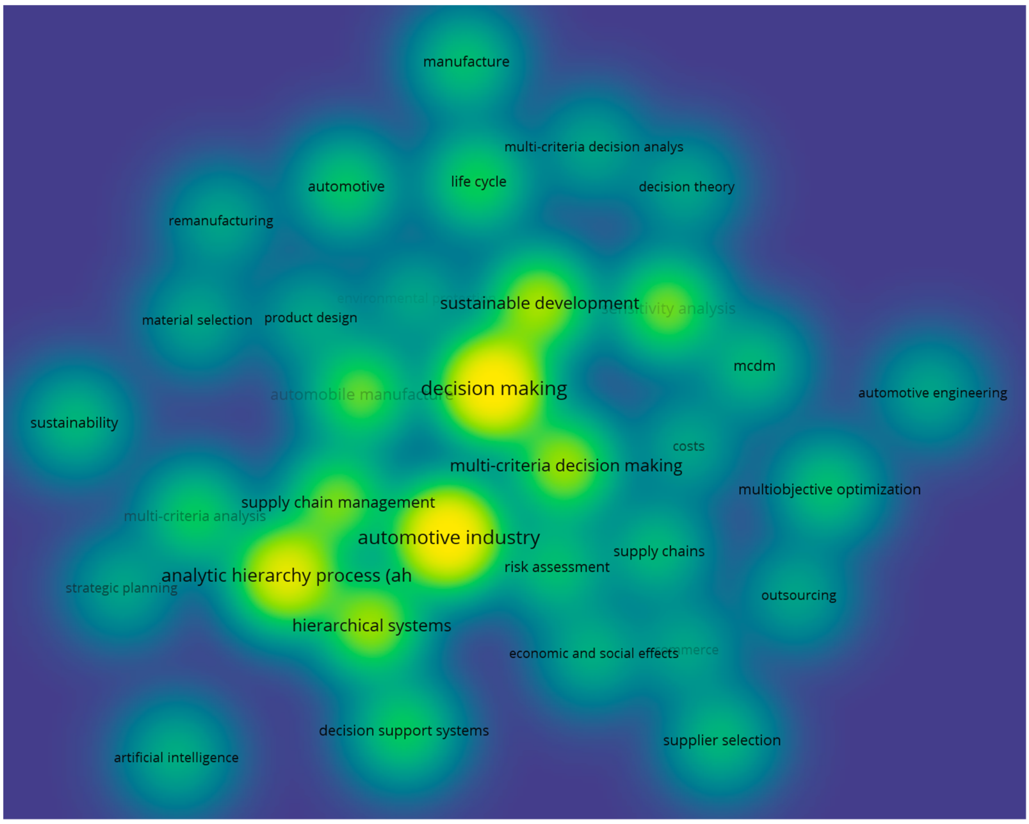

Figure 4. Density of the network. Source: our elaboration with VOSviewer software.

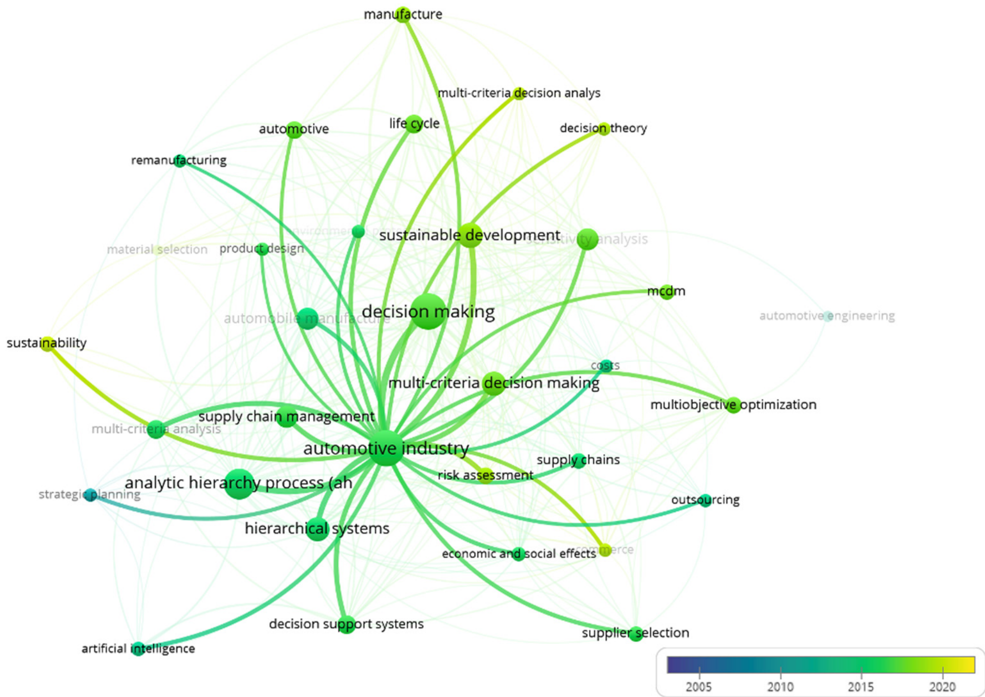

Figure 5. Evolution of the network over time. Source: our elaboration with VOSviewer software.

The importance that MCDM methods are assuming in the academic debate with respect to the automotive sector is confirmed by the evolution over time of the volume of articles published on the subject.

Figure 6 shows the evolution of the research area in terms of volume of scientific production. From 2004 to 2012, there was an almost constant scientific production. Since 2012, there has been an increase in articles leading to a doubling of the articles produced on the subject. In 2020, scientific production on the issues of the use of MCDM methods in the automotive sector quadrupled. These numbers confirm a growing academic interest in this research field. In Figure 6, the Simple Moving Average (SMA) has been added (Johnston et al. 1999). The SMA allows you to analyze the historical series and identify trends. From the analysis of the articles for years and SMA, two historical phases are possible: the first historical phase (from 2004 to 2012) and the second historical phase (from 2013 to 2022).

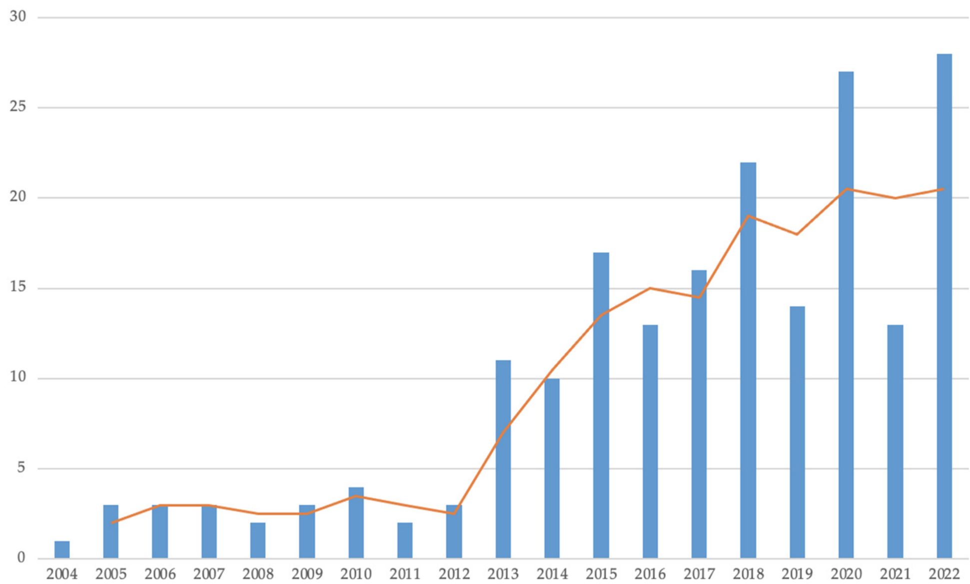

Figure 6. Analysis of articles for years. Source: our elaboration.

3.2. *Analysis of Contributions*

In recent years, the complexity that has characterized decision-making problems in the automotive sector has greatly increased (Xu et al. 2012). For this reason, DMs have increasingly relied on decision support systems such as MCDMs (Ülengin et al. 2014). In addition to supporting the DM in the choice process, MCDMs are used for the need to use advanced techniques for managing the complexity of production and logistics processes (Montmain et al. 2015) in a highly competitive sector. MCDM methods have been widely used as tools to compare the effects of adopting new manufacturing strategies in the automotive sector (Alhuraish et al. 2016). In this study, we identify not only the main methods used in the automotive sector but also how they were built by the different authors, referring to the construction steps of the MCDMs identified by Cinelli et al. (2020).

Table 3 reports the characteristics of the phases and elements (for more details, see Cinelli et al. 2020) that we have analyzed in the articles identified in the previous section.

Table 3. Steps and elements of analysis for building MCDMs.

<table>
<tr><th colspan="2">Step I—Problem Formulation</th><th colspan="2">Step II—Decision Recommendation</th><th>Step III—Qualitative and Technical Support</th></tr>
<tr><td rowspan="4">Problem Type</td><td>a—Problem Statement</td><td rowspan="9">Definition of preference</td><td>f—Elicitation of Preferences</td><td>h—Easiness of Use</td></tr>
<tr><td>1: Choice 2: Ranking 3: Sorting</td><td rowspan="3">1. Direct
1a: Subjective Weights, 1b: Subjective Imprecise Weights, 1c: Objective Weights, 1d: No Weights, 1e: Pairwise Comparison, 1f: Criteria interaction, 1g: Preference Model Scoring Function, 1h: Preference Model Binary relations, 1l: Preference Model Decision Rules</td><td>1: High 2: Medium 3: Low</td></tr>
<tr><td>b. Alternatives</td><td>i—Processing Time</td></tr>
<tr><td>1: Stable 2: Incremental</td><td>1: High 2: Medium 3: Low</td></tr>
<tr><td rowspan="7">Criteria</td><td>c—Structure</td><td></td><td>L—No. Alternatives/Criteria:</td></tr>
<tr><td>1: Flat 2: Hierarchical</td><td rowspan="4">2: Indirect
2a: Incremental Frequency, 2b: One time, 2c: Elicitation Approach Assignment, 2d: Comparison, 2e: Ordering, 2f: Pairwisesome</td><td>1: High 2: Medium 3: Low</td></tr>
<tr><td>d—Measurement Scale</td><td rowspan="5">M—Software Support:
1: Yes, 2: No, 3: Yes with Graphical or DSS</td></tr>
<tr><td>1: Ordinal 2: Interval 3: Scale</td></tr>
<tr><td>e—Performance Type</td></tr>
<tr><td rowspan="2">1: Determinate 2: Uncertain</td><td rowspan="2">g—Aggregation</td><td rowspan="2">1: Compensation Level Between Criteria
2: Consistency
3: Dependency of Decision Context</td></tr>
<tr></tr>
</table>

Source: our elaboration.

In Appendix A, Table A1 shows the main areas of application in the automotive sector in which the MCDMs have been used. The authors, the MCDM methods and the details of how they have been constructed, taking into account Table 3, are also reported.

From the analysis of Table A1, in Appendix A, and Figure 7, it emerges with particular importance that in almost all cases, the authors have used ranking methods to solve decision-making problems, and few authors in recent studies have analyzed sorting problems (see, Larrodé et al. 2012; Unver et al. 2020; Fattoruso and Barbati 2021; Fattoruso et al. 2022a). It also emerges that the most widely used measurement scale is the ordinal one and that mostly determined decision-making problems are analyzed. It should also be noted that the application of preferences occurs in most cases directly by means of a comparison in pairs. Another interesting aspect is that few authors use software for the construction of MCDMs.

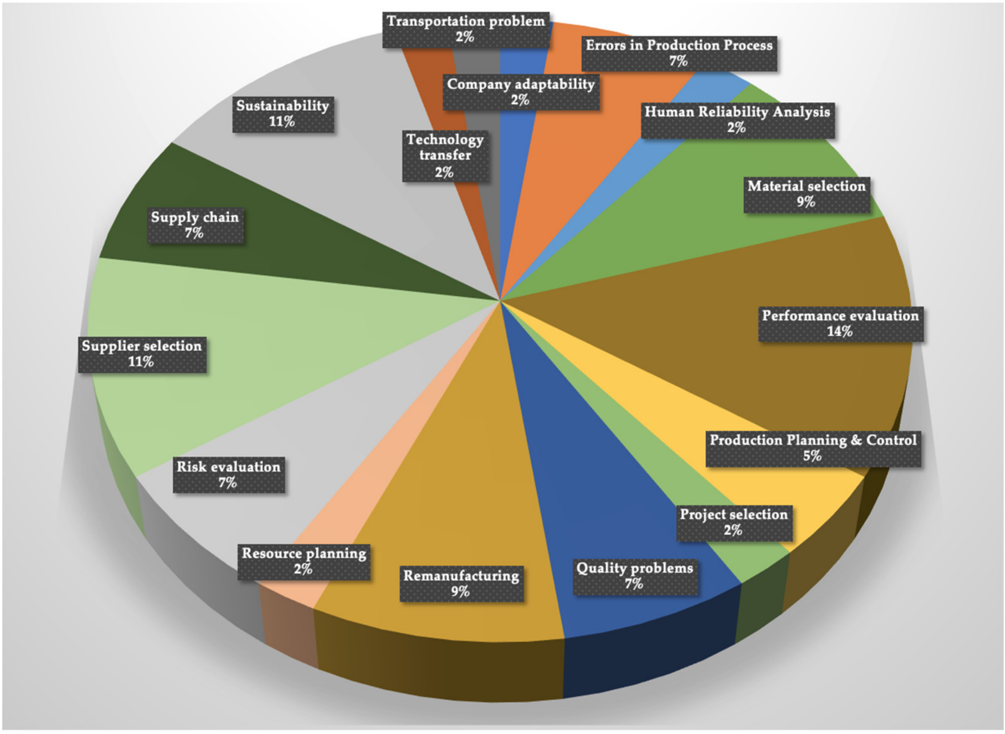

Figure 7. Areas of application of MCDM methods in the automotive sector. Source: our elaboration.

Figure 7 shows the application areas of MCDM methods in the automotive sector, while Figure 8 defines the main MCDMs used in the different application areas of the automotive sector.

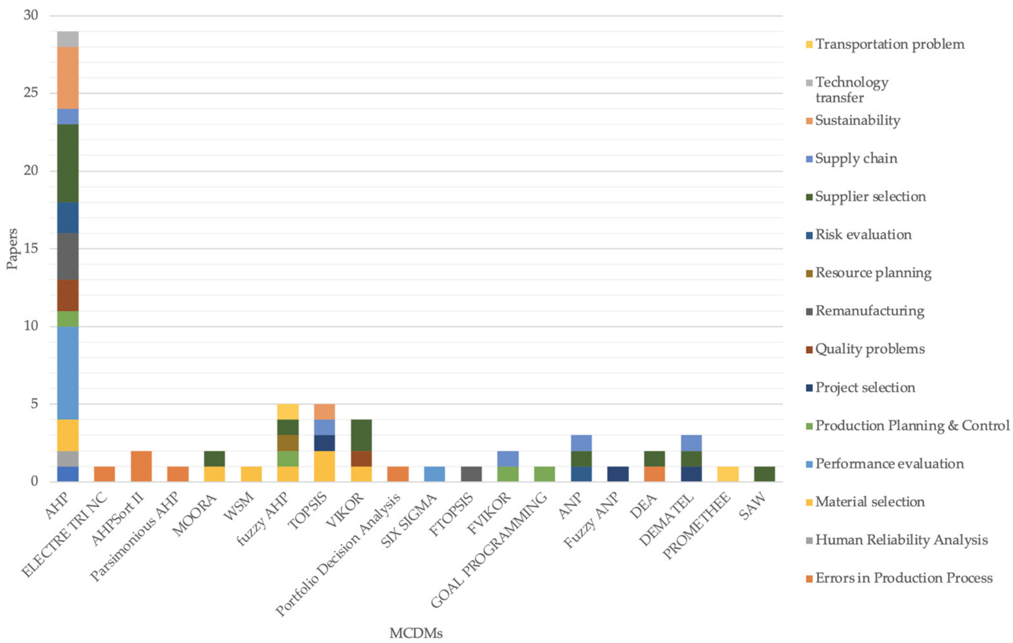

Figure 8. MCDMs used in the automotive sector. Source: our elaboration.

In particular, it is possible to observe in Figure 7 that the areas with a greater number of studies are: *Performance Evaluation* (14%), e.g., Sirikrai and Tang (2006) present an AHP-based model to evaluate the performance of an automotive company in Thailand to improve industrial competitiveness; *Supplier Selection* (11%), e.g., Kull and Talluri (2008) use the AHP for risk management in supply chains with the aim of making it operational and effectively incorporating supply risk measures into the supplier assessment process; *Sustainability* (11%), e.g., Pagone et al. (2020) use the TOPSIS method for the selection of materials for manufacturing, taking into account the dimension of sustainability. In particular, the authors note that additional sustainability influences decision making by going against the tide of established decision-making trends in the automotive sector; *Material Selection* (9%), e.g., Moradian et al. (2019) analyzes the phenomenon of material selection in an automotive company using a combination of different MCDM methods. In particular, they use AHP combined with MOORA, TOPSIS and VIKOR; *Remanufacturing* (9%), e.g., Abdulrahman et al. (2015) use the AHP method to support the managers of a Chinese auto company in choosing internal and external remanufacturing practices; *Errors in production process* (7%), e.g., Fattoruso et al. (2022a) use the AHPSort II for the classification of errors in production processes, defining with the use of the Portfolio Decision Analysis the errors that have the greatest impact on production processes, taking into account the budget constraints of an automotive company for the resolution of errors; *Risk Evaluation* (7%), e.g., Topcu et al. (2018), used AHP to identify and prioritize the risk factors when assembling mixed models in the automotive industry for a leading automotive company in Turkey.

Figure 8 shows that, in most cases, the method used is the AHP (Cristea and Cristea 2021; Putri and Irianto 2014; Tian et al. 2014) or their evolution as ANP (e.g., Unver et al. 2020; De Felice and Petrillo 2013) or Fuzzy AHP (e.g., Küçükoğlu et al. 2017; Dang et al. 2022). Much of the literature uses the AHP method (Saaty 1988) as it can be used to solve problems of different types and because it allows taking into account qualitative and quantitative evaluations (Partovi and Burton 1993). The other methods frequently used are TOPSIS (e.g., Jahan et al. 2022), VIKOR and DEMATEL (Moradian et al. 2019).

Starting from the identification of the main steps (Table 3) for the construction of MCDM methods, we have identified the phases in which the DMs can be involved:

- Problem statement: involvement for the definition of the type of problem (choice, ranking or sorting);
- Criteria: involvement in the definition of the criteria structure (flat or hierarchical); measurement scale and performance type.
- Definition of preference: in particular, the involvement in the elicitation of preferences phase;
- Qualitative and technical support: involvement in defining the number of criteria or alternatives, use of software; feedback on the understanding of the method in its use or in its processing time.

Figure 9 shows the phases in which the DMs were involved in the construction of the MCDMs. Taking into consideration that among the methods most used in the literature there is AHP, we report the results we have found: it is possible to note that in the construction of the AHP, the DMs are involved in 38% of cases for problem statements; 28% in the definition of the criteria structure; 90% in the definition of elicitation of preferences; 24% were involved for feedback on the easiness of use of the methods and 24% for feedback on the software. In 100% of cases, the DM is instead involved in determining the number of alternatives and/or criteria. These data were not found for MOORA (50%), TOPSIS (80%), VIKOR (75%) and ANP (67%).

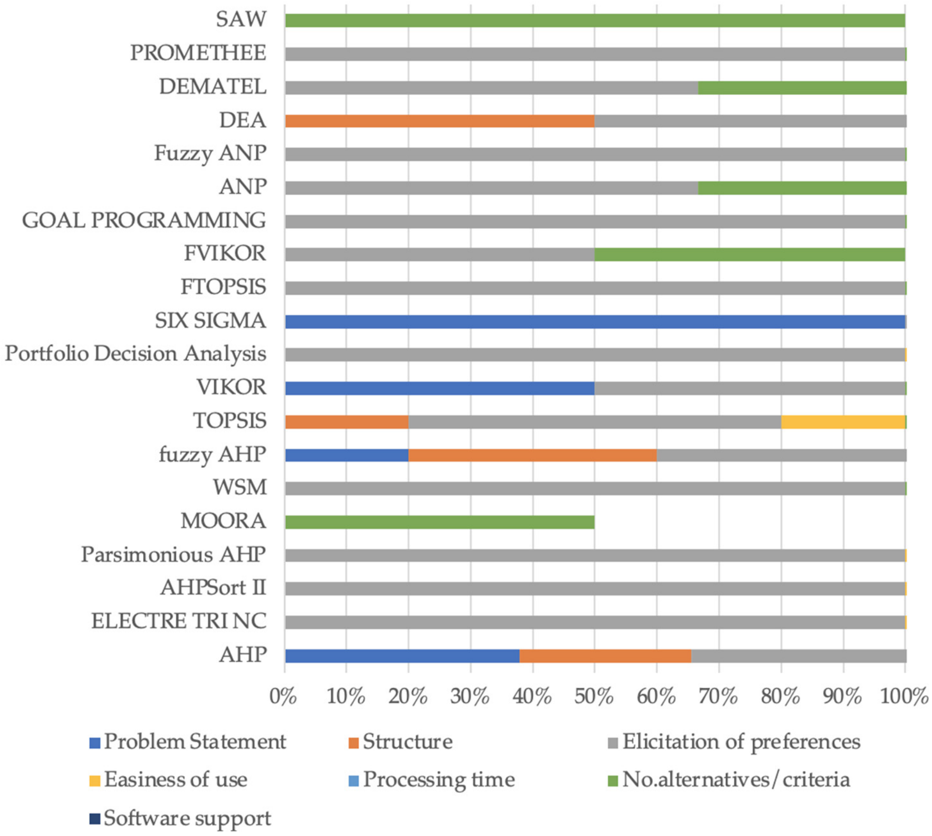

Figure 9. The involvement of entrepreneurs in the construction of MCDMs. Source: our elaboration.

3.3. Contributions to Knowledge and Implications for Practice

The research aimed to describe if and which MCDM methods are used in the automotive sector and to explore if and at what stage of construction of the method the DM intervenes. From the analysis of the contents, it is possible to reflect on some aspects.

It is interesting to note that from the analyzed papers, it emerges that the most used MCDMs are methods belonging to the family of Multi Attribute Decision Making (MADM) (Hwang and Yoon 1981) methods used in the presence of discrete decision-making processes with a finite number of alternatives. Recall that MADM methods allow identifying the best alternative among those considered and/or to draw up an order of inferred preferences with respect to several criteria considered at the same time (Tzeng and Huang 2011). These methods include AHP, MACBETH, ELECTRE, PROMETHEE and so on.

The presence of papers focused on Multi-Objective Decision Making (MODM) (Roijers and Whiteson 2017) that we recall is lower, they define a continuous decision-making approach and can therefore include an infinite number of choice solutions, and the number of alternatives is not predetermined; the objective of the MODMs is, at first, the search for admissible solutions and, in a subsequent phase, the identification of the best compromise (Ruzika and Wiecek 2005).

Reflecting on the data and contributions available to us, this propensity is due to the fact that many authors analyze decision-making problems for problems evaluated a posteriori. In this sense, MADM plays a role in controlling the choices made (see, e.g., Moradian et al. 2019), in analyzing the best solutions to the decision problem (see, e.g., Larrodé et al. 2012), or in demonstrating their usefulness for DM in solving a problem (see, e.g., Baidya et al. 2018). We note that in most of the papers analyzed in this paper, the authors use MADM in a static way (see, e.g., Subramoniam et al. 2013; Hussain et al. 2017; Halili 2020). In these cases, the role of the DM remains marginal and intervenes only in some phases of the construction of the method.

From the contributions analyzed in this work, the papers that integrate MADM methods with MODM methods are interesting. For example, in the article by Fattoruso et al. (2022a), the AHPSort II method is integrated with an interactive method such as the analysis of multi-objective portfolio decisions. From the article, it emerges that the DM is involved in both the construction of the MADM and MODM methods. However, it is clear that the DM is more involved in the construction of the MODM method. According to several authors (Hwang and Masud 1979; Branke et al. 2008; Miettinen et al. 2016) one can divide MODM methods based on the role of the DM in the solution process into four classes: (1) no-preference methods, in which there is no articulation of preferences by the DM; (2) a priori methods, in which the DM defines the preferences before the solution process; (3) interactive methods, where the DM defines the preferences progressively during the solution process, and (4) a posteriori methods that require the preferences of the DM preference before the solution process.

In this sense, we can propose a reflection on the diversity inherent in the interactive MODM methods (see Greco et al. 2001) with MADM methods. When interactive methods are used, the form of involvement of the DM is necessary for the construction of the method itself, and therefore, the involvement of the DM is intense and continuous (see, e.g., Barbati et al. 2018), while the MADM methods provide forms of involvement of the DM that are more discontinuous and less frequent (Ishizaka and Nemery 2013). As can also be seen from the data available to us, the DM is involved only in some phases and not in the entire process of constructing the methods themselves (see, e.g., Larrodé et al. 2012; Cristea and Cristea 2021).

Another interesting element emerged from the analysis of the contributions. Recent studies (Montmain et al. 2015; Fattoruso et al. 2022a; Ammirato et al. 2022; Fattoruso et al. 2022b) have used MCDM methodologies to support automotive companies in order to integrate the methodologies in Internet-based (IT-based) technologies of companies (Gubbi et al. 2013), in particular, Internet of Things (IoT) technologies (Ammirato et al. 2019). These works bear an interesting testimony to the active involvement of DM in the several stages of building MCDM methods to address real problems in automotive companies. It can be pointed out that the involvement of the DM has triggered a process of learning the method (Canonico et al. 2021) that has led to a greater awareness of decision-making problems, as well as awareness of the method and its usefulness for facing problems.

Proposing the use of MCDM for the resolution of concrete problems in companies and the subsequent integration in the IoT systems of companies could be a viable approach for scholars to encourage and export MCDMs in the extra-academic world. This process could be simplified precisely by greater involvement of the DM in the construction of MCDM methods in order to simplify their understanding and the potential of their use.

4. Conclusions

This article aims to provide a descriptive and explorative analysis of the literature to understand whether MCDM methods are used in a complex sector such as automotive and if the DMs are involved in the construction of the methods.

The articles were collected on SCOPUS and Web of Sciences (WoS) databases using 2004–2022 as the reference period. The identification of the main documents to be used for the review followed the PRISMA guidelines. In particular, 167 relevant documents were selected and analyzed using the VOSviewer software, focusing on papers with a focus on the automotive industry. The analysis of the results focused primarily on the collection of articles by analyzing the connections that exist between them through an analysis of the scientific landscape. Secondly, the contributions made to the scientific community were analyzed.

The analysis that was carried out in this work highlights that in the period 2013–2022, there was an important increase in works focused on the use of MCDM methods in the automotive sector. It emerged that the main methods used are AHP or its evolution, TOPSIS VIKOR and DEMATEL.

From the analysis of the contents, it is possible to conclude that the DM is involved only in some phases of construction of the MADM methods while instead, it has a continuous involvement in the construction of the MODM methods, which, until now, seem to have a more limited space of application in the automotive sector.

Another interesting aspect that emerges from the analysis of the contents is that when the DM is actively involved in several phases of the construction of the MCDM methods, a learning process of the method used is triggered, which makes its usefulness more appreciated. It should be noted that the use of software for the construction of MCDM methods represents an important factor in the reuse of methodologies by the DM.

The limitations of this work can be identified in the exclusive exploratory analysis. The work could be enriched in the future by structuring a more systematic analysis of the literature also proposing comparisons with other application sectors of the MCDM methods. Among the future directions of research, there is an analysis focused on the role of the DM in the different types of MCDM methods (MADM and MODM) by carrying out a comparative analysis, highlighting the limits and advantages of using them.

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Appendix A

Table A1. Application area and characteristics of MCDMs in the automotive sector.

			Step I					Step II				Step III			
Application Area	**Authors**	**Methods**	**a: Problem Statement**	**b: Alternatives**	**c: Structure**	**d: Measurement Scale**	**e: Performance Type**	**f: Elicitation of Preferences**	**f1: If Direct**	**f2: If Indirect**	**g: Aggregation**	**h: Easiness of Use**	**i: Processing Time**	**l: No. Alternatives/Criteria**	**n: Software Support**
Company Adaptability	Larrodé et al. (2012)	AHP	2	1	2	1	1	1	1f	0	2	1	3	2	3
Errors in Production Process	Fattoruso and Barbati (2021)	ELECTRE TRI NC, AHPSort II	2	1	2	1	1	1	1f	0	2	2	2	1	1
	Fattoruso et al. (2022a)	AHPSort II, Portfolio Decision Analysis	2	1	2	1	1	1	1l	0	2	2	2	1	3
	Ammirato et al. (2022) Fattoruso et al. (2022b)	Parsimonious AHP, DEA	1	1	2	1	1	1	1f	0	2	2	2	2	1
Human Reliability	Petruni et al. (2019)	AHP	1	1	2	1	1	1	1f	0	2	1	3	2	1
Material Selection	Moradian et al. (2019)	AHP, MOORA, TOPSIS and VIKOR	1	1	2	3	1	1	1f	0	2	1	3	3	2
	Jahan et al. (2022)	WSM, WPM, TOPSIS,	1	1	2	1	1	1	1f	0	2	1	2	3	2
	Wang and Li (2022)	fuzzy AHP	1	1	2	1	1	1	1f	0	2	1	1	3	2
	Ali et al. (2015)	AHP	1	1	2	1	1	1	1f	0	2	1	3	1	3

Table A1. *Cont.*

			Step I						Step II			Step III			
Application Area	**Authors**	**Methods**	**a: Problem Statement**	**b: Alternatives**	**c: Structure**	**d: Measurement Scale**	**e: Performance Type**	**f: Elicitation of Preferences**	**f1: If Direct**	**f2: If Indirect**	**g: Aggregation**	**h: Easiness of Use**	**i: Processing Time**	**l: No. Alternatives/Criteria**	**n: Software Support**
Performance Evaluation	Sirikrai and Tang (2006)	AHP	1	1	2	1	1	1	1f	0	2	1	3	3	2
	Gothwal and Raj (2018)	AHP	1	1	2	2	1	1	1f	0	2	1	3	2	2
	Alhuraish et al. (2016)	AHP, SIX SIGMA	1	1	2	3	1	1	1f	0	2	1	3	3	3
	Chahid et al. (2014)	AHP	1	1	2	3	1	1	1f	0	2	1	3	3	2
	Cristea and Cristea (2021)	AHP	1	1	2	3	1	1	1f	0	2	1	3	2	3
	Parthiban and Zubar (2013)	AHP	1	1	1	3	1	1	1f	0	2	1	1	3	2
Production Planning and Control	Muerza et al. (2014)	AHP	1	1	2	3	1	1	1f	0	2	1	1	2	3
	Küçükoğlu et al. (2017)	FAHP, FTOPSIS, FVIKOR, GOAL PROGRAM-MING	1	1	2	3	1	1	1f	0	2	1	3	3	2
Project Selection	Vinodh and Swarnakar (2015)	Fuzzy ANP, DEMATEL, TOPSIS	1	1	2	3	1	1	1f	0	2	2	2	2	2
Quality Problems	Putri and Irianto (2014)	AHP	1	1	1	3	1	1	1f	0	2	1	1	3	2
	Zhou et al. (2018)	VIKOR	1	1	2	3	1	1	1c	0	1	2	2	2	2
	Baidya et al. (2018)	AHP	1	1	2	3	1	1	1f	0	2	1	3	2	2
Remanufacturing	Abdulrahman et al. (2015)	AHP	1	1	1	3	1	1	1f	0	2	1	1	3	2
	Subramoniam et al. (2013)	AHP	1	1	1	3	1	1	1f	0	2	1	3	3	2
	Tian et al. (2014)	AHP	1	1	2	3	1	1	1f	0	2	1	3	2	2
	Yang et al. (2017)	Fuzzy TOPSIS	1	1	1	3	1	1	1c	0	1	2	2	2	2
Resource Planning	Kahraman et al. (2010)	FAHP	1	1	2	3	1	1	1f	0	2	2	2	2	2
Risk Evaluation	Kull and Talluri (2008)	AHP	1	1	2	1	1	1	1f	0	2	3	3	3	2
	Topcu et al. (2018)	AHP	1	1	2	1	1	1	1f	0	2	3	3	3	2
	Unver et al. (2020)	ANP	2	1	2	3	1	1	1f	0	2	2	2	1	2

Table A1. *Cont.*

					Step I					Step II				Step III	
Application Area	**Authors**	**Methods**	**a: Problem Statement**	**b: Alternatives**	**c: Structure**	**d: Measurement Scale**	**e: Performance Type**	**f: Elicitation of Preferences**	**f1: If Direct**	**f2: If Indirect**	**g: Aggregation**	**h: Easiness of Use**	**i: Processing Time**	**l: No. Alternatives/Criteria**	**n: Software Support**
Supplier Selection	Hadian et al. (2020)	VIKOR-AHP	1	1	2	1	1	1	1c	0	1	2	2	2	2
	Luthra et al. (2017)	AHP-VIKOR	1	1	2	2	1	1	1f	0	2	1	3	2	2
	Chul Park and Lee (2018)	AHP-DEA	1	1	1	3	1	1	1f	0	2	1	1	3	2
	Suraraksa and Shin (2019)	AHP	1	1	2	3	1	1	1f	0	2	1	3	2	2
	Dang et al. (2022)	fuzzy AHP	1	1	2	3	1	1	1f	0	1	2	2	2	2
	Sahu et al. (2022)	AHP, DEMATEL, ANP, MOORA, SAW	1	1	2	1	1	1	1c	0	1	2	2	1	2
Supply Chain	Junaid et al. (2019)	AHP-TOPSIS	1	1	2	3	1	1	1f	0	2	2	2	2	2
	De Felice and Petrillo (2013)	ANP	1	1	2	3	1	1	1f	0	2	2	2	1	2
	Kumar Singh and Modgil (2020)	DEMATEL, fuzzy-VIKOR,	1	1	2	3	1	1	1f	0	2	1	2	3	2
Sustainability	Salvado et al. (2015)	AHP	1	1	2	3	1	1	1f	0	2	1	3	3	2
	Shao et al. (2016)	AHP	1	1	2	3	1	1	1f	0	2	1	3	3	2
	Pagone et al. (2020)	TOPSIS	1	1	2	3	1	1	1c	0	2	1	3	3	3
	Hussain et al. (2017)	AHP	1	1	2	3	1	1	1f	0	2	1	3	3	2
	Stoycheva et al. (2018)	AHP	1	1	2	3	1	1	1f	0	2	1	3	2	2
Technology Transfer	Halili (2020)	AHP	1	1	2	3	1	1	1c	0	2	2	2	2	3
Transportation Problem	Kabir and Sumi (2015)	FAHP PROMETHEE	1	1	2	2	1	1	1f	0	2	1	3	3	2

Source: our elaboration.

Table A2 shows all the acronyms of the MCDMs shown in Table A1.

Table A2. Abbreviation of MCDMs.

Abbreviation	Full Name
AHP	Analytic Hierarchy Process
AHPSort II	Analytic Hierarchy Process Sorting II
ANP	Analytic Network Process
DEA	Data Envelopment Analysis
DEMATEL	DEcision MAking Trial and Evaluation Laboratory
ELECTRE TRI NC	Elimination Et Choix Traduisant la Realité TRI NC
Fuzzy AHP (or FAHP)	fuzzy Analytic Hierarchy Process
Fuzzy ANP (or FANP)	Fuzzy Analytic network Process
FTOPSIS	Fuzzy Technique for Order Preference by Similarity to Ideal Solution
FVIKOR	Fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje
MOORA	Multi-Objective Optimization by Ratio Analysis
Parsimonious AHP (or PAHP)	Parsimonious Analytic Hierarchy Process
PDA	Portfolio Decision Analysis
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
SAW	Simple Additive Weighting
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
WSM	Weighted Sum Model

Source: our elaboration.

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