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ORIGINAL RESEARCH

Multi-criteria classification, sorting, and clustering: a bibliometric review and research agenda

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Abstract

Multi-criteria decision analysis (MCDA) has been increasingly adopted to solve decision-making problems involving multiple options and multiple criteria. These methods have been proven to improve the analytic rigor, transparency, and auditability of the decision-making process by integrating the performance of options in different criteria and balancing subjective preferences from different stakeholders. This review aims to map the academic research on multi-criteria sorting, classification and clustering methods, and highlights the key research trends and avenues by conducting a bibliometric analysis. We contribute to the body of knowledge in multi-criteria decision analysis in four ways: (1) identifying the most influential articles on this topic, (2) mapping the research on multi-criteria sorting, classification and clustering methods, (3) visualizing the trends in this field of research through network analysis, and (4) highlighting areas for future research. The results of this study help academics and practitioners to navigate the literature on MCDA methods, provide a map of existing evidence, and recommend promising avenues for future research.

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1 Introduction

Multicriteria decision analysis (MCDA) methods and techniques have been widely used to solve complex real-world problems. Rooted in operations and management science, these methods have been increasingly popular among managers to help them address complex decision problems that have conflicting objectives with high uncertainties (Wang et al., 2009). In practice these techniques help managers evaluate a set of possible courses of action, select the most preferred options, and sort the options into ordered classes from the best to the worst ones (Durbach & Stewart, 2012). The popularity of these methods is due to their practicality and flexibility. For the former, MCDA is needed to allocate finite resources between competing alternatives (Diaby et al., 2013). For the latter, these techniques integrate hard data with subjective preferences (Dolan, 2010).

The typical MCDA process is to define the objectives, select the criteria to measure the objectives, determine the alternatives, change the scales of the criteria into commensurable units, pinpoint criteria weights that reflect the relative importance of the criteria, choose and apply a mathematical algorithm for ranking alternatives, and choose an alternative (Ananda & Herath, 2009).

In discrete MCDA (finite set of alternatives), some of the most widely used methods include Preference Ranking and Organization Method for Enrichment Evaluation (PROMETHEE), Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Elimination et Choice Translating Reality (ELECTRE), Simple Multi-attribute Rating Technique (SMART), Multi-attribute Utility Theory (MAUT), Simple Additive Weighting (SAW), and Case-based Reasoning (CBR) (Velasquez & Hester, 2013; Wang et al., 2016). MCDA methods have been used to solve complex problems in numerous fields, including supplier evaluation and selection (Guo et al., 2014), climate change (Dawit et al., 2020), autonomous vehicles (Wang et al., 2021), healthcare (Mardani et al., 2015), solid waste management (Tsai et al., 2020), and water resource management (Banihabib et al., 2019), to name a few.

Given the popularity of this field, a number of literature reviews have been conducted in several areas, including supply chain management (Dutta et al., 2021), energy (Wang et al., 2009), and geographic information systems (GIS) (Malczewski, 2006a). Also, we can mention Zopounidis and Doumpos's (2002) work, written two decades ago, as a reference review in the field, particularly when it comes to MCDA classification and sorting. Despite considerable progress of this field, the literature lacks a study presenting an up-to-date comprehensive map of discrete MCDA methods and applications in classification problems (the assignment of alternatives into predefined nominal homogenous classes (Zopounidis & Doumpos, 2002)), sorting problems (the assignment of alternatives into predefined ordinal homogenous groups (Zopounidis & Doumpos, 2002)), and clustering problems (grouping the alternative into homogenous clusters as the alternatives in the same cluster would be more similar to each other compared to those in other clusters (Meyer & Olteanu, 2013)). However, the significance of MCDA applications in classification, sorting (Alvarez et al., 2021), and clustering (Mahdiraji et al., 2019) has been emphasized in the recent MCDA literature.

This review aims to (1) identify the most influential articles in discrete MCDA literature, (2) map the research on multi-criteria classification, sorting and clustering methods, (3) visualize the trends in this field of research through network analysis, (4) highlight areas for future research.

The rest of the paper is organized as follows: We begin with highlighting the research method used to conduct our bibliometric analysis in Sect. 2, followed by the results of our analysis in terms of publications, key contributions, and current trends (Sect. 3). Then, Sect. 4 discusses the main findings in relation to the major clusters in MCDA[1] classification, sorting and clustering methods, while Sect. 5 concludes and summarizes some future research directions.

2 Research method

The literature on multi-criteria classification, sorting, and clustering will be mapped following the standard steps of science mapping suggested by Zupic & Čater (2015). Using the *bibliometrix* R-package, we performed bibliometric analyses in five steps, as Aria & Cuccurullo (2017a) suggested. The different steps and software tools used are highlighted in Fig. 1.

Previous bibliometric analyses conducted in relation to discrete MCDA, were area-specific. For example, specific to finance (Zopounidis et al., 2015). This review is not limited to a specific area of application but will span all areas of reach within discrete MCDA, focusing on classification, sorting and clustering methods. Articles were obtained from Web of Science (WoS), up to the end of May 2021. Articles were identified using the following search string:

((TS = (Classif* OR Sort* OR Cluster*) AND TS = (MCDA OR MCDM OR MADM OR MADA OR "Multiple criterion decision" OR "Multi criterion decision" OR "Multicriterion decision" OR "Multiple criteria decision" OR "Multi criteria decision" OR "Multicriteria decision".

OR "Multiple attribute decision" OR "Multi attribute decision" OR "Multiattribute decision" OR "Multiple attributes decision" OR "Multi attributes decision" OR "Multiattributes decision"))) OR (TS = ("Multicriteria classification" OR "Multicriteria sorting" OR "Multicriteria clustering" OR "Multi criteria classification" OR "Multi criteria sorting" OR "Multi criteria clustering" OR "Multiple criteria classification" OR "Multiple criteria sorting" OR "Multiple criteria clustering")).

A total of 1921 documents in English were retrieved. After performing a deep scanning of documents, we excluded irrelevant studies and selected 675 studies (of which 25 are early-access studies) as our final sample. Our final sample includes 659 articles and 16 reviews.

We used *bibliometrix* to extract statistical information, and VOSViewer to visualize networks. To perform the analyses, we imported the BIB files containing full records and cited references to *bibliometrix.* Excel files were extracted from this software to produce the tables presented in our results section. VOSViewer was used to visualize *.net files generated by *bibliometrix.*

[1] In the remainder of this paper, MCDA refers to discrete MCDA, i.e., MCDA problems involving a finite set of alternatives.

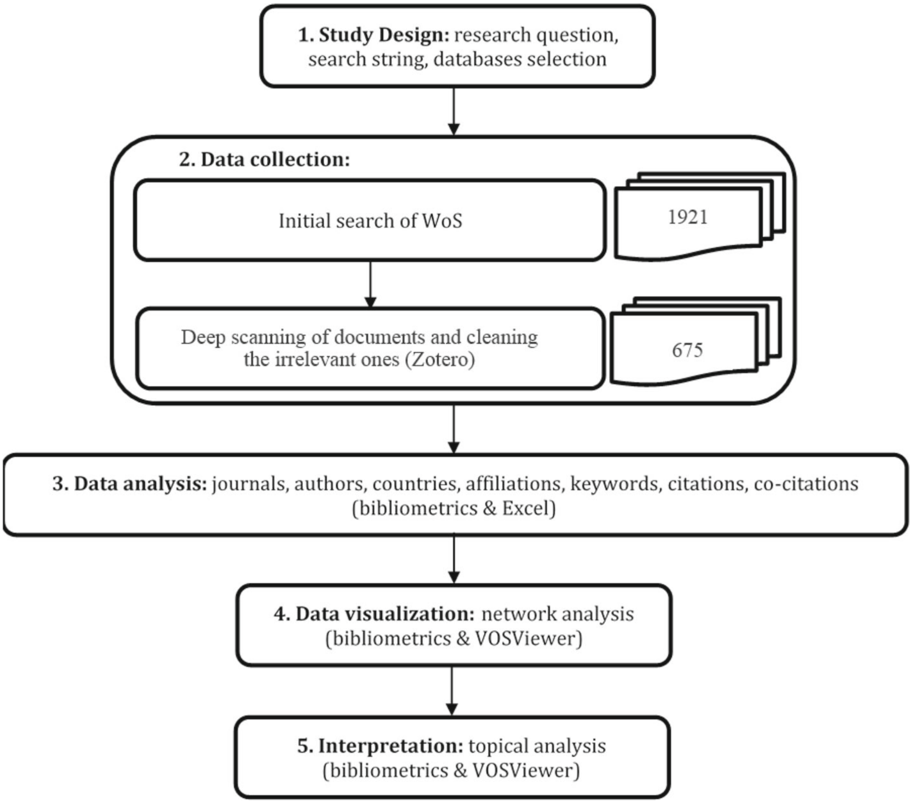

Fig. 1 Five stages of literature mapping

3 Results

To identify the research trends on MCDA classification, sorting, and clustering methods, we use bibliometric analysis that shows the overall trends in publications, the most influential contributions, and the current trends.

3.1 Publications

According to Steuer & Na's (2003) work, the first contributions of MCDA started to appear during the 1950s and 1960s. Particularly, the number of publications that used MCDA methods to classify, sort, or cluster alternatives has started to increase in the 1990s and has increased exponentially from single digits to double digits from 2010 onwards and to triple digits (117 articles) in 2020 (as illustrated in Fig. 2).

Table 1 presents the list of the journals with the most contributions, indicating the total number of publications (NP), total citations (TC), and TC/NP (average citations) scores. The *European Journal of Operational Research* stands out with 46 articles, 4063 citations, and an average citation score of 87.78. The *Applied Soft Computing* and *Applied International Journal of Information Technology & Decision Making* both follow with high NP, 14.

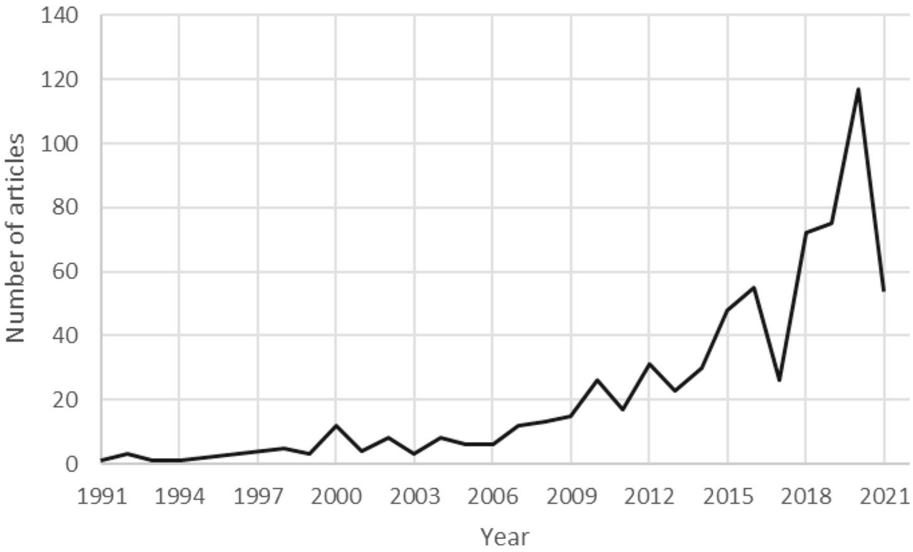

Fig. 2 Yearly publications (1990–2021)

Table 1 List of journals with most contributions

#	Journal	NP	%	TC	TC/NP
1	European journal of operational research	46	7.42	4063	87.78
2	Applied soft computing	14	2.27	454	32.09
3	International journal of information technology & decision making	14	2.27	278	19.64
4	Journal of multi-criteria decision analysis	12	1.86	296	25.56
5	Sustainability	12	1.86	180	15.56
6	Expert Systems with applications	10	1.65	409	39.75
7	Arabian journal of geosciences	9	1.44	86	9.571
8	Computers & operations research	9	1.44	540	60
9	IEEE access	9	1.44	67	7.429
10	Omega-international journal of management science	9	1.44	269	29.86
11	Annals of operations research	8	1.24	255	33
12	Soft computing	8	1.24	139	18
13	International journal of intelligent systems	6	1.03	157	24.4
14	Journal of the operational research society	6	1.03	140	21.8
15	Mathematical problems in engineering	6	1.03	73	11.4
16	Modeling earth systems and environment	6	1.03	93	14.4
17	Renewable energy	6	1.03	318	49.4
18	Sustainable cities and society	6	1.03	86	13.4
19	Computers and electronics in agriculture	5	0.82	428	83.25
20	Ecological indicators	5	0.82	116	22.5

NP: total number of publications; %: percentage of publications in the dataset of 675 articles; TC: the total citations of a journal; TC/NP: average number of overall citations per article of a journal

Other journals with most contributions are the *Journal of Multi-Criteria Decision Analysis* (TC: 296, TC/NP: 25.56), *Sustainability* (TC: 180, TC/NP: 15.56), and *Expert Systems with Applications* (TC: 409, TC/NP: 39.75).

3.2 Key contributions

Prolific authors who have made in making contributions to research on classification, sorting and clustering MCDA methods are listed in Table 2. Roman Slowinski, Salvatore Greco, and Benedetto Matarazzo are the most cited authors. Constantin Zopounidis, Michalis Doumpos, and José Rui Figueira lead with the most contributions. Moreover, Constantin Zopounidis and Benedetto Matarazzo have the highest h_index score.

Tables 3 and 4 present the origins of the publications using MCDA for classification, sorting, or clustering. China leads with the most contributions (113 articles), owing to the publications from Sichuan University, North China Electric Power University, and PLA University of Science and Technology. India comes second with 54 articles, of which 15 come from the Systems Research Institute. Brazil comes third with 53 articles, of which 47 come from the Federal University of Pernambuco. Greece leads with an average citation score of 39.06. Moreover, Poland and France have high average citation scores of 92.42 and 51.84, respectively.

By examining the total number of citations (TC) and the yearly number of citations (TC/Y), the most relevant articles are listed in Table 5. Greco et al.'s (2001) article is the most cited work, with 52.3 yearly citations. This article states the main advantages of the extended rough set theory to classification and soring compared to classical MCDA theories. Zopounidis & Doumpos's (2002) work is the second most cited article, with 20 yearly citations. This article reviewed and summarised different forms of MCDA classification/sorting models. The third most cited article is Keshavarz Ghorabaee et al. (2015), work which introduces a new method of Evaluation based on Distance from Average Solution (EDAS) for multi-criteria inventory classification (MCIC) problems. Greco et al.'s (2002a) study is the fourth most cited article classifying and comparing attributes considering preference orders in the description of objects by condition and decision attributes. The fifth most cited article is Greco et al.'s

Table 2 Prolific authors

#	Author	NP	TC	*h*_index
1	Slowinski R	26	3502	22
2	Greco S	22	2850	21
3	Matarazzo B	6	1920	6
4	Zopounidis C	24	1219	19
5	Doumpos M	23	1189	18
6	Figueira JR	17	923	13
7	Ishizaka A	13	658	10
8	Mousseau V	9	634	6
9	Roy B	5	516	5
10	Dias LC	10	447	10

NP: total number of publications; TC: the total citations; *h*-Index: calculated based on author contributions to this field. Authors are listed in descending order of total citations

Table 3 Most productive countries (corresponding authors)

#	Country	NP	%	TC	TC/NP
1	China	113	20.09	1962	17.34
2	India	54	9.59	752	13.93
3	Brazil	53	9.36	552	10.46
4	Greece	41	7.31	1607	39.06
5	Turkey	40	7.08	491	12.32
6	Italy	35	6.16	1254	36.11
7	Iran	28	5.02	490	17.32
8	France	24	4.34	1266	51.84
9	Poland	24	4.34	2258	92.42
10	Portugal	24	4.34	868	35.53

NP: total number of publications; %: percentage of publications in the dataset of 675 articles; TC: the total citations per country; TC/NP: average number of overall citations per country

Table 4 Institutes with the most contributions

#	Affiliations	Country	NP
1	Technical University of Crete	Greece	55
2	Federal University of Pernambuco	Brazil	47
3	University of Tehran	Iran	44
4	Poznan University of Technology	Poland	42
5	University of Catania	Italy	36
6	University of Portsmouth	United Kingdom	33
7	Vilnius Gediminas Technical University	Lithuania	26
8	University of Coimbra	Portugal	24
9	University of Lisbon	Portugal	22
10	Islamic Azad University	Iran	17
11	Sichuan University	China	15
12	Systems Research Institute	India	15
13	University of Electronic Science and Technology of China	China	15
14	The Federal University of Technology Akure	Nigeria	14
15	National Technical University of Athens	Greece	14
16	University of Waterloo	Canada	14
17	Kyungpook National University	South Korea	13
18	PLA University of Science and Technology	China	13
19	University of Palermo	Italy	13
20	University of Lisbon	Portugal	13

Note: Top 20 institutes are listed

Table 5 The most cited articles

#	Authors	Year	Title	Journal	Total citation	TC/year
1	Greco S; Matarazzo B; Slowinski R	2001	Rough sets theory for multi-criteria decision analysis	European journal of operational research	1051	52.55
2	Zopounidis C; Doumpos M	2002	Multicriteria classification and sorting methods: a literature review	European journal of operational research	378	19.89
3	Keshavarz Ghorabaee M; Zavadskas Ek; Olfat L; Turskis Z	2015	Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS)	Informatica	325	54.17
4	Greco S; Matarazzo B; Slowinski R	2002	Rough approximation by dominance relations	International journal of intelligent systems	296	14.80
5	Greco S; Matarazzo B; Slowinski R	2002	Rough sets methodology for sorting problems in presence of multiple attributes and criteria	European journal of operational research	292	15.37
6	Pawlak Z; Slowinski R	1994	Rough set approach to multiattribute decision-analysis	European journal of operational research	271	10.04
7	Mousseau V; Slowinski R	1998	Inferring an ELECTRE tri model from assignment examples	Journal of global optimization	230	10.00
8	Hatami-Marbini A; Tavana M	2011	An extension of the ELECTRE I method for group decision-making under a fuzzy environment	Omega-international journal of management science	198	18.00
9	Figueira JR;Greco S; Roy B; Slowinski R	2012	An overview of ELECTRE methods and their recent extensions	Journal of multi-criteria decision analysis	172	17.2
10	Mousseau V; Slowinski R; Zielniewicz, P	2000	A user-oriented implementation of the ELECTRE-TRI method integrating preference elicitation support	Computers and operations research	163	7.4

(2002b), with 15 yearly citations. Greco et al. (2002b) present a novel methodology rooted in the rough sets approach and discuss its application in multi-criteria sorting and classification problems. Pawlak & Slowinski's (1994) review of the rough set theory for MCDA sorting problems is the sixth most cited article. This article characterizes the rough set methodology for different particular classes of decision problems by using several practical examples.

Mousseau & Slowinski's (1998) work is the seventh most cited article focusing on multiple criteria sorting problems. The work presents an interactive approach that infers the parameters of an ELECTRE TRI model from assignment examples. Hatami-Marbini & Tavana's (2011a, 2011b) work is the eighth cited article presenting a new extension of the ELECTRE I method to classify a set of alternatives. The nineth most cited article is Figueira et al.'s (2013), with 17.2 yearly citations. This article reviews the main characteristics of the ELECTRE family methods designed for different types of MCDA problems, including classification and sorting MCDA problems. Mousseau et al. (2000) is the tenth cited article with 7.4 yearly citations. It proposes a user-oriented implementation of the ELECTRE Tri method integrating functionalities that assist the decision-maker in the inference of preferential parameters from assignment examples.

4 Keyword analysis

To list the most utilized and relevant keywords, we examined authors' keywords and performed a keyword co-citation analysis. Four clusters (Table 6) have emerged from analyzing the authors' keywords. Keyword network analysis can excellently present the intellectual structure of a field of study by generating a keyword map based on the frequent co-occurrence of a pair of keywords within a series of studies (Ding et al., 2001).

Table 6 The most frequent keywords and their variations

Keyword	Cluster	Frequency
TOPSIS	1	28
Performance	1	27
Fuzzy	1	17
Extension	1	12
Weights	2	21
ELECTRE-Tri	2	10
Ordinal regression	2	10
Classification	3	59
Algorithm	3	28
Aggregation operators	3	14
Rough set approach	3	12
Preference disaggregation	3	10
Management	4	59
AHP	4	31
GIS	4	49
Risk	4	19

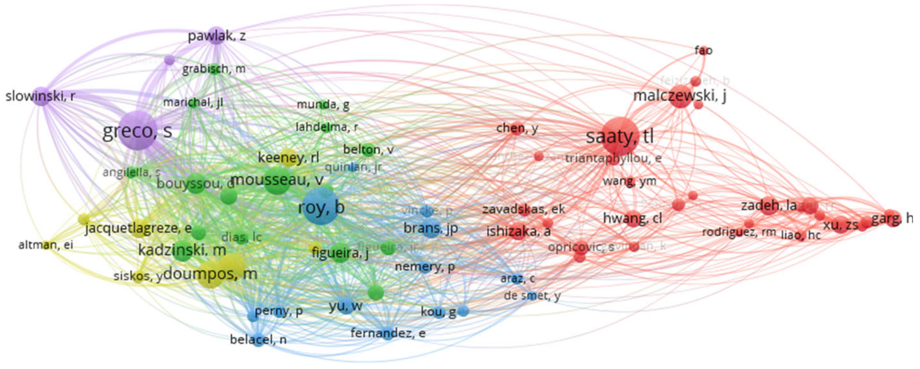

Fig. 3 Authors' co-citation network

Since there were several general terms in the generated clusters, we did not consider them in the final table, making the table more purposeful and instructive. In this regard, general terms (i.e. "model", "selection", "decision-making", and "criteria") have not been shown, and terms that can convey meaningful messages are presented in the final table. The first cluster contains the terms "TOPSIS", "Performance", "Fuzzy", and "Extension". The second cluster includes the terms "Weights", "ELECTRE-Tri", and "Ordinal Regression", and the third cluster contains the terms "Classification", "Algorithm", "Aggregation Operators", "Rough Set Approach", and "Preference Disaggregation". The terms in the final cluster are "Management", "AHP", "GIS", and "Risk".

Author co-citation analysis, introduced by White & Griffith (1981), enables researchers to understand the intellectual structure of a field (Börner et al., 2003). Author co-citation analysis identifies prominent authors by analyzing citation records (White & McCain, 1998) and reveals the significance that researchers attach to a cited article (Danvila-del-Valle et al., 2019). In author co-citation analysis, the more often a study is cited, the more influential and pivotal it will be considered in developing a focal area (Chen, 1999). In addition, author co-citation analysis can help detect the schools of thought within a field of research (Aria & Cuccurullo, 2017b). For clarity, we here provide brief descriptions of how author co-citation analysis works. Given that there are two references, one to paper A and one to paper B, if paper C cites both papers A and B, it indicates a co-citation relationship between paper A and paper B (Small, 1973). In this study, using VOS Viewer, we performed author co-citation analysis to explore the prominent studies in the field. Figure 3 presents the five clusters that emerged out of the author co-citation analysis. Since we noticed that clusters two and three are focused mainly on different types of outranking methods, we merged both clusters into one cluster and used a single label for them. We labeled the cluster in red as "AHP, TOPSIS, Fuzzy modeling, GIS", and the clusters in green and blue as "Outranking methods". Also, the cluster in yellow and purple were labeled as "Additive utilities and preference disaggregation approaches" and "Rough sets and rule-based approaches", respectively.

5 Discussion and future research directions

Our results show that the trends in this field can be classified into the four clusters highlighted in Table 7 and discussed below.

Table 7 Major clusters in MCDA research for classification, sorting, and clustering

Clusters	Most cited authors	Most cited articles	Articles that cited the most cited works[a]	Labels
1	Saaty, T.L, Malczewski, J, Zadeh, L.A, Ishizaka, A, Xu, Z.S	Saaty (1988), Saaty (1990), Saaty (1986), Malczewski (2004), Malczewski (2006b), Zadeh (1983), Ishizaka and Lusti (2004), Ishizaka and Labib (2011), Xu et al. (2008), Xu and Xia (2011), Zadeh (1996)	Arabameri et al. (2019), Zolekar and Bhagat (2015), Ullah et al. (2020), Xu et al. (2019), Ishizaka et al. (2012), Liu et al., (2020), Li et al. (2013), Faraji Sabokbar et al. (2016)	AHP, TOPSIS, Fuzzy modeling, GIS
2	Brans, J.P, Yu, W, Belacel, N, Fernández, E, Roy, B, Mousseau, V, Kadziński, M, Bouyssou, D, Figueira, J	Brans and Vincke, (1985), Figueira et al. (2005), Zopounidis and Doumpos (1999), Fernandez et al. (2008), Fernández et al. (2017), Belacel (2000), Zopounidis and Doumpos (1999), Peng et al. (2011), Kou et al. (2012), Roy (1990), Roy (2010), Mousseau et al. (2000), Mousseau et al. (2003), Mousseau and Slowinski (1998), Kadziński and Słowiński (2015), Kadziński et al. (2014), Bouyssou, (1986), Figueira et al. (2009), Figueira and Roy (2002)	Lolli et al. (2015), Certa et al. (2017), Almeida-Dias et al. (2010), Almeida-Dias et al. (2012), Kou et al. (2020), Song and Peng (2019), Figueira et al. (2013), Sánchez-Lozano et al. (2014);Certa et al. (2017), Angilella and Mazzù (2015), Atici et al. (2015), Mailly et al. (2014)	Outranking methods
3	Zopounidis, C, Doumpos, M, Jacquet-Lagrèze, E	Zopounidis and Doumpos (1999), Zopounidis and Doumpos (2000b), Zopounidis and Doumpos (2000a), Jacquet-Lagreze and Siskos (1982), Jacquet-Lagreze (1995)	Zopounidis and Doumpos (2002); Doumpos and Zopounidis (2011), Gaganis et al. (2006), Kadziński et al. (2013), Palha et al. (2016)	Additive utilities and disaggregation approach
4	Greco, S, Slowiński, R, Pawlak, Z, Błaszczyński, J	Greco et al. (1999); Greco et al. (2000), Slowiński et al. (1988), Slowinski and Vanderpooten (2000); Pawlak (1985), Pawlak, (1997), Błaszczyński et al. (2007), Błaszczyński et al. (2011), Grabisch (1996), Greco et al. (1999)	Greco et al. (2001), Greco et al. (2002)b, Cinelli et al. (2015), Pawlak and Sowinski (1994), Luo et al. (2018), Corrente et al. (2017), Benabbou et al. (2017), Chai and Liu (2014)	Rough sets and rule-based approaches

[a]To remove the time bias, we have selected the articles with the highest average yearly citation

5.1 Cluster 1-AHP, TOPSIS, fuzzy modeling, GIS

AHP and TOPSIS are both popular and useful techniques in MCDA (Olson, 2004; Podvezko, 2009). The bibliography analysis shows several studies using AHP and TOPSIS in classification, sorting, and clustering problems. Twenty-two percent of the retrieved studies in this bibliography have used AHP and TOPSIS techniques. Among the retrieved studies that used AHP, 73, 13, and 14 percent have used AHP for classification, sorting, and clustering problems, respectively, while, among the retrieved studies that used the TOPSIS technique, 56, 26, and 18 percent have used AHP for classification, sorting, and clustering problems, respectively. This shows that AHP is used mostly in classification problems, and TOPSIS is used considerably not only in classification problems but also in sorting and clustering problems.

Using the AHP technique, Zolekar & Bhagat (2015) analyze land suitability for agriculture in hilly zones, developing a GIS-based multi-criterion decision-making approach. In this way, they classified the lands in the four classes with respect to their suitability for agriculture. Ishizaka et al. (2012) claimed that the regular AHP technique is not well suited to sorting problems and needs some adjustments. They introduce an extended model named AHPSort used for the sorting of alternatives into ordered classes. In addition, AHPSort requires fewer comparisons than regular AHP, a characteristic that facilitates decision-making in large-scale problems. Li et al. (2013) contend that it is not easy to meet the consistency requirement of a comparison matrix in AHP. Finding a solution for this difficulty through a revised questionnaire and a convenient method for determining the consistency requirement, Li et al. (2013) propose an improved AHP suitable for use in MCDA sorting problems. They use their technique to classify risks associated with an open-cut subway construction.

Faraji Sabokbar et al. (2016) propose the TOPSIS-Sort method, using upper and lower limit profiles to determine the different groups and calculate closeness coefficients of alternatives according to the TOPSIS procedure. Later, de Lima Silva & de Almeida Filho (2020) suggest a novel TOPSIS model for Multiple Criteria Ordinal Classification. They state that the new TOPSIS method, TOPSIS-Sort-B, is better suited to sorting problems than the model proposed by Faraji Sabokbar et al. (2016).

The use of fuzzy sets for the approximate reasoning and for dealing with the concept of computing with words was introduced by (Zadeh, 1983). The fuzzy language has had many applications in various fields since its inception. A considerable number of MCDA works can be used in the literature developed in various fuzzy environments (Arora & Garg, 2018; Sun et al., 2016). Liu (2007) integrates multiple-criteria decision-making and fuzzy logic to cluster 146 countries in terms of environmental sustainability. In our retrieved studies, the fuzzy approach has been used with AHP and TOPSIS more than other MCDA techniques. For example, Xu et al. (2019) integrate an extended version of AHP under a fuzzy environment with interval type-2 fuzzy sets to sort a group of suppliers in terms of sustainability in supply. Although AHP and TOPSIS have been used in classification, sorting, and clustering problems in different fields, including geography, healthcare, management, and energy, among the retrieved studies that used AHP and TOPSIS techniques, more than sixty percent are used in geography and particularly for enhancement in Geographic Information System (GIS). For instance, Arabameri et al. (2019) use both AHP and TOPSIS to develop a GIS-based multi-criteria decision analysis, enabling decision-makers to plan preventive measures concerning risky classes. The main advantage of Arabameri et al.'s (2019) methodology is its potential in dealing with missing or incomplete data.

5.2 Cluster 2-outranking methods

Outranking MCDA models use priority functions and outranking relations to compare the attributes according to the criteria (Roy, 1991). The PROMETHEE, and ELECTRE methods, which were introduced by J.-P. Brans and P. Vincke (1985) and Roy (1991), respectively, are typical of this field. Outranking MCDA methods have been used considerably in classification, sorting, and clustering problems (Alvarez et al., 2021). Twenty-four percent of the retrieved studies in this bibliography have used outranking MCDA methods. Among the retrieved studies that used the ELECTRE method, 46, 47, and 7 percent have used ELECTRE for classification, sorting, and clustering problems, respectively. On the other hand, among the retrieved studies that used the PROMETHEE technique, 37, 34, and 29 percent have used PROMETHEE for classification, sorting, and clustering problems, respectively. This shows that PROMETHEE is used for classifying, sorting, and clustering attributes, whereas ELECTRE is used mainly for classifying and sorting.

Using the PROMETHEE technique, Lolli et al. (2015) propose a novel MCDA method to sort the failure in a failure mode and effects analysis, which is a well-known analysis for correlating the failure modes of a system to their effects. Kou et al. (2020) evaluate different MCDA-based methods in terms of their performance in text classification and conclude that PROMETHEE is the best method according to their test. Hatami-Marbini & Tavana (2011a, 2011b) propose an alternative fuzzy MODM method by extending the Electre I method to consider the uncertain and linguistic assessments provided by decision-makers. ELECTRE TRI is an outranking technique that is proposed for dealing with the uncertainty of the decision-maker during the decision-making process through the introduction of specific thresholds (Almeida-Dias et al., 2010). Mailly et al. (2014) use an extended version of ELECTRE TRI to classify many world locations into four climate categories.

In multi-criteria clustering, outranking methods and the PROMETHEE technique, in particular, have been used relatively more than other MCDA methods. De Smet & Guzmán's (2004) paper, an impressive work in multi-criteria clustering, proposes a clustering framework based on the preference structure obtained from the PROMETHEE technique. The work proposes an extension of the well-known k-means algorithm to the multi-criteria context. Later, some works present new formulations for the multi-criteria ordered clustering problems, enabling decision makers to order clusters partially (i.e., Rosenfeld et al., 2021) or completely (i.e., De Smet et al., 2004 and Sarrazin et al., 2018) and to outline a relational multicriteria clustering. Another important step forward in multi-criteria clustering was when Ishizaka and Labib 2011) introduced a new divisive hierarchical clustering algorithm using the Monte Carlo stochastic algorithm and PROMETHEE technique. Their algorithm allows researchers to obtain the optimum number of clusters, as well as to take into account uncertainty and imprecision, such as the ill-determination of weights and the preference thresholds.

Although the PROMETHEE and ELECTRE methods are widely used for classifying, sorting, and clustering attributes, a few other types of outranking MCDA methods are used in the literature of MADM classification, sorting, and clustering. For example, Angilella & Mazzù (2015) use stochastic multi-criteria acceptability analysis (SMAA) to assign Small and Medium-sized Enterprises (SMEs) to different risk classes.

5.3 Cluster 3-additive utilities and preference disaggregation approach

Many MCDA methods have been developed based on preference disaggregation. The preference disaggregation approach revolves around estimating an additive utility function via the analysis of the global judgments of the decision-maker (Zopounidis & Doumpos, 1997). UTilites Additives (UTA) is a well-known preference disaggregation method based on ordinal regression analysis enabling decision-makers to minimize the misclassification error between the classes of attributes (Jacquet-Lagreze & Siskos, 1982). There are variants of the UTA method, including UTilite´s Additives DIScriminantes (UTADIS), UTA$^{\text{star}}$, and UTA$^{\text{GMS}}$ that have been used in different MCDA problems (Doumpos & Zopounidis, 1998; Kadziński et al., 2012). Among the retrieved studies that used additive utilities and preference disaggregation approach, 62, 33, and 5 percent have used it for classification, sorting, and clustering problems, respectively. This shows that additive utilities and preference disaggregation approaches are used mainly for classifying, sorting, and clustering.

Paying special attention to the UTA family, Zopounidis & Doumpos (2002) review different forms of MCDA classification and sorting models, as well as their different aspects of the model development process. Using UTADIS, Gaganis et al. (2006) develop a classification MCDA method to classify several banks from different countries. Kadziński et al. (2013) introduce an extended UTAGMS method to sort alternatives effectively in case of conflict between decision-makers. Moreover, Palha et al. (2016) apply a modification of the UTADIS method, ROR-UTADIS, to sort attributions in a supply chain problem, while Babashov et al. (2020) use it for drug formulary decisions. The UTADIS method has also been used in developing multi-criteria clustering algorithms. Esmaelian et al. (2020), employing the UTADIS method, propose a new multi-attribute preference disaggregation method called DISclustering. Their algorithm allows decision-makers to assign alternatives to each cluster based on comparing the global utility values with the utility thresholds.

5.4 Cluster 4-rough sets and rule-based approaches

In MCDA, exemplary decisions can be inconsistent because of hesitation of the decision-makers or limited discriminatory power of criteria (Greco et al., 2002a). These inconsistencies convey important information and also cannot be considered as a simple error or noise. The rough set theory, proposed by Pawlak (1982), helps decision-makers make more robust decisions dealing with inconsistency problems by separating certain and doubtful knowledge extracted from exemplary decisions (Greco et al., 1999). Among the retrieved studies that used rough sets and rule-based approaches, 61, 36, and 3 percent have used them for classification, sorting, and clustering problems, respectively. This shows that rough sets and rule-based approaches are essentially used for classifying sorting rather than clustering.

Greco et al. (2001) define exploitation procedures of the set of decision rules to sort attributes. Using the dominance-based rough set approach, Cinelli et al. (2015) develop a classification MCDA method. Moreover, Luo et al. (2018) introduce an extension of the dominance-based rough set approach by using an incremental learning technique for hierarchical multi-criteria classification. Corrente et al. (2017) propose a multiple criteria hierarchy process rooted in ordinal regression with additive value for a soring problem in the banking sector. Extracting valuable uncertain information for rule induction, Chai & Liu (2014) propose a novel Believable Rough Set Approach (BRSA) to sort different suppliers.

5.5 Future research directions for MCDA classification, sorting and clustering

The reviewed literature revealed at least the following four future research directions.

5.5.1 Uncertainty modeling

Uncertainty modeling appears as a major research line in recent and future MCDA studies. As mentioned in Pelissari et al. (2021), uncertainty, imprecision and inconsistency are inevitable in real-world decision problems. They have been addressed in several ways in sorting, classification and clustering MCDA approaches. Fuzzy modeling seems to be a privileged tool, as demonstrated in Cluster 1 with fuzzy extensions to most popular MCDA methods such as PROAFTN (Al-Obeidat et al., 2019) for classification, Fuzzy AHPSorting (Greco et al., 2019) or IT2FS AHPSort II (Xu et al., 2019) for sorting, and CLUS-MCDA (Maghsoodi et al., 2018) for clustering. The SMAA method has also been extensively applied to overcome uncertainty about MCDA input data and increase models' robustness (see Pelissari et al.'s (2021) study for a recent review on SMAA). The trend seems to be ongoing, with recent methods combining fuzzy modeling and the SMAA framework, such as the Fuzzy-SMAA FlowSort (Pelissari et al., 2019). Other more original approaches account for another form of uncertainty related to temporality. For instance, based on ELECTRE-Tri, Mouhib and Frini (2021) proposed TSMAA-TRI to handle multi-period evaluations, while Bouzayane and Saad (2020) proposed the MAI2P method as a multicriteria classification approach based on the rough set theory for the incremental periodic prediction (*MAI2P*). Hybrid approaches seem to be the future of MCDA classification, sorting and clustering methods integrating fuzzy and stochastic modeling with sensitivity and robustness concerns.

5.5.2 Interaction between criteria and non-monotonicity

Since the seminal work of Grabish (1997) on fuzzy integrals to model interaction between criteria, there has been an increasing interest in accounting for potential criteria interactions in the criteria aggregation process in MCDA. Criteria interaction implies that the contribution of a given criterion to the overall assessment of an alternative may depend on the values taken by other criteria. Fuzzy integrals can capture interaction among criteria by attributing a weight of importance to every subset of criteria as opposed to a single criterion. Recent works such as Arcidiacono et al. (2021) propose to model interactions between criteria that are hierarchically structured for sorting MCDA problems. A special case of the fuzzy integrals, the Choquet integral based on a 2-additive capacity (non-additive weights for the criteria under consideration), is used to find all minimal sets of pairs of interacting criteria representing the preference information provided by the decision-maker. Ishizaka & Pereira (2020) developed the ANPSort method to handle interdependent criteria in sorting, while Costa et al. (2020) proposed the CAT-SD method for classification. In addition, several recent studies have combined DEMATEL and ANP to model criteria interactions in clustering problems (Abellana & Mayol, 2021; Xu et al., 2020).

In the literature reviewed, many recent works, such as Liu et al. (2019) for sorting or Boujelben (2017) for clustering, consider interacting criteria as an important issue to be addressed in the future extensions of their models.

Another trend consists of relaxing the monotonicity constraint for criteria. Kliegr (2009) introduced the UTA-NM method on additive non-monotonic utility functions. His work was followed by that of Ghaderi et al. (2017) and Liu et al. (2019) who used preference learning approaches to assess potential non-monotonic marginal utilities in sorting and classification problems. Other more recent works such as Guo et al. (2019) and Kadziński et al. (2020) have focused on non-monotonicity in MCDA sorting.

5.5.3 Composite indicators

A rather recent area of application for MCDA is the construction of composite indicators. A recent literature review on this topic (Greco et al., 2019) showcases the considerable growth of this research field, its relevance and practical importance for MCDA. The authors explain that the input of MCDA methodological approaches is paramount, especially considering weighting and aggregating aspects. More specifically, the contribution of non-compensatory aggregation methods Greco et al. (2021) addressed the drawback of full compensation, one of the major criticisms related to composite indicators. Uncertainty and robustness concerns have also been dealt with, with the introduction of the SMAA method. For instance, Doumpos et al. (2016) used it to create a composite index to assess the overall financial strength of 1200 cross-country banks under different weighting scenarios. Greco et al. (2018) used SMAA to deal with the issue of weighting in composite indicators by taking into consideration the whole set of potential weight vectors. SMAA has also been applied in the work of Angilella et al. (2018), considering a hierarchical structure and interacting criteria.

5.5.4 Data-driven and preference-learning approaches

In MCDA, the elicitation of preference parameters remains an important issue. Each decision model is based on a certain number of parameters, such as weights, preference and indifference thresholds, representing the preferences of the decision maker. While it is crucial for the quality of the recommendation supplied by the adopted model, the elicitation of preferential information is a burden for the decision maker, as it requires considerable cognitive effort. The recourse to exemplary decision approaches (preference disaggregation and rule-based decision approaches presented in clusters 4 and 5), in which preference information is inferred from decision examples, has been a prevalent trend in recent years. This trend has been acknowledged and confirmed in the recent survey by Erişkin (2021), in which the authors review recent sorting and classification MCDA methods in light of machine learning and data-mining techniques. MCDA clustering has also witnessed extensive growth with the input of machine-learning techniques and algorithms. Data-driven and statistical learning techniques are particularly relevant to solve problems with large sets of alternatives and/or criteria. The "curse of dimensionality," as mentioned by Erişkin (2021), has been often overlooked by the MCDA community that will benefit from statistical learning approaches that put particular emphasis on the increase of a problem's domain and address it with efficient techniques.

6 Conclusion

Using classification, sorting, and clustering models for real-world problems provides decision-makers with advanced processed information that could help them make critical and intelligent decisions. MCDA techniques have played a significant role in this context, and their applications in classification, sorting, and clustering problems have been attracting ever-growing attention. Conducting a bibliometric analysis, we explored the literature of MCDA classification, sorting, and clustering from May 31, 1990, to May 31, 2021. In particular, we analyzed 675 relevant scientific articles and reviews retrieved from the Web of Science database to get a multi-dimensional understanding of the research field. Based on the bibliometric results, we discussed publication growth trends, the countries and institutes of the publications, top contributing journals and authors, as well keywords co-occurrence and authors' co-citation networks. We identified four major areas of research, in terms of the methodological approaches, labeled *"AHP, Fuzzy modeling, GIS"*, *"Outranking methods"*, *"Additive utilities and preference disaggregation approach"*, and *"Rough sets and rule-based approaches"*. The findings indicated that the research area *"AHP, Fuzzy modeling, GIS"* is the most popular one. Moreover, we explained how different MCDA techniques in each research cluster have been applied to solve classification, sorting, and clustering problems.

In the reviewed literature, recent trends and future research avenues for MCDA classification, sorting and clustering seem to be focused on four main directions. The first consists of addressing the uncertainty surrounding multicriteria decision problems using different modeling tools such as fuzzy sets and their extensions and the SMAA method to account for multiple plausible sets of value parameters and input data. The second future research direction involves the integration of criteria interactions and non-monotonicity with the use of Choquet integrals and other methods such as DEMATEL and ANP for interacting criteria, and preference learning techniques to model non-monotonicity. As a third future research vein the use of exemplary decision approaches and the integration of machine learning and statistical learning techniques appears to be a prevailing and ongoing trend. Finally, among the different areas of application for MCDA methods, composite indicators are standing out as a field where MCDA approaches are being extensively used to summarize complex multi-dimensional issues with considerable implications for policy-making and real-world decision problems.

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