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Cognitively Inspired Multi-attribute Decision-making Methods Under Uncertainty: a State-of-the-art Survey

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Abstract
In the last decades, the art and science of multi-attribute decision-making (MADM) have witnessed significant developments and have found applications in many active areas. A lot of research has demonstrated the ability of cognitive techniques in dealing with complex and uncertain decision information. The purpose of representing human cognition in the decision-making process encourages the integration of cognitive psychology and multi-attribute decision-making theory. Due to the emergence of research on cognitively inspired MADM methods, we make a comprehensive overview of published papers in this field and their applications. This paper has been grouped into five parts: we first conduct some statistical analyses of academic papers from two angles: the development trends and the distribution of related publications. To illustrate the basic process of cognitively inspired MADM methods, we present some underlying ideas and the systematic structure of this kind of method. Then, we make a review of cognitively inspired MADM methods from different perspectives. Applications of these methods are further reviewed. Finally, some challenges and future trends are summarized. This paper highlights the benefits of the synergistic approach that is developed based on cognitive techniques and MADM methods and identifies the frontiers in this field.

Keywords Multi-criteria decision-making · Cognitive complex information · Fuzzy cognitive map · Future directions

Introduction

Real-world decision-making problems are often too complex to be considered through a single criterion. In order to solve problems with multiple attributes, multi-attribute decision-making (MADM) methods are developed, which significantly enhance the ability of decision-making methods. As a cognitive process, MADM refers to selecting the optimal solution by evaluating alternatives in the presence of multiple attributes. The number of alternatives for MADM problems is predetermined and limited. Basically, MADM methods can be roughly grouped into two categories [1]: (1) Outranking techniques. The outranking methods are based on pairwise comparison of alternatives, like ELECTRE (Elimination et Choix Traduisant la Realité in French, Elimination and Choice Expressing the Reality) [2] and PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) [3]. (2) Multi-attribute utility and value theories. This kind of method usually assigns a utility to each alternative and includes UTA (utility additives) [5], AHP (analytic hierarchy process) [6], ANP (analytic network process) [7], MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) [8], etc. There is a growing body of literature that recognizes the importance of MADM methods in many fields of human life, such as healthcare [9, 10], transportation [11–14], manufacturing [15–18], and business [20, 21].

With the rapid developments of the social economy and technology, the demand for intelligent decision support has been heightened. The main challenge faced by decision makers (DMs) is to identify the cognition and judgments close to the human brain to improve the quality of decision-making. Cognitive computation, a computing system

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to mimic human thought processes, has been proposed to realize knowledge representation and brain-like computing. Cognitive scientists explored human mental abilities by observing language, perception, memory, attention, reasoning, and emotion [22]. As an interdisciplinary subject, cognitive computation uses methods from psychology, biology, signal processing, physics, information theory, mathematics, and statistics to enable machines to learn, think, and make correct decisions like human brains. In the era of big data, many technological innovations, such as information analysis, natural language processing, and machine learning, are also employed in cognitive computation systems, which make it possible to handle the immense volume of data with complex structures. As human thoughts and perceptions are usually vague and uncertain, it is difficult to represent such information in the form of a precise number that is intolerant of imprecision and partial truth. Thus, the fuzzy theory was proposed and has been often employed to capture some subjective information in the decision-making process. To solve complex realistic problems, it is important to adopt the cognitive computation process and fuzzy theory in MADM to provide DMs with extraordinary insights under the cognitive information environment.

During the last decades, due to the high uncertainty and complexity of the socio-economic environment, cognitive procedures have a growing influence on MADM [23–25]. Developments in other theories such as linguistics, information theory, and data science have also brought an impressive cognitive revolution in decision-making [22]. Thus, cognitively inspired MADM methods have received considerable critical attention and have been a major area of interest within the field of decision-making. Moreover, recent trends in artificial intelligence techniques have led to a proliferation of studies focusing on cognitively inspired MADM, which is seen as a key step in the direction of intelligent support of human–machine cooperation in problem solving. It is worth noting that cognitively inspired MADM methods are not a replacement for the actual human DMs by artificial decision systems, but an effective tool to support DMs to realize their decision intensions and enhance the existing decision strategies. In decision-making and reasoning, cognitively inspired methods have a competitive advantage over conventional methods in identifying and characterizing the effects of information technologies [26]. It can offer better capabilities to handle different types of data and assist DMs to obtain accurate information in the cognitive and complex environment so that they can make intelligent, informative, and reasonable decisions. Beginning with [27], steady progress has been made in the expansion of cognitive decision-making theories. There have been a series of contributions focusing on the application of cognitively inspired MADM methods in various areas, such as enterprise resource management [28] and medical information technology assessment [26].

This paper aims to summarize the present position of cognitively inspired MADM methods. To do so, the development trend of cognitively inspired MADM methods and the distributions of publications concerning publishing journals and regions are summarized. Then, we provide a comprehensive investigation of the system architecture of the cognitively inspired MADM method and clarify the advantages of this type of method. Furthermore, cognitively inspired MADM methods are introduced from different perspectives. After that, real-world applications are discussed in relevant areas, including economic applications, industrial applications, information technologies, public services, and healthcare management. Finally, the current challenges with cognitively inspired MADM methods are outlined, and based on these, the future trends are presented to guide the development in this field.

This paper is organized as follows: "Statistical Analysis of Studies on Cognitively Inspired MADM Methods" focuses on the statistical analysis of the publications of cognitively inspired MADM methods. "The Basic Process of Cognitively Inspired MADM" describes the basic structure of the cognitively inspired MADM methods. In "Classification of Cognitively Inspired MADM Methods," a series of methods with their primary ideas are overviewed. The related applications are summarized in "Application Fields of Cognitively Inspired MADM Methods." "Challenges and Trends for the Future" concentrates on the current challenges and future directions. This paper ends up with some conclusions in "Conclusions."

Statistical Analysis of Studies on Cognitively Inspired MADM Methods

In this section, to present a general introduction to the basic information of cognitively inspired MADM methods, we summarize some statistical results of published papers in this field in terms of published time, journals, and regions.

Development Trend of Cognitively Inspired MADM Methods

In the 40 years since the pioneering attempt of John Payne to make decision research "more cognitive," a large number of studies from cognitive psychology have been applied to conventional decision-making methods [29]. To present the development of cognitively inspired MADM methods, we select the related publications in the Web of Science Core Collection by setting the search topic as "cognitive" and "multiple attribute decision making." As many scholars take the terms "multiple attribute decision making" and "multiple criteria decision making" as interchangeable, the topic "multiple criteria decision making" is also adopted. Besides, as a reference, when the search topic is set as "cognitive" and "decision making," the

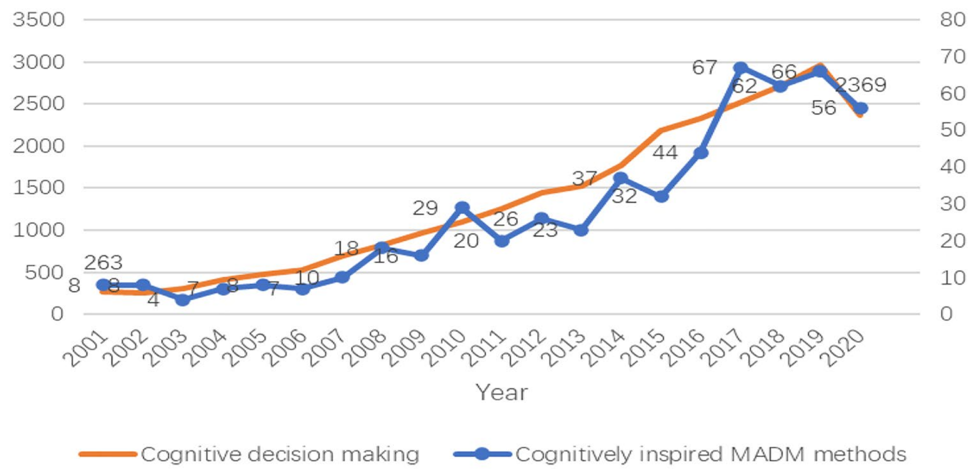


Fig. 1 The number of published papers from 2001 to 2020

related publications are also selected to illustrate the development of cognitive decision-making. For the purpose of observing the research trend of cognitively inspired MADM methods, the growth in the number of annual academic papers in this field from 2001 to 2020 is manifested in Fig. 1.

As can be seen in Fig. 1, cognitive decision-making has developed rapidly during the 20 years. By 2020, the number of publications has reached 2369, compared with only 263 in 2001. Similarly, the number of cognitively inspired MADM methods saw a rising trend, growing from 8 in 2001 to 56 in 2020. Despite some fluctuations, the number of published papers increases steadily. It is worth noting that there was a significant increase from 2010 to 2020, during which time MADM is increasingly affected by issues arising with the rapid development of information technologies. In 2020, the number of published papers in this field has reached 56 and will continue to grow. To sum up, although cognitively inspired MADM is still a novel and developing direction, the growth rate of the number of papers is obviously accelerating since 2015. This means that cognitively inspired MADM methods have attracted more attention from researchers and have a wide range of broad application prospects in the era of big data.

Distribution of Related Publications

To have a glance at the distribution of publications related to cognitively inspired MADM methods, in this subsection, we go through the statistical analysis of main research in this field. Due to the limited space, Fig. 2 shows ten journals sorted based on the number of academic works.

Based on Fig. 2, the most relevant papers were published in the *European Journal of Operational Research* journal, where the number of papers is 12. The second position is held by the journal *Cognitive Computation* with a publication frequency equal to 7. Each of the journals *Journal of Cleaner Production*, *Expert Systems with Applications*, and *Information Sciences* published 6 papers. Some articles were published in *Advances in Intelligent Systems and*

Fig. 2 Distribution of journals (items with frequency ≥ 3)

Table 1 The country/region distributions of publications

	Country/region	*Number of publications*	*Proportion*
1	USA	201	32.1%
2	China	103	16.5%
3	UK	79	12.7%
4	Canada	41	6.6%
5	Portugal	33	5.3%
6	Australia	30	4.8%
7	Germany	27	4.3%
8	France	25	4.0%
9	Italy	24	3.8%
10	India	23	3.7%
11	Spain	22	3.5%
12	Brazil	17	2.7%
	Total	625	100%

Computing (5), *Annals of Operations Research* (4), *Journal of the Operational Research Society* (3), *Applied Soft Computing* (3), and *Technological and Economic Development of Economy* (3). We can find that these journals are very influential journals in their fields, especially in operational research and computer science. This result reveals that the development of computer science further results in the application of cognitively inspired MADM methods in intelligent decision support.

After that, an exploration into the regional distribution of published papers is provided in Table 1.

As displayed in Table 1, the USA led with 201 publications, which contributed 32.1% of all papers during the whole period. It was followed by China with 103 academic papers, accounting for 16.5%. The UK ranked third and contributed 79 academic papers (12.7%). Subsequently, the percentages of published papers in the regions of Canada and Portugal are 6.6% and 5.3%. Then, the published papers in other 6 countries varied slightly ranging among 4.8% in Australia, 4.3% in Germany, 4.0% in France, 3.8% in Italy, 3.7% in India, and 3.5% in Spain. The lowest positions related to the region are occupied by Brazil, constituting 2.7%. The statistical results indicate that most of the scholars studying cognitively inspired MADM are from the USA. China and the UK have also left profound influence in this field. For further exploring the structures and dynamics of the related publications, we split the whole period into two phases: 1900–2009 and 2010–2020. It is noted that 1900 is the earliest time that the Web of Science can retrieve.

In Fig. 3, it is noticeable that the USA always takes first place in the two different stages. From the perspective of growth date, with only 4 publications, China ranked seventh in the previous period; however, it jumped to second place by contributing 99 published papers in the latter period. In contrast, Canada fell to fourth place in the latter period. Besides, before 2010, there were also blanks of research in this field in India and Spain. As time goes on, this phenomenon has changed. The number of papers on cognitively inspired MADM methods published by scholars in various regions has increased significantly from 2010 to 2020.

In conclusion, cognitively inspired MADM has attracted more and more attention from all over the world in the last decade. However, despite a significant increase of the related publications in each country, the distributions are still highly unbalanced at the regional level. The USA, China, and the UK contributed 59.5% of all papers during the entire period.

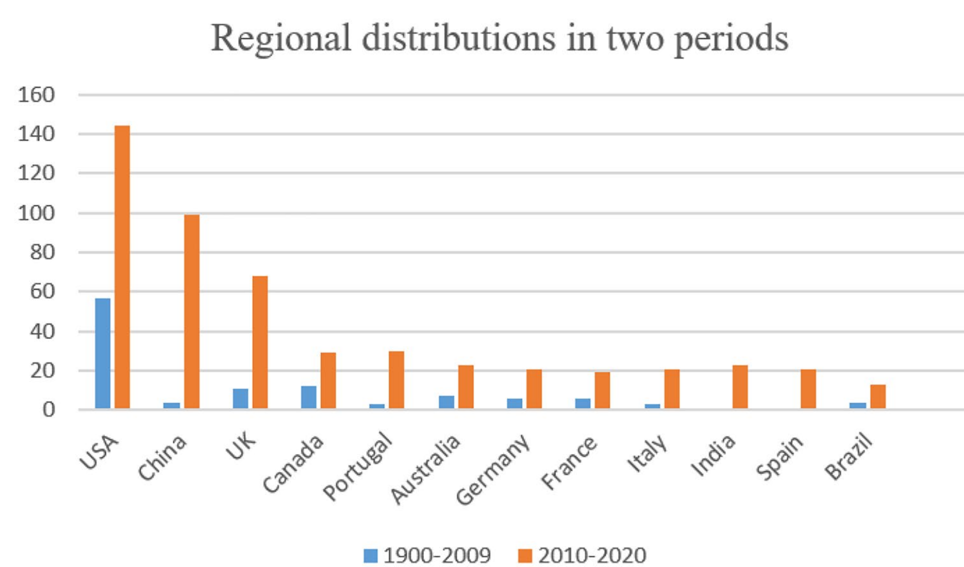


Fig. 3 Regional distributions in two periods

The Basic Process of Cognitively Inspired MADM

As conventional decision-making methods are limited in their ability to realize humanlike intelligence, in recent years, the rapid development in artificial intelligence and big data has brought considerable attention to the application of the cognitive computation process in decision support. With the goal of enhancing the description of realistic problems as well as improving the ability of decision-making theory, cognitively inspired MADM methods may be seen as the first step in the direction of intelligent support of man/machine cooperation. Based on the underlying theories, intelligent decision support systems are able to be implemented in various fields, such as smart city, cognitive healthcare, and intelligent evaluation system.

As mentioned before, cognitively inspired MADM methods are not intended to replace real DMs, but instead to assist DMs in their attempt to formalize decision intension. It depends on data and mines the potential of those data to enable the machines to cognize the objective world from the perspective of human thinking. Here we first explain how the cognitively inspired MADM methods support DMs (as shown in Fig. 4) [30].

Based on cognitive theory from cognitivism, the observable decision-making behaviors of DMs and the corresponding consequences can be collected. Then, the cognitive model is adopted to define the problem, represent the decision information, and formulate possible solving strategies for DMs. The main difference between conventional decision-making methods and cognitively inspired methods is that algorithmic development is driven by cognitive information or cognitive models. The cognitively inspired MADM methods are proposed as effective tools for constructing intelligent decision support systems, which realize the data fusion and interaction between DMs and machines. As shown in Fig. 5, the basic structure of the intelligent decision support system consists of DMs, cyberspace, and machines.

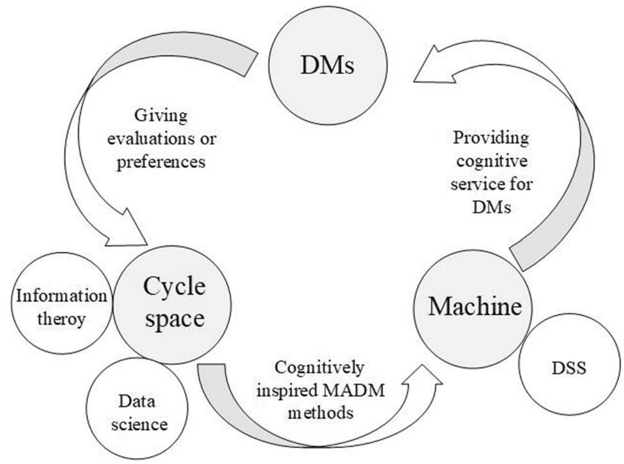
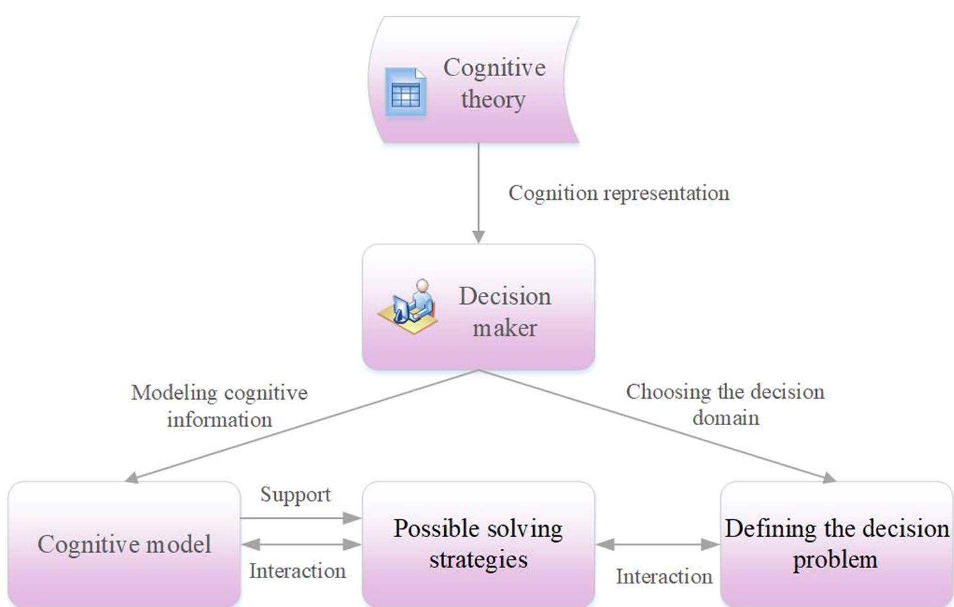


Fig. 5 The DM-centered cognitive cycle

According to [22], the machine refers to hardware facilities, such as computer networks, terminal devices, and robots. Meanwhile, the cycle space is composed of information stored in the virtual network. The basic process of the DM-centered cognitive cycle includes three steps: (1) When faced with realistic decision-making problems, DMs would provide some new interpretation for the existing information and then give their evaluations or preferences, which can mine the potential of these data. (2) Through the

Fig. 4 Cognitively inspired MADM methods for DMs



processing of information theory, data science, and other tools, the information will be stored in the cycle space. (3) Algorithms including cognitively inspired MADM methods play a role in improving the intelligence of machines by cognizing cognition based on data and information. Thus, machines can explore more internal requirements of DMs, develop a deeper understanding of human thinking, and then provide intelligent cognitive services to support DMs in solving complex problems.

It is obvious that cognitively inspired MADM methods are mainly based on information and data. The first step of the decision-making process emphasizes the transformation and utilization of initial information that is represented by data with various structures. Thus, how to depict cognitive information is worthy to be noticed. Moreover, it is necessary to employ effective information fusion technologies in the decision-making process to improve the accuracy of available information. After that, the most crucial part of cognitively inspired MADM methods is to analyze and process information to achieve intelligent decision-making. Since the most influential features of a MADM method are assisting DMs to understand and structure the decision criteria, the model capability of the possible interactions between the criteria, and transforming assessments from DMs into meaningful judgment structures [31], the cognitively inspired MADM methods are generally proposed to deal with problems with multiple and conflicting attributes under complex, uncertain, and cognitive environments. The decision support system requires this kind of method to make rational decisions and provide higher computational efficiency. In summary, as a new type of decision mode, the development of cognitively inspired MADM methods can not only enrich the modern decision theory but also provide important information sources for the realization of intelligent decision-making.

Classification of Cognitively Inspired MADM Methods

Cognitively inspired MADM methods help to establish the structure of the problem from the cognitive perspective. The issue of developing appropriate evaluation tools for use in the design and analysis of realistic MADM problems is considered to be of great importance. In this section, to identify the differences and similarities of cognitively inspired MADM methods, they are summarized from three angles, i.e., methods for modeling cognitive information, methods based on the fuzzy cognitive map (FCM), and methods combined with some cognitive computation process. In these three categories, a lot of methods with their primary ideas are overviewed.

Cognitively Inspired MADM Methods for Modeling Cognitive Information

Due to the complexity and vagueness of objective issues as well as human thinking, there always exists uncertainty in the MADM process. Therefore, managing and modeling uncertain information under a cognitive environment is important for the acquisition of desirable solutions. For the purpose of representing human perception and reasonably describe the decision information, the fuzzy theory has come to perform important notes in fruitful research. Some representative methods are summarized in Table 2 for visually showing their distinct characteristics.

To fully reflect the characteristics of human cognitive performance including affirmation, negation, and hesitation, the intuitionistic fuzzy set (IFS) was proposed by Atanassov and Gargov [32], consisting of a membership function, a non-membership function, and a hesitancy function. Besides, depicting cognitive information in the form of IFS makes it possible to handle the situation where DMs express their evaluation values by using real numbers. This fact encourages researchers to develop cognitively inspired MADM methods that are established on the ground of IFSs. For example, with the aim of presenting a framework for a knowledge measure of IFSs, Farhadinia [33] introduced a cognitively inspired MADM methodology, which takes both the fuzziness and intuitionism concepts into account. As the weights of attributes definitely affect the final results of the alternative ranking, the determination of attribute weights plays a key role in the decision-making process. Thus, based on the proposed knowledge measures, a weight determination method was also introduced. Considering the complexity of the cognitive process involved in the personalization of learning management systems, a novel MADM approach was developed based on IFSs, which significantly improved the efficiency and effectiveness of the teaching process and enriched the

Table 2 Some representative cognitively inspired MADM methods

Nos	Techniques	References
3	IFS	[32] [33] [34]
1	Interval-valued intuitionistic fuzzy set	[43]
1	Ordered weighted hesitant fuzzy set	[24]
1	Linguistic interval hesitant fuzzy sets	[35]
1	Dual hesitant fuzzy preferences	[36]
1	Uncertain linguistic information	[37]
1	Interval neutrosophic uncertain linguistic variables	[38]
1	Linear partial ordering	[39]
1	Hybrid Z-information	[40]
1	Linguistic Z-numbers	[41]
1	Incomplete preference information	[42]

users' experience [34]. In order to pay more attention to highly non-linear problems with interaction effects among multiple attributes, an interval-valued intuitionistic FCM was constructed and then adopted to represent criteria in MADM, where the edges represent interaction effects among the criteria. This method helped DMs to deal with complex MADM problems in dynamic and unstructured environments [43]. Other extensions of fuzzy sets have also made efforts in cognitively inspired MADM methods. For reflecting the hesitancy and uncertainty of DMs' cognitions, some highly intuitive tools, including the ordered weighted hesitant fuzzy set [24], linguistic interval hesitant fuzzy sets [35], dual hesitant fuzzy preferences [36], uncertain linguistic information [37], interval neutrosophic uncertain linguistic variables [38], different formats of preference information [140], etc., were employed to elicit cognitive information given by DMs. In order to assess participants' knowledge and determine the priority of engineering characteristics, a linear partial ordering approach was presented, which can reduce the cognitive burden of designers and engineers in quality function deployment [39].

Considering the reliability of cognitive information, a MADM method with hybrid Z-information was developed on the basis of a ranking aggregation algorithm. The mathematical structure of this method is straightforward and the calculating process is simple, which shows huge advantages over some other methods [40]. With linguistic Z-numbers, an extended TODIM (an acronym in Portuguese of interactive and multi-criteria decision-making) method was proposed based on the Choquet integral [41]. It can more comprehensively reflect the cognition of DMs and improve the reliability of decision information. Due to the cognitive limits of humans, DMs may apply heuristics to reduce information processing investment at the expense of an increased error rate. A feedback mechanism was established as a viable solution to extend DMs' cognitive limitation and with MADM tasks. Moreover, the proposed method made it easier for non-experts to understand, which indicated that it was also appropriate to be applied to the decision support system [44]. Since few papers have focused on the rationality of DMs, Pei established novel decision-making models to deal with multi-attribute assessment problems including incomplete preference information. The confidence level and cognitive dissonance of DMs are involved in the entire decision-making process [42].

Cognitively Inspired MADM Methods Based on FCMs

Cognitive maps, as a causal-based mapping technique, were proposed to represent social knowledge in the research conducted by political scientist Robert Axelrod, which utilized arrow diagrams to organize concepts of complex problems. However, it is too restrictive to employ cognitive maps for the construction of the knowledge base because causality is usually vague. In general, human thinking occurs sometimes, very little, possibly true, more or less, etc. The fuzziness of human cognition brings vague knowledge sources to knowledge base building. Thus, with the aim of adapting to this feature, the FCM was introduced to assist in solving complex and highly non-linear problems under uncertainty, where decision concepts are linked to represent causal reasoning [45]. Figure 6 shows an example of a FCM in which the causal relationship that influences the tactical target value of a bridge is fuzzy rather than precise [45].

Remark 1 In military science, the strategic targets, mission tactics, and battlefield facts are linked through fuzzy causality to produce a net utility. As the front edge of the theater moves, the possibility of using a random bridge increases.

It can be found that FCMs are fuzzy causal graphs, where nodes represent descriptive concepts and edges indicate positive or negative relationships between those concepts. In general, fuzzy numbers or linguistic terms are employed to describe the degree of relationship between concepts, the cumulative impact of which is transformed by a non-linear activation function [43]. For example, suppose that there are n concepts in a FCM. The value of the $i-$th concept is assigned as c_i. In addition, fuzzy weights w_{ji} are used to indicate whether there is a relationship between the $i-$th concept and the $j-$th concept or not. If $w_{ji} > 0$, then there exists positive causality; if $w_{ji} < 0$ then, there exists negative causality; if $w_{ji} = 0$, then there is no relationship between c_i and c_j. Following the definition of FCM, the value of the $i-$th concept for the next iteration can be obtained by the calculation rule:

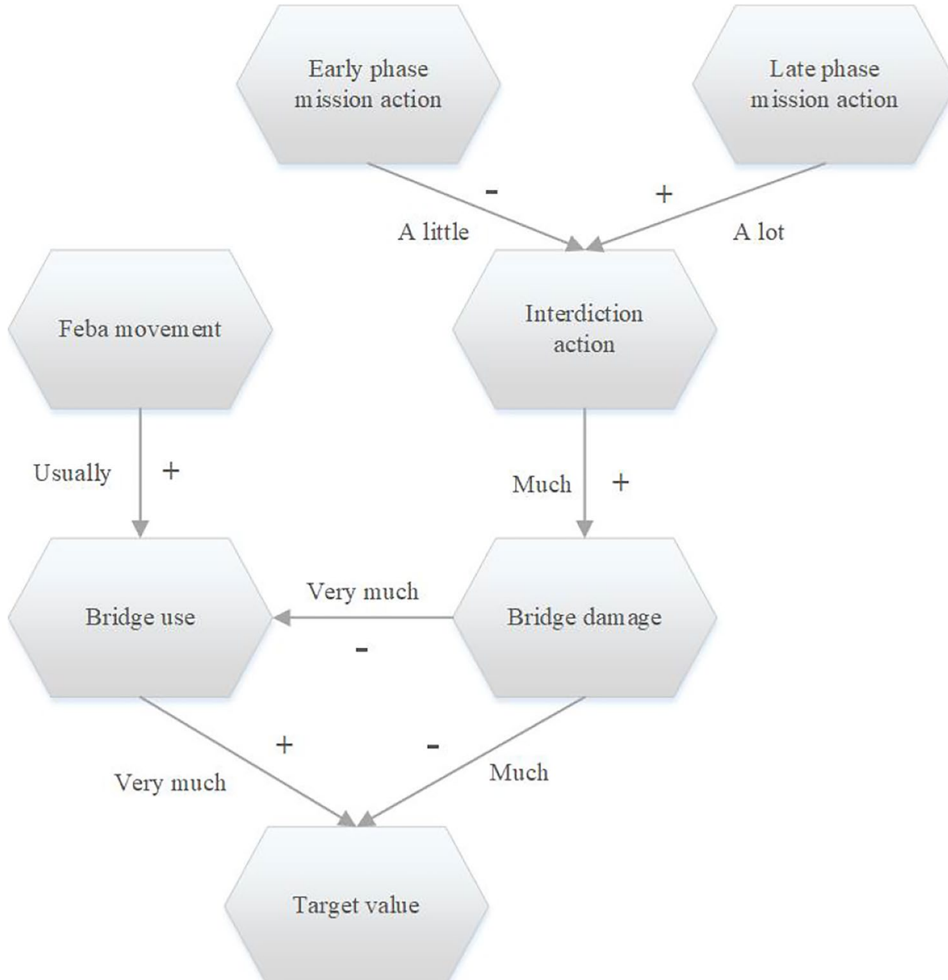
$$c_i^{k+1} = f\left(c_i^k + \sum_{\substack{j=1 \\ j \neq i}}^{n} c_j^k \times w_{ji} \right) \tag{1}$$

where c_i^k refers to the value of the $i-$th concept at the iteration k, c_i^{k+1} refers to the value of the $i-$th concept at the iteration $k+1$, and f is a threshold function. This illustrates that the new value of a concept for the next iteration should be derived based on all edges connected to this concept. A complete framework of this six-step procedure in FCMs can be clearly illustrated in Fig. 7 [46].

Step 1. Determination of concepts. The concept nodes should be defined and denoted as c_i with $i = 1, 2, ..., n$.

Step 2. Identifying causality links. DMs are required to determine the direction of causal relationships among concepts in three categories: positive, negative, and null.

Fig. 6 Bridge target value FCM



Step 3. Fuzzy set assignment. DMs need to decide the degree of causality by using fuzzy sets.

Step 4. Weight matrix construction. According to values provided by DMs, the weight matrix is established.

Step 5. Fuzzy cognitive mapping iterations. For the purpose of deriving the value of each attribute and the priority ranking, iterations are calculated by the threshold function.

Step 6. Obtaining the value of each concept. The values of concepts can be determined after several iterations.

Pieces of evidence from different fields suggest that FCMs can play an important role in MADM because they enable DMs to rapidly compare their mental models with the actual situation, thus making the evaluation more convenient. For sure, a lot of researchers investigating cognitively inspired MADM have proposed some decision-making methods that incorporated FCMs into MADM problems, which are summarized in Table 3.

Owing to the modeling capacities of FCMs, a hybrid MADM approach was proposed by combining TOPSIS

Fig. 7 Flowchart of the FCM

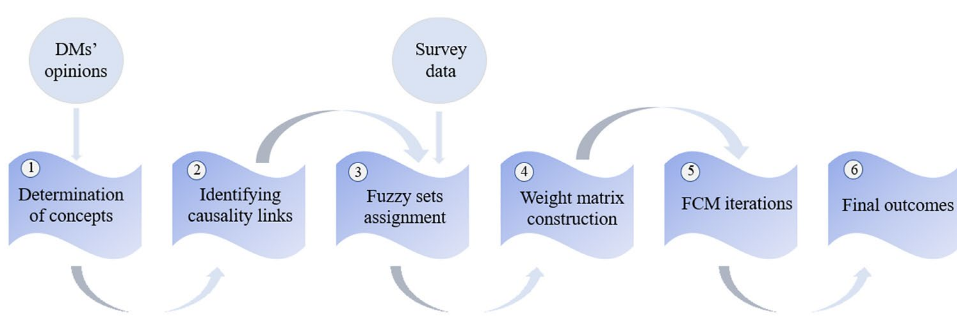


Table 3 Some representative cognitively inspired MADM methods based on FCMs

Nos	Techniques	References
1	FCM + TOPSIS	[31]
1	FCM + multi-attribute value theory	[47]
1	FCM + the Nash bargaining game	[48]
1	FCM + affinity diagram + DEMATEL + Dempster–Shafer evidence theory	[49]
1	FCM + multi-criteria analysis	[50]
2	FCM + multi-attribute evaluation	[51, 52]
1	Intuitionistic cognitive map	[46]
1	TOPSIS + interval-valued intuitionistic FCMs	[53]

(technique for order of preference by similarity to ideal solution) with FCMs, which can effectively model interdependencies among attributes in an uncertain environment [31]. To guide policymakers in strategic decisions, a decision support framework was established based on the integration of stakeholder analysis, cognitive mapping, and multi-attribute value theory [47]. In this approach, cognitive mapping was applied to identify relevant objects and attributes. With the support of the Nash bargaining game, a new structure and logic of FCM were proposed to assist in the supplier selection process, which effectively overcomes the shortcoming of conventional FCMs in distinguishing important concepts in complex problems [48]. In order to improve the performance of high-risk emergency systems, affinity diagram, DEMATEL (Decision Making Trial and Evaluation Laboratory), FCM, and Dempster–Shafer evidence theory were integrated to construct a MADM model, which has the capability to determine and optimize critical success factors in the system [49]. Various types of attributes can be fused in this model, including technical, economic, political, and social attributes. Benefiting from the advantages of FCMs in simulating human thinking, an intervention approach involving a multi-attribute evaluation method and the FCM was introduced to develop projects aimed at alleviating problems related to teenage pregnancy [51]. Furthermore, as capturing DMs' cognition and reasoning is crucial in the process of evaluating alternatives, an integrated MADM approach was proposed, which attempted to work with the FCM and directly achieve problem structuring and evaluation [52]. After generating multiple attributes and estimating their importance in sustainable resource management, cognitive mapping was presented as a tool to carry out the evaluation of the cross-indicator interaction [50].

Although FCMs have incorporated a high level of uncertainty in modeling relationships between attributes, many realistic problems are filled with great uncertainty in a dynamic environment, making it difficult to determine the values of attributes and the corresponding relationships in the form of a precise number. Thus, several generalizations of FCM have also been proposed and applied to MADM problems to address this issue.

In order to define the cause-and-effect relationships between attributes, Dogu and Albayrak [46] introduced an intuitionistic cognitive map (ICM) approach. The intuitionistic fuzzy set, which was employed to express DMs' knowledge, was defined as [54]:

$$I = \{\langle x, \mu(x), \nu(x)\rangle | x \in U\} \tag{2}$$

$$\pi(x) = 1 - \mu(x) - \nu(x) \tag{3}$$

where U is a finite universe; $\mu(x)$ and $\nu(x)$ indicate the membership degree and the non-membership degree of I, respectively, and satisfy the conditions $\mu(x) : U \to [0,1]$, $\nu(x) : U \to [0,1]$, and $0 \le \mu(x) + \nu(x) \le 1$; and $\pi(x)$ indicates the hesitancy in the mathematic model. Then, with the basic framework of FCM, the equation of the ICM is given as:

$$c_i^{k+1} = f\left(c_i^k + \sum_{\substack{j=1 \\ j \neq i}}^{n} c_j^k \left[\mu\left(w_{ji}\right) - h_s \cdot \pi\left(w_{ji}\right) \right] \right) \tag{4}$$

where $\mu\left(w_{ji}\right)$ is the membership degree of w_{ji}, $\pi\left(w_{ji}\right)$ is the indeterminacy membership degree of w_{ji}, and h_s is the coefficient of the application field, especially $h_s \in [0,1]$. It is worth noting that there is an assumption in the proposed method: $\left|\mu\left(w_{ji}\right)\right| > \left|\pi\left(w_{ji}\right)\right|$, which means that the influential value is always greater than the value of hesitation.

It was observed that DMs often feel difficult to provide reasonable information under the interaction of fuzzy decision criteria. To effectively overcome this issue, hybrid MADM methods were proposed by combining TOPSIS with interval-valued intuitionistic FCMs [53]. Similarly, the interval-valued intuitionistic fuzzy set (IVIFS) was defined as [55]:

$$I = \left\{ \left\langle x, \left[\mu^L(x), \mu^U(x)\right], \left[\nu^L(x), \nu^U(x)\right] \right\rangle | x \in U \right\} \tag{5}$$

where $\left[\mu^L(x), \mu^U(x)\right]$ represents the interval membership degree of x belonging to the IVIFS, $\left[\nu^L(x), \nu^U(x)\right]$ represents the interval non-membership degree of x, $0 \le \mu^L(x) \le \mu^U(x) \le 1$, $0 \le \nu^L(x) \le \nu^U(x) \le 1$, and $0 \le \mu^U(x) + \nu^U(x) \le 1$. Then, through applying the addition and multiplication operators of the IVIFS, the consecutive concepts' states were derived as:

$$c_i(k+1) = f\Big(\big\{\big[\mu^L(x), \mu^U(x)\big], \big[v^L(x), v^U(x)\big]\big\}(k) + \bigoplus_{\substack{j=1 \\ j\neq i}}^{n} \big(\big\{\big[\mu^L(x), \mu^U(x)\big], \big[v^L(x), v^U(x)\big]\big\}(k) \otimes \Big\{\Big[u^L_{w_{ji}}(x), u^U_{w_{ji}}(x)\Big], \Big[v^L_{w_{ji}}(x), v^U_{w_{ji}}(x)\Big]\Big\}\big)\Big) \tag{6}$$

where $w_{ji} = \Big\{\Big[\mu^L_{w_{ji}}(x), \mu^U_{w_{ji}}(x)\Big], \Big[v^L_{w_{ji}}(x), v^U_{w_{ji}}(x)\Big]\Big\}$ represents the crisp weight. After successive iterations, the weights of attributes can be obtained and then utilized in the alternative ranking process. This method can deal with the imprecise representation of attributes, contradictory decisions of different DMs, and interactions among these attributes.

Cognitively Inspired MADM Methods Combined with Cognitive Techniques

Although most cognitively inspired MADM methods are established from the above aspects, there still exist some researches combined with other cognitive tools, which are summed up in Table 4.

Specifically, in the group decision-making process, even if DMs are interested in achieving the same goal, they think about the problem from different perspectives, which usually results in cognitive conflicts in a group. A level 2 group decision support system was constructed to resolve cognitive conflicts by combining the cognitive feedback mechanism with the multi-attribute utility theory [56]. Similarly, a policy-modeling group performance support system was established by integrating structured decision-making methods and computer-supported cognitive feedback that employed multi-attribute utility analysis and social judgment analysis. It has been proven that the developed system can help the group achieve higher agreement [57]. The cognitive process that leads the DMs to evaluate the attribute values of the alternative is an important subject in psychological judgment and decision-making research. Westenberg and Koele focused on methodological and conceptual issues related to this field and discussed the development of the research paradigms used to investigate multi-attribute judgment and selection [58]. In order to transform qualitative concepts to quantitative data in MADM problems, the cognitive cloud model–based method was applied to real assessment [59]. Moreover, the research on MADM methods is increasingly challenged by issues arising with behavioral data on cognitive strategies. A Bayesian method was proposed in [60], which can evaluate whether it is most likely to generate empirical data vectors through equal weight rules or compensation strategies. This study also discussed the potential extensions of the general methods to other applications in behavioral decision research. With the rapid development of the social economy, large-scale decision-making gradually has emerged and encountered a series of cognitive and computational challenges. It is insufficient for many existing methods to deal with MADM problems with more than six attributes. To address this scaling in complexity, Ziegler and Lewis introduced a methodology to induce preferences for iterative attribute subsets by using principles of the hypothetical equivalents and inequivalents method [75].

In recent years, concept-cognitive learning, which is an interdisciplinary study of concept lattices and cognitive learning, has attracted a lot of attention and become a hot research direction among three-way decisions and granular computing [76]. The three-way decision model, which makes decisions from the viewpoint of cognition, has proposed a mathematical technique to independently process concept-cognitive learning based on true, false, and uncertain regions. Some researchers believed that the three-way decisions were built on a solid cognitive foundation and can provide cognitive advantages and benefits [19]. Thus, the combination of the three-way decision and MADM has provided a new research perspective for solving real problems. For example, to illustrate the properties of loss functions in three-way decisions, the concepts of relative loss functions and inverse loss functions were defined. Subsequently, considering all of the criteria in MADM problems, the MADM-based three-way decisions were introduced including new calculation methods of loss functions and some decision rules [64]. To solve MADM problems in fuzzy information systems, a reflexive fuzzy alpha-neighborhood operator was proposed to deal with fuzzy numerical data. With the

Table 4 Some representative cognitively inspired MADM methods combined with cognitive techniques

Nos	Techniques	References
1	Cognitive feedback mechanism + multi-attribute utility theory	[56]
1	Multi-attribute utility analysis + social judgment analysis	[57]
1	Behavioral decision theory	[58]
1	Cognitive cloud model–based method	[59]
1	A Bayesian method	[60]
1	Hypothetical equivalents and inequivalents method	[61]
7	The three-way decision model	[62–68]
6	Granular computing	[69–74]

constructed fuzzy epsilon-neighborhood classes, a probabilistic rough fuzzy set model and a MADM-based three-way decision model were established [68]. Moreover, some three-way group decision rules were deduced in the hesitant fuzzy linguistic environment to address the selection of green suppliers [66]. A three-way group decision-making model based on the multi-granulation hesitant fuzzy decision-theoretic rough set over two universes was developed to deal with multi-criteria group decision-making (MCGDM) problems [67]. In order to manage and rank sustainable scenarios, an inclusion measure-based hesitant fuzzy linguistic multi-granulation three-way decisions over two universes approach was established for MCGDM problems [65]. In the fractional orthotriple fuzzy environment, five methods were proposed to address the expected loss and the corresponding three-way decisions were also derived for MADM problems [63]. Considering the risk appetite of DMs, a series of decision analysis methodologies for three-way decisions were designed in the framework of TODIM [62].

To effectively handle group decision-making problems in a multi-criteria context, a lot of research has discussed how to reveal human cognitive operation from the perspective of granular computing. Based on the framework of granular computing, a method was developed to manage linguistic information in the MADM process. In this method, the semantics and the distribution of linguistic variables are defined by the optimization of a certain criterion rather than being initially established, which makes linguistic values more operable [69]. A granulation analysis method based on granular computing was employed to improve the accuracy of decision results [74]. By combining a feed-forward artificial neural network with the granular computing rule extraction, a classifier that can train neural networks was formed and applied to process MCGDM [70]. In order to deal with MCGDM problems with interval-valued neutrosophic information, the multi-granulation probabilistic model, as one of the granular computing-based methods, was developed [73]. The four-way intuitionistic decision space was introduced as a multi-attribute information classification method by employing granular computing to generate a more precise level of decision rules [71]. Through the fusion of granular computing and three-way decision, multi-dimension problem-solving methods were presented to investigate scheme synthesis and solution space analysis for MCGDM problems [72].

Application Fields of Cognitively Inspired MADM Methods

In this section, we review recent realistic applications regarding cognitively inspired MADM methods (as shown in Table 5). As cognitively inspired MADM methods have been widely applied, the application papers can be organized as the following areas.

Economic Applications

With the rapid development in the social economy in recent years, cognitively inspired MADM methods have received a lot of attention from researchers in the field of economics, which is one of the most popular application areas among these references. In order to evaluate enterprise resource planning (ERP) implementation risks, several effective tools including FCM, fuzzy preference programming, are employed to enhance the failure mode and effects analysis (FMEA) method [28]. Due to the ability of stochastic data envelopment analysis (DEA) in analyzing complex information, a MADM method was proposed based on stochastic DEA cross-efficiency with ordinal variable, which has been successfully applied to assess the sustainable operation performance of 15 listed banks in China [78]. As MADM on consumer goods such as products and services is worth investigating, a simplified consumer decision scenario was developed for consumer decision strategies [81]. Furthermore, many cognitively inspired MADM methods have tackled real performance evaluation problems in this field. For example, a multi-expert architecture was built up to evaluate credit risk for small and medium enterprises [77]. A hybrid fuzzy multi-criteria group evaluation and statistics method was developed to assess financial statement quality [79]. A MADM method based on a reasoning map was proposed to evaluate the leadership capabilities of team members so as to provide useful suggestions for their employers [52]. In addition, different decision-making models equipped with cognitive techniques have been carried out for various applications such as the housing market [82], policy support [47], e-commerce [83], and group budgetary decisions [51].

Information Technologies

The rise of information technology has brought opportunities and challenges to intelligent MADM. Meanwhile, the demand for information technology that can support MADM also increases. Although a large number of decision support systems (DSSs) have been developed to assist users in organizing decision-making activities, it is difficult for experts to directly interpret model results due to the complexity of DSSs. To overcome this issue, a novel concept for the generation of textual explanations for multi-criteria decision analysis was introduced, which lay a foundation for the construction of DSSs [99]. Based on the cognitive feedback and multi-attribute utility (MAU) theory, MADM techniques were established for group DSSs to structure information and aid in solving cognitive conflict among DMs [56, 98]. Some new normalization

Table 5 Application fields of cognitively inspired MADM methods

Application area	Application	Frequency	Reference
Economic applications	ERP	1	[28]
	Evaluation	5	[52, 77–80]
	Strategy support	3	[47, 51, 81]
	Housing market	1	[82]
	E-commerce	1	[83]
	Hotel location selection	1	[84]
Industrial applications	Vehicle-related applications	2	[85, 86]
	Handover channel selection	1	[87]
	Sustainability prioritization of energy systems	1	[88]
	Product selection	4	[86, 89–91]
	Maintenance strategy decision	1	[80]
	Enterprises choosing appropriate 5G partners	1	[92]
	Inventory classification	1	[139]
	Supplier selection	6	[4, 40, 43, 53, 93, 94]
Information technologies	Artificial intelligence project assessment	1	[95]
	Software reliability assessment	1	[96]
	Intelligent systems	3	[34, 49, 97]
	DSS	4	[56, 98–100]
	Cognitive networks	3	[61, 101–103]
	Idle spectrum selection algorithm	1	[104]
	Network selection strategy	1	[105]
	Automated cognitive workload assessment	1	[106]
	Development of next-generation wireless environment	1	[107]
	Assembly design decision	1	[108]
Public services	Urban regeneration	2	[109, 110]
	Water resource management	3	[59, 111, 112]
	Critical facilities in combating the terrorism	1	[113]
	Forest resource management	2	[50, 114]
	Sustainable energy alternative selection	1	[115]
	E-government information resource integration	1	[116]
Healthcare management	Assessment of healthcare waste treatment alternatives	1	[117]
	Schizophrenia treatment techniques	1	[118]
	Patient-centered decision-making	1	[119]
	Bipolar disorder diagnosis	1	[120]
	Clinical rehabilitation	1	[121]

models were constructed to evaluate software reliability [96]. This work illustrated the feasibility and practicability of the proposed models in both the MADM and GDM processes. In the context of intelligent systems, a MADM method with intuitionistic fuzzy numbers was presented to learn management system personalization [34]. A hybrid intelligent model was proposed to evaluate critical success factors for a high-risk emergency system [49]. Under the dual probabilistic linguistic environment, the weighted correlation coefficient was explored as a measure for the application of artificial intelligence [95]. To meet the node transmission requirements of the Internet of things, a spectrum allocation optimization algorithm was established based on an immune algorithm with cognitive radio technology [104]. A modeling framework was designed for an emergency operating procedure, which can reduce cognitive errors in the process of accident resolution through MADM methods and simulations [97]. Moreover, some cognitively inspired MADM models have been applied to evaluation and selection processes, such as efficient free channel selection under wireless environment [107], network selection strategy [105], and automated cognitive workload assessment [106]. Also, cognitive networks were hot application fields for cognitively inspired MADM methods [61, 101–103].

Industrial Applications

The applications in industries mainly focused on the supplier section, which has a significant influence on the competitiveness of the entire supply chain network and even decides the success or failure of the supply chain. Thus, for the purpose of obtaining high-quality products at a lower cost, researchers have made an effort to enhance the MADM methods for supplier selection. To better describe the hesitancy and uncertainty of DMs' preference information, different types of information expressions were utilized as tools in the supplier selection process, such as type 2 neutrosophic number [94], hybrid Z-information [40], interval-valued intuitionistic sets [43, 53], and picture fuzzy sets [93]. FCMs were also employed to process cognitive information, which significantly improved the efficiency and convenience of supplier selection [4, 43]. Besides, taking the cognitive behaviors of DMs hidden in their evaluation information into account, Yang et al. [86] designed a bidirectional projection method with normal wiggly hesitant fuzzy linguistic information for EV power battery recycling mode selection. An integrated decision support framework was established to assist in ammonia production systems [88]. This work provides a methodological contribution to the sustainability priority of the energy system. Aiming at improving the reliability and safety of an avionic system, cognitive uncertainty information processing was applied to MADM to support maintenance strategy selection [80]. To save production costs and improve efficiency, a linear partial ordering approach was developed to capture DMs' knowledge and prioritize engineering characteristics [39]. In the era of service-oriented manufacturing, rapid evaluation methods were employed for production selection [89, 122], production line assessment [90], etc. Also, some effective approaches are applied to robot selection [91], 5G partner selection for enterprises [92], water framework directive [138], etc.

Public Services

As we all know, public service like policymaking plays a critical role in the development of our society. However, the unpredictability and novelty exhibited by public service always make it difficult for DMs to handle the relevant MADM problems. Cognitive techniques provide intelligent support to address this issue. A series of research gives public administrators a sight into how the cognitively inspired MADM approaches can be applied to develop alternative strategies in public issues, such as urban planning and urban regeneration [109, 110], water resource management [59, 111, 112], and forest resource management [114]. In addition, a novel mathematical approach was applied to marine disaster monitoring for emergency management [116], which broke through the limitations of diverse cognitive viewpoints in the decision-making process. In the energy analysis and planning process, a qualitative TOPSIS method was presented to assist the selection of sustainable energy alternatives [115]. To support the decision-making process in national defense plans, a fuzzy integrated vulnerability assessment model was constructed for critical facility vulnerability assessment [113].

Healthcare Management

Arising with the high medical needs of patients, healthcare management has received more and more attention. Due to inherent uncertainties in the management and treatment of healthcare waste, a multi-level hierarchical structure and fuzzy logic have been employed in a MADM process for the selection of treatment alternatives [117]. With the aim of improving the accuracy of clinical diagnosis and treatment, some comprehensive mathematical approaches have been carried out [118, 119]. For example, a yin-yang bipolar fuzzy cognitive TOPSIS method was introduced for bipolar disorder diagnosis [120]. A cognition-based method was proposed to select an appropriate treatment plan for dysphagia rehabilitation [121].

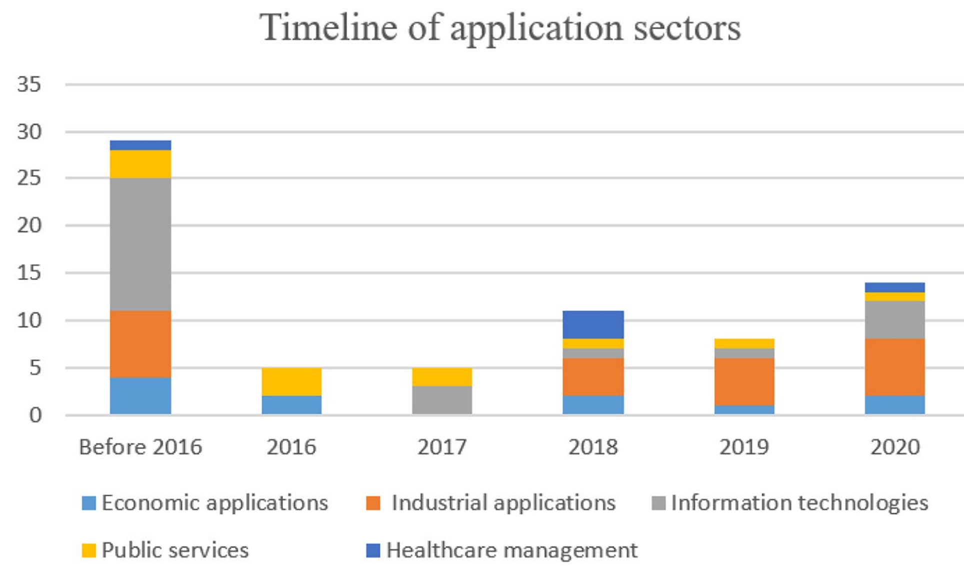
Summaries

To further analyze the application of cognitively inspired MADM methods in various fields, 64 papers that applied cognitively inspired MADM methods in solving real decision-making problems were reviewed. The timeline of these application sectors is provided in Fig. 8.

As shown in Fig. 8, there is an upward trend in the frequencies of applications throughout the period from 2016 to 2020, except in the case of the year 2019. Before 2016, the applications of cognitively inspired MADM methods in the field of information technology accounted for the largest proportion. Meanwhile, the industrial applications and economic applications held middle positions, closely followed by the applications in public services. However, it is obvious that industrial applications have grabbed more attention from researchers in recent years. In addition, how to solve complex decision-making problems in public service is a major concern of experts in public administration. Thus, the frequency of applications in public services has also remained stable.

In order to clearly illustrate the application status of those methods, Fig. 9 is provided to manifest the application areas in Table 5 and their corresponding proportions. From Fig. 9, we can see that the application in information technologies has the largest proportion at 31%, compared to only 7% in healthcare management. In other application fields, industrial applications have a higher percentage (28%), followed by economic applications (18%) and public services (16%).

Fig. 8 The timeline of application sectors



Challenges and Trends for the Future

The increasing complexity of the decision environment has made actual decision-making more difficult when considering a diversity of factors, which may contain social, psychological, and economic considerations. Meanwhile, with the development of the social economy and information technology, the requirement for high-quality MADM methods is increasing. Considering that the ambiguity of human cognition leads to obstacles in the representation

Fig. 9 The proportions of applications

of DMs' knowledge, cognitively inspired MADM methods have been developed to address problems with multiple and interrelated criteria. As an emerging research direction, there are not many academic papers in this field, but cognitively inspired MADM methods have good research prospects with the further development of intelligent decision-making. Here we raise some problems in current research and open questions that are worth solving and answering. Also, some corresponding possible future trends that can be envisioned based on the review of this field are presented.

Improvement from the Perspective of Modeling Cognitive Information

It is acknowledged that transforming linguistic judgments of DMs into meaningful preference structures is one of the most influential features of MADM methods. In conventional MADM problems, the weights of attributes and the performances of alternatives are assumed to be completely precise. However, due to the limitation of human cognition, it is hard for DMs to express their evaluation information in the form of crisp numbers. In our regard, the fuzzy theory has offered an appropriate modeling approach to deal with uncertainty in decision-making problems with multiple attributes. Although some fuzzy sets, including intuitionistic fuzzy sets, interval-valued intuitionistic sets, picture fuzzy sets, etc., have been employed to represent cognitive information in the MADM process, it is unrealistic to use only several techniques to solve various decision-making problems because different attributes suit different types of modeling [123]. There have been a large number of fuzzy tools, such as interval type 2 fuzzy sets [124], generalized type 2 fuzzy sets [125], hesitant fuzzy sets [126], and Pythagorean fuzzy sets [127]. Future studies could be dedicated to investigating MADM methods using techniques from the abovementioned fuzzy set theories. Moreover, as DMs prefer to express their assessments with natural language, linguistic variables were introduced as a flexible way to model cognitive information, which is more in accordance with people's descriptive conventions. Linguistic term sets can improve the flexibility and reliability of the existing methods by providing effective information for DMs in the MADM process. Thus, considering cognitive competence and psychological factors of the DMs, it is beneficial to establish a conceptual MADM framework for knowledge representation under a linguistic environment [127], including virtual linguistic term set [128], hesitant fuzzy linguistic term set [129, 130], probabilistic linguistic term set [131], dual probabilistic linguistic term set [132], 2-tuple linguistic variables [133], etc.

Development of Cognitively Inspired MADM Methods Based on FCMs

FCM offers better capabilities to address knowledge representation because it can model positive and negative causal relationships simultaneously. The overview in this paper illustrates that the depth and breadth of the application of FCM in cognitively inspired MADM methods can be further enhanced.

1. FCMs have shown outperformance in capturing behaviors of systems in the long term [134]. Threshold functions play an important role in the decision-making process since their shape has an impact on specific problems. For the purpose of increasing the flexibility of FCMs, different types of threshold functions should be exploited to obtain better processing of original decision information. Also, there are various variants of FCMs, including fuzzy cognitive networks [135], evolutionary FCMs [136], etc. It is also necessary to adopt different types of FCMs to develop the corresponding MADM algorithms for specific purposes.
2. In most of the MADM methods combined with FCMs, FCMs have been utilized to capture interactions among attributes. Nevertheless, FCMs have the potential to support the whole process of the integrated MADM method, from characterizing problem structures to establishing rational methods. For example, in addition to investigating relationships between attributes, the modeling capacity of FCMs makes it also reasonable to simulate decision scenarios. With the advantages of processing cognitive information, it is worthy to use FCMs to simulate different scenarios and collect ultimate concept values in future research on MADM approaches.
3. Although a lot of studies have provided convincing evidence that they can play a pivotal role in the realistic decision-making process, few studies have employed FCMs as tools to MADM. The previous research has proven that outcomes derived from the MADM methods combined with FCMs are understandable and accurate. However, the existing MADM models were developed by integrating FCMs and several classical decision-making methods such as TOPSIS. Although they have offered an appropriate modeling approach to deal with some MADM problems, realistic decision-making will become more complicated and need more advanced methods to solve. During the last decades, there has been a great proliferation of works on MADM, which means that FCMs have application prospects in many other effective MADM methods.

Development of Cognitively Inspired MAGDM Methods

As a mechanism for integrating views of DMs based on rules, group decision-making plays an increasingly important role in solving realistic decision-making problems. Due to different cognitive levels, social experience, and professional backgrounds, DMs may have different opinions on the same issue, leading to conflicting outcomes. Thus, designing appropriate rules to regulate conflicts in a group is a topic that still needs to be studied. Furthermore, the difficulty of evaluating alternatives with respect to multiple attributes, the limitation of DMs' cognitions, and the necessity of making reasonable decisions make the development of cognitively inspired methods indispensable to solve complicated MCGDM problems.

There has been a considerable amount of studies on concept-cognitive learning. However, few studies focus on multi-source data, heterogeneous data, unstructured data, or big data from the perspective of parallel computing to improve learning efficiency in solving MADM problems. Thus, it is necessary to develop computing techniques for concept-cognitive learning based on granular computing and information fusion. Other unsolved problems are also worth studying, such as reducing the redundancy of attributes in the calculation and information fusion of multi-source data [76] and dealing with the ambiguity of continuous-valued attributes in complex data [137].

Application Prospects

With the improvement of people's living standards, healthcare management will catch more and more attention. Many complex medical management affairs, such as patient classification and medical data analysis, put forward higher requirements for experts to make accurate decisions. Thus, there is still an urgent need to develop kinds of MADM methods by employing cognitive techniques to support medical DSS. Moreover, the cognitive analysis of hospital staff can be used not only for basic research but also for improving the DSS by feeding the information back to the system. Meanwhile, the requirements of customers need to be explored in the sales area, which indicates that cognitively inspired MADM methods have application prospects in preference analysis of customers. Also, considering there always exist difficulties and uncertainties in the selection processes of many fields, cognitively inspired MADM methods can be applied to industry, agriculture, manufacturing, resource management, etc.

Conclusions

The emergence of cognitively inspired MADM methods enriches the theoretical framework in MADM and greatly promotes the development of intelligent decision-making. It presents excellent modeling ability in processing complex information, which makes it of significant importance to MADM both from theoretical and practical points of view.

In this paper, we have gone through the recent contributions about cognitively inspired MADM methods and attempted to provide a comprehensive review in this field. Firstly, some statistical analyses of published papers regarding cognitively inspired MADM have been unfolded from two aspects: the development trend and the distribution of related publications. We have seen a steady increase in the number of academic papers in this field. As to this fact, more investors have their sights on the cognitively inspired MADM methods in recent years. After that, the system architecture of cognitively inspired MADM has been illustrated. Then, a comprehensive overview of different types of cognitively inspired MADM approaches has been provided, which concludes the contributions of these methods to modern decision-making. After analyzing the theoretical knowledge, practical applications have also been summarized, which concludes that cognitively inspired MADM methods make great effects on practical applications. We have ended by discussing some challenges and future trends in this field.

To sum up, this work offers an up-to-date overview of cognitively inspired MADM methods. It illustrates that the important and influential advances of employing cognitive techniques to the MADM process have guiding significance for later research on this topic.

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Declarations

Competing Interests The authors declare no competing interests.

Informed Consent This paper does not involve human participants and/or animals.

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