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A Review of Large-scale Group Decision-making: Research Progress and Prospects

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Abstract. *With the development of the Internet and big data in the past decade, the decision-making environment has become increasingly complex. The traditional group decision-making theory and method have also undergone profound changes, developed into large-scale group decision-making (LSGDM), which become a hot spot in decision-making science, and it also has broad application prospects in actual decision-making. This paper systematically sorts out and reviews the main research results in the field in recent years, expounds on the research hotspots, problems, and challenges faced in this research field, and points out the development direction in the future. Existing research in the field focuses on the establishment of social networks and different forms of information fusion, exploration of clustering methods, conflict detection, and behavior management in the process of consensus reaching. Through in-depth analysis of existing research results, it is found that dynamic and socialized LSGDM under the environment of artificial intelligence, big data, and blockchain is a very promising research direction, which is worthy of further exploration.*
Keywords: large-scale group decision-making; review; challenges; future directions

1. Introduction.

Since the French first used mathematical models [1] to study group decision-making (GDM), GDM has gradually become the focus of decision-making. With the tremendous development of social media and e-democracy technology in the past decade, GDM has also undergone profound changes, showing new characteristics: 1) The scale of GDM is larger, ranging from more than a dozen to hundreds and thousands; 2) Decision makers (DMs) come from a wider range of sources, and their knowledge, experience, and individual characteristics are diverse; 3) The decision attribute/standard system is larger, and the relationship between attributes is more complex; 4) The decision-making problem develops from single-objective and static mode to multi-objective and dynamic mode. These characteristics determine the development of GDM toward LSGDM, which not only brings new research perspectives for GDM but also new opportunities and challenges for the development of GDM theories and methods.

Large-scale group decision-making is a process in which no less than 20 DMs [2,3] participate in judging or evaluating the provided (limited set of) alternatives based on several criteria/attributes, reducing participant disagreement, and finally obtaining a ranking of decision options or selecting the best alternative. LSGDM can make full use of the experienced wisdom of multiple DMs, take advantage of different knowledge structures, overcome the shortcomings of a single decision-maker (DM), and make the decision results more objective and closer to reality. LSGDM are widely [2] present in various fields of society, economy, and management, such as emergency decision-making for heavy natural disasters [4,5] or major emergency decisions- COVID-19 [6], project evaluation and project selection [7], subway line construction, and resource allocation [8], economic efficiency evaluation [9–11].

LSGDM generally has a complete solution process, mainly including group preference structure analysis, trust network establishment, different forms of preference information fusion, group clustering, conflict detection, and behavior management in the consensus reaching process (CRP). Each step will affect the scientific rationale of the final decision-making result. Through the efforts of scholars at domestic and abroad, the theory and method system of LSGDM has been continuously improved and has many achievements. Starting from the key steps in solving LSGDM, this paper systematically sorts out and reviews the development status and research hotspots of LSGDM theories and methods, comments on the problems and challenges, and discusses the development directions in the future of LSGDM.

This study is structured as follows: Section 2 analyzes the development of LSGDM using bibliometric analysis tools while classifying the existing literature according to the key steps in addressing LSGDM. In section 3, we introduce the research hotspots. Section 4 mainly discusses the problems and development trends of current LSGDM research. In section 5, concluding remarks are given.

2. Literature review.

2.1. A bibliometric analysis of the LSGDM. In the "WOS" core database, we entered the keyword "large-scale group decision-making" to find 1539 articles in recent ten years. Figure 1 shows the annual distribution of articles in the recent ten years. Figure 2 shows the main distribution journals and their impact factors.

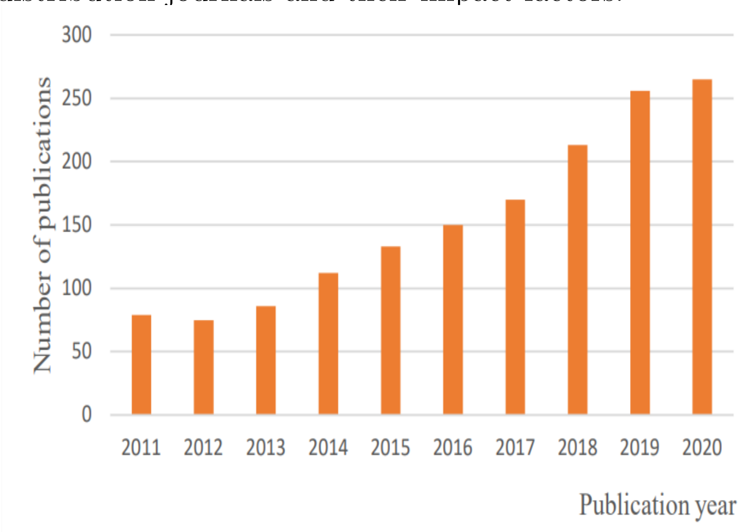


FIGURE 1. Distribution of the selected publications by year

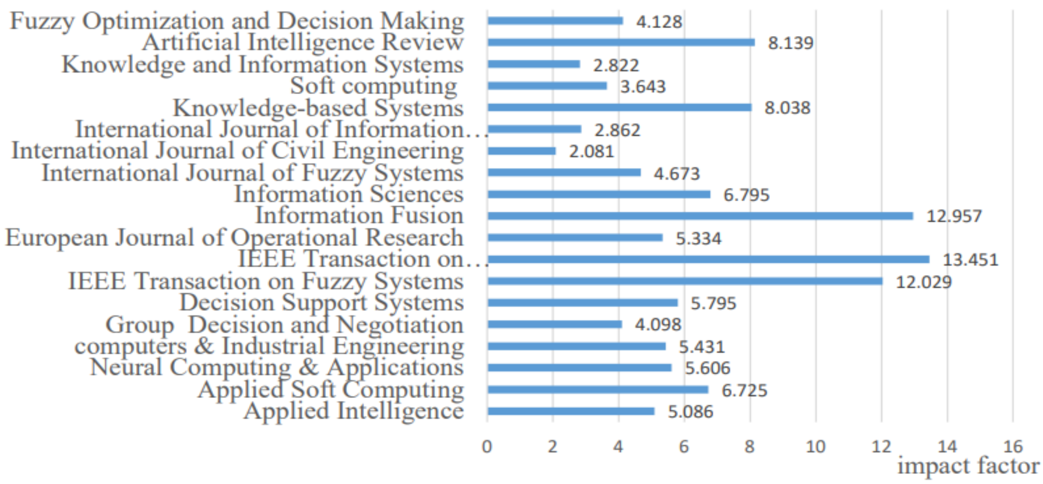


FIGURE 2. Distribution of the selected publications by contributing journals

It is obvious from Figure 1,2 that the direction of LSGDM has gradually received attention from scholars in the last decade, and most of the published journals are related to computer science. As Ding et al. [2] and Tang and Liao [9] said, the development of big data and artificial intelligence provides technical support for LSGDM, mining decision information, processing decision information, mining the relationship. For example, collect data from various sources, such as social media, mobile data, medical data, and electronic medical records, to help scientific decision-making. These massive data should be stored through big data storage tools. These tools can be traditional database management systems (DBMS) or large-scale parallel processing (MPP). Process different decision information through machine learning technology, such as cluster analysis and social network analysis (SNA). The decision results are obtained through fuzzy set, cloud computing and granular computing. The development of these technologies makes it possible for LSGDM to develop towards complex and high data-driven aspects. In order to better explore the development process of LSGDM, we use the VOSviewer to get the evolution of keyword co-occurrence time in recent 10 years from 1833 articles, as shown in Figure 3, where keywords represent nodes, and node size represents the frequency of keywords. The higher of frequency, the larger of node.

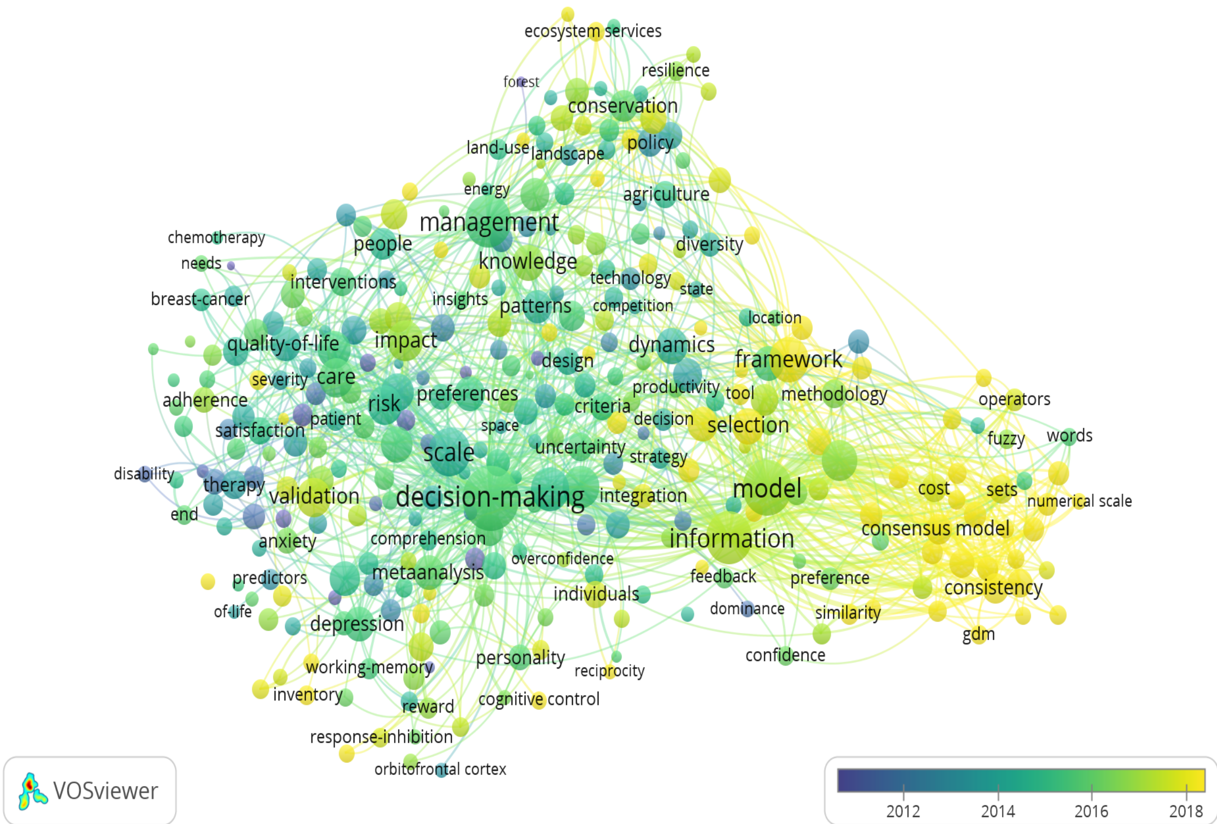


Figure 3. Timeline map of keywords co-occurrence for LSGDM

It is clear from Figure 3 that the decision problems are associated with scale and policy at the beginning, and then move toward larger scale, more complex relationships, and information uncertainty. For example, there are uncertainty and dynamics in keywords. At the same time, it can be seen that social networks and risk have been combined with LSGDM issues in recent years, making the issue involves interest groups from different backgrounds, such as experts, organizations, and individuals in keywords. In addition, the LSGDM problems not only consider the historical behavior and current decision-making information but also appear feedback, prediction, and behavior management in recent years. In order to systematically review and analyze the development of LSGDM theories and methods. Firstly, this paper searched for articles with high impact factor and high citation and keywords of "large-scale group decision making" in the title and abstract on the "WOS" and "Scopus" databases, and reads the abstract, 80 papers with high impact factors and high citation were selected. Secondly, through carefully reading these articles, 75 journal papers and conference theories closely related to the methods of LSGDM were selected. Then the paper is categorized by carefully reading them from the key steps in solving the LSGDM. By constructing the co-occurrence network of authors on LSGDM in the "WOS" core database in recent years, as shown in Figure 4, it is found that the authors of references in this paper are active and are in the core position of development in this field. Therefore, the articles selected for analysis have high academic value in this field.

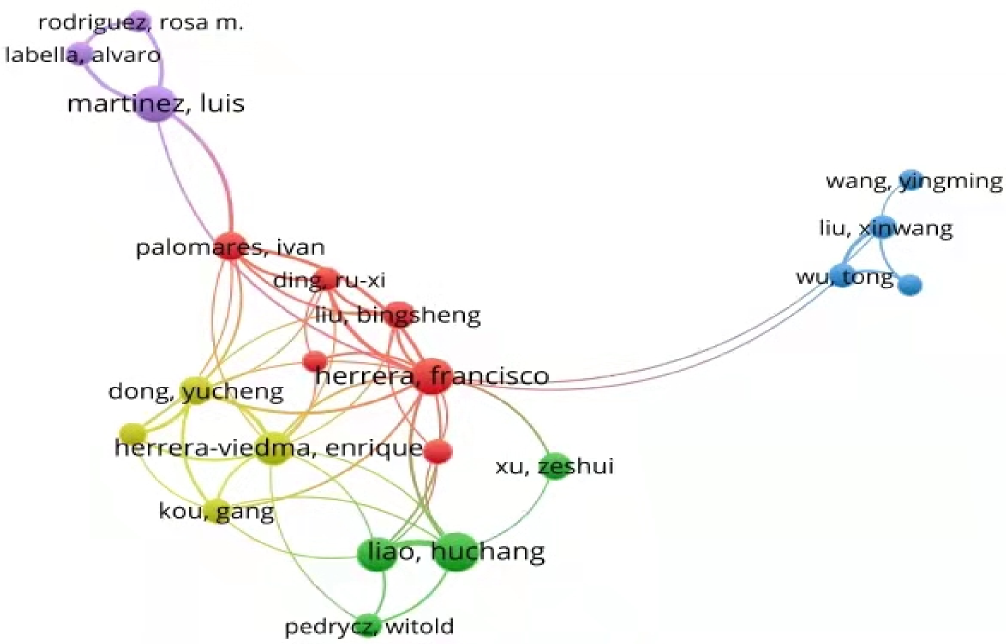


FIGURE 4. The active authors in the LSGDM research field

2.2. **Characterization of LSGDM.** As mentioned in literature [2,3,10–12] large-scale group decision-making has the following elements:

1) A discrete finite set of alternatives $X = \{x_1, x_2, ..., x_n\}(n \geq 2)$, which represent the possible solutions to this problem;

2) Let $E = \{e_1, e_2, ..., e_I\}(I \geq 20)$ represents the DM set.We use the set $\{1, 2, ..., I\}$ to represent the DMs' indexes;

3) Let $U = \{u_1, u_2, ..., u_N$be the set of attributes/criteria, and N is the number of criteria/attributes for assessing the alternatives in the LSGDM.

4) Let the vector $\xi \in R^{N\times1}(\xi = [\xi_1, \xi_2, ..., \xi_N]^T)$ be the weight vector of criteria/attributes, meeting the condition of: $\xi_n \in [0, 1](n = \{1, 2, ..., N\})$ and $\|\xi\|_1 = \sum_{n=1}^{N} \xi_n = 1$

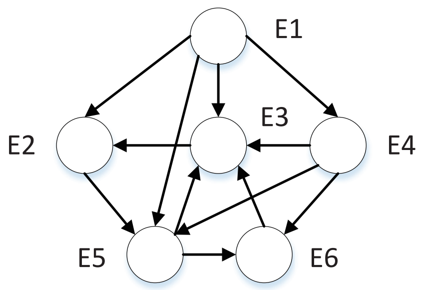
2.3. **Social network establishment and information fusion.** DMs may present different forms and incomplete decision information due to their own experience, knowledge, and understanding of the evaluation object, which requires the transformation and fusion of different preference forms. At the same time, considering the social relations of DMs, in order to cluster more accurately, it is necessary to fuse the information of DMs in advance. The preference information of DMs is mainly divided into two types: deterministic and uncertain. Among them, deterministic is mainly presented in the form of real numbers. Early studies focused on deterministic preference information, such as Wu et al. [3] addressed the problem of selecting the optimal solution for LSGDM with deterministic multiplicative preference relations and proposed the optimal group selection based on minimizing the logarithmic square compatibility of the group, and then the optimal group selected the final solution. Du et al. [13] proposed a clustering method based on trust opinion similarity deterministic preference relationship to reduce the size of DMs. In this section, uncertain preference representation will be used for classification, as shown in Table 1, mainly including existing research and preference representation methods used.

Table 1. Classification of uncertain preference representation and related authors

Categories	Name	Literatures
	Fuzzy Sets (FSs)	Zheng et al. [14]
	Hesitant Fuzzy Sets (HFSs)	Liang et al. [15], Zheng et al. [16], Liu et al. [17]
Fuzzy values	Interval Type-2 Fuzzy Sets (IT2FSs)	Tian et al. [12], Wu et al. [18]
	Interval-Valued Intuitionistic Fuzzy Sets (IVIFSs)	Liu et al. [19], Du et al. [20], Xu et al. [21]
	Generalized trapezoidal fuzzy numbers (GTFNs)	Wu et al. [22]
Preference Relations	2-Tuple Fuzzy Linguistic Preference Relations (2TFLPRs)	Zhang et al. [23], Song et al. [24]
	Fuzzy Preference Relations (FPRs)	Quesada et al. [25], Zhou et al. [26] , Liu et al. [27]
Linguistic Information	Interval-Valued 2-Tuple Linguistic(IV2TL)	Wu et al. [28], Xu et al. [29], Liu et al. [30]
	Interval Valued Intuitionistic Linguistic (IVIL)	Liu et al. [31]

Different types of fuzzy sets are used to represent uncertainty, such as fuzzy set, hesitation fuzzy set, intuitionistic fuzzy set, probability fuzzy set, and so on. The uncertainty is described using the membership function. Considering the practical problems, due to their own experience, knowledge, and understanding of the evaluation object, DMs give different hesitation for different attributes or provide incomplete information, so it involves information fusion for the supplement. Before executing the clustering algorithm, it is necessary to fill in the missing decision information first, and then check and fill the set of hesitant fuzzy elements to ensure that the hesitation of each attribute feature is the same. Before information fusion, considering that the social relationship among DMs often affects the proposal and modification of DMs' preferences, the wide application of social networks has laid a theoretical foundation. Social network analysis mainly studies the relationship among social entities, including centrality, reputation, trust, and so on. There are three traditional expressions of trust relationships in SNA [12,32,33], as shown in Table 2.

Table 2. Different representation schemes in Social Network Analysis

Sociometric	Graph	Algebraic
$A=\begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$		$\begin{bmatrix} E_1RE_2 & E_1RE_3 \\ E_1RE_4 & E_1RE_5 \\ E_2RE_5 & E_3RE_2 \\ E_4RE_3 & E_4RE_5 \\ E_4RE_6 & E_5RE_3 \\ \mathrm{E}_5RE_6 & E_6RE_3 \end{bmatrix}$

Sociomatrix: Relationship data usually appears in two forms: 0 or 1. 0 means that there is no direct trust relationship and 1 means that there is a direct trust relationship.

Graph: The network is regarded as a graph composed of nodes connected by lines.

Algebraic: the advantage of this representation is that it allows us to distinguish several different relationships and represent combinations of relationships.

Scholars gain relationships among DMs by establishing social networks, such as trust [10, 13, 28, 33–35], conflict [11, 24], reputation [36, 37], and so on. The obtained social relations are used for information fusion or clustering. Information fusion is generally completed by aggregation operator or improved aggregation operator.

Aggregation operators are mainly used to supplement missing decision information, fuse information, and expand fuzzy elements. In 1988, Yager [38] introduced an aggregation technology based on a sequential weighted average scheme. Since then, the aggregation strategy has been widely used in LSGDM. Wu et al. [33] proposed a sequential weighted average operator induced by trust scores to aggregate the trust values obtained from different trust paths. Tian et al. [12] proposed to aggregate the trust relationship among DMs based on the trust order weighted average operator (TIOWA) to supplement the information of DMs. Xu and Carol [39] raised a trust aggregation operator based on path centrality to aggregate the results of trust propagation. In order to describe the information fusion mechanism among interactive evaluation values in the context of hesitant binary language, Wang [40] constructed hesitant binary language average operator and hesitant binary language advantage weighted average operator to solve the problem of expert information fusion in the decision-making process. In addition, because the trust model in social networks is established based on the "current" actions or behaviors of experts, reflecting the actual relationship among experts, collaborative filtering algorithms are an estimation method that uses "historical" information. Wu et al. [34] proposed an incomplete decision information estimation method by combining multiple trust propagation paths into a set path based on the use of the path sorting induced sequential weighted average (P-IOWA) operator.

2.4. **Clustering methods.** A distinctive feature of LSGDM different from traditional GDM is that there are a large number of DMs, ranging from tens to hundreds or thousands. Therefore, it is very important to reduce the dimension of DMs for LSGDM problems. Clustering can divide DMs into different subgroups, which is an effective means to reduce the scale. In this paper, the following two categories are classified according to whether the clustering method needs to specify the number of clusters in advance:

1) Distance-based clustering algorithms

The most common clustering algorithms are k-means, fuzzy C-means (FCM), and fuzzy equivalence relations (FERs), which require determined clustering centers and the number of clusters in advance. In the k-means clustering algorithm, a point belongs to only one cluster. In this algorithm, all data objects are divided into k clusters according to k predefined centers. The objective function of the k-means algorithm is:

$$\min d = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^{(j)} - c_j\right\|^2 \tag{1}$$

$\left\|x_i^{\mathrm{j}} - c_j\right\|^2$ represents the distance from the data object $x_i^j$to the cluster center c_j.

Tang and Liao [41] used the k-means algorithm to classify the preference of DMs in a heterogeneous LSGDM environment. In addition, they used square error and contour to determine the initial center and k value. Fuzzy clustering allows data objects to belong to different clusters with different membership degrees, and its process is similar to k-means. Wu et al [18] proposed an improved k-means clustering algorithm to divide DMs with uncertainty. Considering that DMs have different backgrounds and psychological cognition and provide heterogeneous preference information, Tang et al. [42] proposed a preference ranking consistency measure, which divides DMs into different subgroups through an ordered k-means clustering algorithm, and determines the appropriate initialization center method and k value for the proposed clustering algorithm. Wu and Xu [43] extended the k-means algorithm to the hesitant fuzzy preference decision-making based on possibility distribution and allowed the group to change dynamically.

The k-means clustering algorithm is a hard clustering algorithm, which is not suitable for fuzzy set clustering. The fuzzy clustering method adds a membership function to the data object. The most representative one is the FCM. The process is similar in K-means.

If a DM has low membership to all clusters, it is considered that the DM has non-cooperative behavior. In view of this situation, Li et al. [44] proposed the FCM algorithm in the language environment based on personalized semantics to divide DMs with similar semantics into a group. Tang et al. [45] divided DMs into different clusters by using FCM based on the defined compatibility. At the same time, the results of clustering are used to search the opinions of DMs to recommend the central DMs. Liu et al. [46] extended the FCM to intuitionistic fuzzy situations and improved the consensus of LSGDM events by using the intuitionistic FCM clustering method to detect and manage potential non-cooperative DMs.

The clustering methods mentioned in the above methods are all based on the distance among DMs or the distance to collective opinions. However, due to the complexity of the LSDM problem, it is not always wise to cluster DMs only considering the similarity/distance of opinions. With the application of social networks, artificial intelligence, and big data in the field, many scholars incorporate the relationship among DMs into the clustering method, which helps to further understand the similarities or differences among DMs. For example, Liu et al. [47] proposed a clustering method based on the alternative ranking with hesitant fuzzy relations, which divides DMs with the similar ranking of alternatives and similar hesitant fuzzy relations into the same cluster.

2) Other clustering algorithms

Hierarchical clustering algorithm divides DMs into clusters by using bottom-up or top-down strategies. The bottom-up strategy builds a cluster from a single data object and then makes the cluster become a larger cluster by merging until all data objects are divided into a single cluster. This strategy is also called cohesion hierarchical clustering. The top-down strategy decomposes the cluster containing all data objects into smaller clusters until each data object belongs to a cluster. This strategy is also called split hierarchical clustering.

Based on the cloud model, Wang et al. [48] extended the traditional agglomerative hierarchical clustering algorithm. They first proposed the clustering and similarity measurement between two clouds, then constructed the similarity matrix, and selected the most similar pair of DMs in each iteration to form a cluster. In a social network environment, Wu et al. [49] used IT2FSs to represent preference information and divided clusters by a cohesive hierarchical clustering algorithm based on the Louvain method. Wu eta al. [7] used the FERs clustering algorithm to solve the selection problem of e-commerce products, and obtained dynamic clustering results by selecting different execution level values. Dong et al. [50] and Liu et al. [27] used grey clustering analysis in solving the LSGDM problem. The clustering algorithm has a similar calculation process with FERs clustering algorithm. The difference is that grey clustering analysis focuses on the relationship before sample characteristics, while fuzzy clustering emphasizes the fuzziness of the cluster to which the sample belongs.

The clustering method based on vector space divides DMs through correlation. This method judges the correlation between two preference vectors by threshold. The relevance of DMs depends on this threshold to determine whether DM should belong to a cluster. For the formed cluster, if the correlation between a vector and the linear combination of all selected vectors in the cluster is greater than or equal to the threshold, the vector is assigned to the cluster. Shi et al. [51] and Xu et al. [52] used the clustering algorithm based on vector space to solve LSGDM. Xu et al. [4] introduced a two-stage consistency method for LSGDM, and the clustering results were obtained through self-organizing mapping (SOM). The individual weights generated by SOM are used to aggregate individual preferences into the preference relationship. This process is divided into two stages: the first is the CRP within a cluster; the second is the handling of all clusters as individuals.

Some studies do not involve any clustering process, such as the LSGDM model based on social network analysis [10, 11]. These studies are mainly used for conflict detection and management. Similarly, there is a paper by Zhang [53], which first assumes that DMs come from multiple pre-existing groups, so there is no clustering process. Xu et al. [5]studied the emergency decision-making scenario of LSGDM. Taking the major explosion accident in Tianjin, China as an example, their decision-making center is composed of the fire department, police department, telecommunications department, and environmental protection department, so clustering is not required.

2.5. **Consensus reaching process.** In the process of solving LSGDM, due to the different attitudes, backgrounds, and motivations of DMs, it is a challenge to reach a consensus. Existing studies have reached a certain consensus when conflicts exist. The CRP refers to making the group reach a certain degree of consensus and get the final decision-making scheme in less or limited iterations. Scholars have studied many different CRP frameworks and methods for LSGDM in different environments. For example: CRP based on social network [2, 12, 17, 24, 28, 34, 39, 54], CRP based on minimum cost [28, 55–57]. The CRP generally includes consensus consistency measurement [46, 50, 58], conflict detection and behavior management [2, 9, 11, 25, 32, 50].

2.5.1. *Consensus consistency measurement.* The consensus level can be determined according to various standards, and the most widely used is to determine the DM's support for the scheme based on the distance function. Since the CRP is mainly to improve consensus, most consistency measurement studies are based on support.

Ding et al. [2], Liu et al. [27], Xu et al. [29] pointed out that the definition of consistency is based on the distance of group preference. Group preference is the sum of all DMs opinions. Consistency is defined as the average level of similarity between a single DM and group preference matrix:

$$CI(R^i) = 1 - \frac{1}{M \times N} d(R^i, R^c) \tag{2}$$

$d(R^i, R^c)$ denotes the Manhattan distance, M and N denotes the number of alternatives and attributes respectively.

The level of group consistency is defined as:

$$GCI = \frac{1}{I} \sum_{i=1}^{I} CI(R^i) \tag{3}$$

Where $CI(R^i)$ represents the consistency level of DM e_i and I represents the number of groups.

In recent years, considering that the CRP is mainly carried out on DMs that contribute less to the consensus, so the conflict degree can be used to reflect the degree of consensus, so scholars also try to express consensus through conflict relations.

Ding et al. [11] believes that different types of conflicts in different environments have different performances in the decision-making process. They divide the conflict into behavior conflict (BC) and opinion conflict (OC). Considering that the opinion conflict and behavior conflict in DMs are similar to the in-degree and out-degree in the conflict network respectively, they give the definitions of opinion conflict and behavior conflict.

OC arises when some DMs oppose DM ei , which may be unintentional. Similar to the in-degree in the conflict network, it indicates how many others have conflicts with DM ei. the OC degree is expressed as:

$$OC_i = \|c_{i,-}\| 1 = \sum_{j=1}^{I} c_{ij} \tag{4}$$

BC occurs when DM e_i is inconsistent with multiple other DMs at the same time, which may be presented intentionally and autonomously. Similar to the out-degree in the conflict network, it indicates that DM e_i conflicts with others, and the BC degree is expressed as:

$$BC_i = \|c_{-,i}\|_1 = \sum_{j=1}^{I} c_{ji} \tag{5}$$

In the conflict network, if $c_{ij} > 0$, it indicates that there is a conflict between DM e_j and e_i and arrow direction $i \leftarrow j$ represents the conflict direction. Similarly, if $c_{ji} > 0$, it means that the conflict direction is $j \leftarrow i$.

Tang et al. [45] divided conflicts into cognitive conflicts and interest conflicts, proposed an inter-cluster conflict detection method and generated a conflict resolution model that can dynamically feedback suggestions. They believe that experts' evaluation of alternatives is usually different with different experiences and educational backgrounds. This kind of conflict can be regarded as cognitive conflict, which is embodied in the evaluation difference. The degree of cognitive conflict between DM e_q and DM e_s is defined as:

$$CC_{qs} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \left| d_{ij}^{q} - d_{ij}^{s} \right| \tag{6}$$

Where d_{ij}^q and d_{ij}^s represent the evaluation values of DM e_q and DM e_s for the $j-th$ attribute of the $i-th$ alternative, respectively.

The conflict of interest is mainly reflected in the difference in the weight of decision-making attributes. The degree of cognitive conflict between DM e_q and DM e_s is defined as:

$$IC_{qs} = \frac{1}{n}\sum_{j=1}^{n}\left|\omega_j^q - \omega_j^s\right| \tag{7}$$

Where ω_j^q and ω_j^s represent the weight values of the $j-th$ attribute of DM e_q and e_s respectively.

Consensus reaching methods in social networks mainly include the minimum cost [59–61], feedback mechanism [44, 54, 62], and penalty mechanism [48, 51, 53, 63]. The minimum cost model encourages DMs to reach a consensus by compensating and adjusting their preferences, and the feedback adjustment mechanism provides DMs with a series of feedback preference modification information. These methods use different methods when dealing with different numbers of DMs. For less than 25 DMs, the feedback mechanism is generally adopted to ensure consensus through weight adjustment. The minimum cost model is suitable for numerical preference relations and is less than 20 DMs. For more than 50 DMs, the penalty mechanism is usually used to adjust the weight to achieve fast and uniform convergence. Table 3 summarizes the above models.

Table 3. Comparisons of the complexity and characteristic of different methods

Methods	Subgroup partition	Weight allocation	Adjustment strategy	Calculation complexity
Minimum cost soft consensus model [60]	No	No	Minimum cost	$o(2n^3+3n^2+2n)$
Similarity confidence consistency model [64]	Yes	Yes	Feedback mechanism	$o(4n^2)$
Trust propagation model [13]	No	Yes	Feedback mechanism	$o(3n^2)$
Social network DeGroot model [65]	No	Yes	Penalty mechanism	$o(3n^2+2n)$

2.5.2. *Conflict detection and behavior management.* Due to the DMs having differences in psychological cognition, background, and knowledge, and the decision-making problem itself is complex and uncertain, there must be preference conflict when experts evaluate the scheme. In addition, the decision-making group has many members and conflicts among members, so it is difficult to form a high consensus on the results. To ensure the effectiveness of results, it is necessary to detect and manage conflicts among the preferences of DMs. Group member preference conflict and consensus are a pair of opposite concepts. Reducing conflict requires increasing consensus. Therefore, some scholars have studied conflicts in LSGDM from the perspective of improving consensus.

Based on the minimum consensus, Cheng et al. [57] proposed a social network group decision-making framework with incomplete language preference and studied the influence of setting fixed parameters to adjust the weight of DMs. Aiming at the reliability of hesitant fuzzy language preference relationship, Liu [17] proposed a LSGDM framework based on consistency. Aiming at the situation that DMs modify their preferences under the time background, two iterative consistency and improvement methods are introduced to modify the weight of DMs to achieve consensus. Zhang et al. [66] proposed two optimal feedback mechanisms based on minimum consistency cost (MCC-PIFM) and maximum fuzzy consistency (MFC-PIFM) based on consistency metrics. Wu et al. [62] proposed a new social network group decision feedback mechanism (SN-GDM), which mainly includes the following two aspects: 1) study the propagation of distributed language trust and the trust relationship between experts; 2) A feedback mechanism based on maximum self-esteem is proposed to generate personalized suggestions, to achieve higher group consensus.

In recent years, the research from the perspective of conflict mainly focuses on conflict detection and behavior management. Conflict detection is mainly carried out from two perspectives by measuring the distance between DM preferences: One is to obtain the conflict by measuring the distance between the DM's preference and the group preference [11,44,48]. Another perspective is to measure the distance between the two preferences of DMs, and then use the aggregation function to aggregate them to obtain the preference conflict between a certain DM and the group [43, 58]. Table 4 summarizes the existing conflict detection methods.

Table 4. Classification of existing conflict detection methods

Categories	Trust Relation	Preference Similarity	Literature
Distance among DMs and group' preferences	No	Yes	Li et al. [44], Wang et al. [48]
Distance between two DM' preferences	No	Yes	Wu et al. [43], Gou et al. [58]
Distance of alternatives sorting	No	Yes	Tang et al. [42]
Social network conflict relationship	Yes	No	Ding et al. [11]
Conflict network of social network and preference similarity	Yes	Yes	Liu et al. [10], Gai et al. [54]

Distance measurement usually draws on existing distance formulas, such as Euclidean distance and Hamming distance, but a small number of studies have proposed new distance formulas for different forms of preference expressions. For example, Wu et al. [22] proposed a distance measurement method based on cosine similarity, and the results show that it has better discrimination. In addition, other scholars use other methods for conflict detection, such as Ding et al. [11] established a conflict social network to represent the conflicted relationship among DMs.

From table 4, the most commonly used conflict detection method is to calculate the preference distance among DMs. Whether it is the preference distance among the DM and the group or the preference distance among DMs, each has its advantages and disadvantages. The former is simple to calculate, but the group preference needs to be obtained first. Different information aggregation methods will affect the calculation of expert conflict levels. The latter considers the preference distance among all experts and doesn't need to obtain group preference, but the computational complexity will increase significantly, especially when the number of DMs is large.

The research on conflict governance is mainly divided into the following two aspects:

1) Conflict management based on preference information

In the process of LSGDM, it is usually necessary to cluster DMs to reduce the scale. In most of the research on conflict behavior governance methods, the usual approach is to use clusters as decision-making units for conflict behavior governance. However, a few studies consider the conflict behavior within and between clusters at the same time, and thus propose a two-stage conflict management method. Xu et al. [4] adjusts intra-cluster and inter-cluster conflicts according to aggregation preference information and group preference information respectively.

As scholars consider the process of conflict management from different perspectives, the conflict management methods have their characteristics. For example, Cai et al. [67] aims to obtain a small conflict level on the premise of ensuring the original preference information of experts and proposes two relative entropy optimization models to calculate the cluster and extreme weight to ensure the minimum conflict. Xiao et al. [68] constructed a model intending to minimize the loss of preference information to ensure the minimum adjustment cost and make the conflict level lower than the threshold. This method has received the most attention. It mainly reduces the level of conflict by adjusting preferences. During the adjustment process, the subjective willingness of experts to adjust [48, 58], the level of conflict reduction [10], and the minimum information loss [68] are considered. Tian et al. [12] combined the comprehensive method of preference adjustment and weight penalty to deal with experts with high levels of conflict. It not only considered the interaction between experts but also the contribution of different experts to the group consensus. Jing and Chao [69] proposed to introduce game rules considering the issue of decision fairness in the process of consensus reaching, and established a consensus model with the minimum compensation cost. At the same time, a simulated annealing algorithm was designed to solve the equilibrium solution.

2) Governance based on the behavior of DMs

Due to the complexity of LSGDM and the individual differences of DMs, DMs experience different behaviors in the process of conflict governance. Some studies consider the behavior of DMs in the process of conflict governance and put forward different methods. Among them, the most considered is non-cooperative behavior. In order to protect minority opinions in the process of emergency decision-making, Xu et al. [70] proposed a comprehensive correction coefficient to deal with the problem that DMs are unwilling to modify their preferences. Quesada et al. [25] calculates the degree of cooperation of DMs in conflict management and then applies it to the unified modal aggregation operator (UMAO) to calculate the weight of DMs to deal with non-cooperative behavior. Considering the moderator fuzzy consensus and private interests, Zhang et al. [66] proposed two optimal feedback mechanisms with personal interests, mainly minimizing the consensus cost under the established consensus threshold and maximizing the fuzzy consensus measure under the given cost budget. Shi et al. [51] used cooperative and noncooperative indices to classify DMs' behaviors in conflict governance into three categories: cooperative leadership behaviors, noncooperative leadership behaviors, and ordinary behaviors, and then rewarded or punished them by updating the aggregation weights using the UMAO.

In the process of conflict governance, the consideration of the behavior makes the decision-making method closer to reality. By considering the different behaviors of the subject, the DMs are divided into different groups, conflict management methods are proposed in a targeted manner, or preference adjustments or weight punishments are carried out, which enhances the scope of application of the method.

3. **Research hotspots.** The characteristics and complexity of LSGDM determine that LSGDM has its unique research characteristics, which is different from traditional decision-making. It needs to consider many influencing factors, which makes its research content very rich. The research hotspots include the following aspects:

1) Trust network establishment and information fusion

Traditional group decision-making often assumes that DMs are independent and have no relationship. However, there are usually different social relations and internal diversity among DMs, which will produce other information [37, 39, 59, 61, 71, 72], such as trust, influence, and reputation. Therefore, using SNA and considering the integration of social relationship information to study LSGDM has become a more effective method to deal with the relationship. Existing studies mostly consider the relationships of trust and credibility in the social network. Although these relationships play an important role in group clustering, opinion evolution, and decision consensus in LSGDM, they are difficult to obtain in real life.

Therefore, studying new methods and new technologies to automatically identify the relationship among DMs will be a hotspot. In addition, the relationship obtained through SNA is often different from how decision information is expressed. DMs are usually good at expressing preference information in different ways. How to integrate the obtained relationship and decision information in different representations to improve the accuracy of decision results is also a difficult point for LSGDM.

2) Clustering methods

The more commonly used clustering methods are clustering based on the preference distance and similarity among DMs, such as the K-means algorithm, the FCM algorithm, and the FER algorithm. In addition to the above clustering methods, some scholars cluster the preferences based on SOM, sparse tables, data envelopment analysis, and discriminant analysis (DEA-DA) and some methods that do not involve the clustering process. These methods can divide DMs into several clusters and have good application prospects. However, there are still other methods based on density and social networks, which have great practical value and application space for LSGDM. In addition to the resssearch on clustering methods, many scholars have studied the distance criteria used in clustering, such as considering DMs' self-confidence [52], willingness [14], emotion [73, 74], trust relationship [13, 16, 34].

3) Consensus reaching process

In LSGDM, DMs usually represent different interest groups and have different educational backgrounds, professional knowledge, and experience levels, which makes them have more complex decision-making behavior and leads to great differences in decision-making preferences. Therefore, CRP is needed to improve consensus and reduce conflict. Scholars mainly focus on conflict detection and behavior management. Most of the existing researches on conflict detection are based on preference distance, such as the preference distance among DMs and the group, or the distance among DMs. Some scholars began to detect conflicts from other directions, for example, Ding et al. [11] studied conflict relationships based on social networks, established conflict networks to detect conflicts. Most scholars believe that after clustering, DMs with similar preference information are divided into a group, so they ignore the conflict in the cluster and use the cluster as a unit to detect the conflict. Because conflicts not only occur between clusters but also exist within clusters, some scholars began to study not only inter-cluster conflicts but also intra-cluster conflicts and put forward corresponding conflict governance methods for conflicts in different stages.

Behavior management is a very important topic in LSGDM. The existing research mainly focuses on several types of behaviors: Overconfidence, non-cooperative behavior, minority opinion, and extreme preference, and puts forward a series of control methods and mechanisms such as identification, feedback, and punishment.

Due to the complexity of DMs and the uncertainty and diversity of behavior, behavior management still has a very broad research prospect. For example:

1) After cluster clustering, there are two levels of consensus relationship within and between clusters. How to manage the consensus of these levels at the same time is an

interesting problem. It is necessary to design a mixed strategy consensus model to ensure high group consensus while maintaining aggregation cohesion.

2) Research on the classification of group conflicts has been troubling many researchers. For example, the identification of cognitive conflicts and conflicts of interest, how to adjust behavior after identification, and how to minimize the preferences of DMs while ensuring group consensus will be of great research value.

4. **Existing issues and development directions.** LSGDM has become a popular and fruitful research direction, but there are also some restrictive factors in the development process. Based on the above analysis, the problems and challenges faced are summarized as follows:

1) In the past ten years, LSGDM has achieved a lot of research results, and many methods to solve the issue in different scenarios [11, 12, 16, 21, 36, 42, 59, 72] have been developed, but a systematic and recognized system has not been generated. In addition, an inevitable problem is how to choose a suitable and effective LSGDM method to solve practical problems, and there is a lack of an evaluation framework composed of unified indicators to evaluate the effectiveness of different methods.

2) Although the trust relationship plays an important role in the environment, it is difficult to obtain in real life. Therefore, it is necessary to study it to automate the identification of trust relationships among DMs. In addition, in the existing research, trust relationship and trust risk are defaulted to be static in the process. However, in reality, the trust relationship and trust risk among DMs will change dynamically in the social network environment [13, 45], which has a certain impact on the risk decision-making process. Taking big data as an important auxiliary tool for LSGDM, combining the objective information mined from big data with the subjective experience of LSGDM, and combining the complex risk factors in the decision-making process to carry out risk identification and control, forming a new big data intelligent risk decision-making theory and method is the key to solve this problem.

3) DMs generally divide clusters according to multiple attributes in LSGDM problems. From a social perspective, DMs may be divided into different clusters or stakeholders based on different attributes, but there is overlap between clusters. In the current clustering method to solve the LSGDM problem, the overlap problem is not considered [12, 16, 26, 44, 45]. If the DM presents cross-cluster overlap, how to manage the problem of LSGDM in the overlap situation is still a challenge. To solve this problem, we need to combine the social network, graph, clustering, and other related theories to divide DMs as scientifically and reasonably as possible.

4) Most clustering methods [18, 41–46] are based on FCM, K-means clustering methods, and their improvements. Such algorithms need to determine the clustering center and the number of clusters in advance, and the clustering results are easily affected by the clustering center. In practice, it is difficult to specify the required cluster center and cluster number. At the same time, the clustering result is unstable and needs iteration. Other types of clustering methods are rarely used in LSGDM research, such as the clustering method based on density peak [75]. This kind of algorithm does not need to manually specify the center and complete clustering through density distribution. It has obvious advantages over FCM and other methods. At the same time, most studies focus on the dimensionality reduction of DMs, and few studies pay attention to attribute dimensionality reduction.

5) In the CRP, most studies consider collective opinions [24, 32, 42–44, 51, 52], ignoring the expertise of DMs. When the DM knows enough about a certain attribute, his opinions may be more authoritative than others. However, in the CRP, ignoring this factor and

blindly pursuing group consensus leads to deviation results. At the same time, when group opinions are aggregated, different aggregation functions may lead to different results, so robustness cannot be guaranteed. In LSGDM, considering not only the trust relationship among experts but also experts' expertise will make the decision-making results more scientific and reasonable.

6) Conflict detection research is mostly based on distance measurement [32, 45, 67], and little research is based on social network relationship analysis. DMs who trust each other in social networks may transmit conflicts, and trust in influence may reduce the conflicts of a certain DM. At the same time, few studies on behavior management only modify preferences according to group feedback and consider the DMs' wishes [14]. When generating feedback opinions, the initial decision-making information of experts should be fully considered, and the wishes of DMs should be protected as much as possible. Each iteration can target the expert with the most conflict, and provide revision opinions according to the DMs with similar trust preferences and similar experts.

Based on the summary of the development status, research hotspots and frontier progress of the LSGDM, and the analysis of the problems and challenges faced, the following development directions of LSGDM are put forward:

1) The advent of the big data era, especially the emergence of artificial intelligence technology (AI), has brought new opportunities to all walks of life. The combination of big data, AI technology will greatly change the traditional decision-making methods and also provide a new development direction and research field for LSGDM. The paradigm of LSGDM is more and more widely used in many fields, such as social media, electronic democratic platforms, the group recommendation system, and the crowdfunding system. The decision-making process increasingly depends on AI and data-driven fusion technology. Many data sources have become valuable resources to assist LSGDM. Obtaining high-value information contained in big data will be a more reliable way to eliminate the adverse impact of DMs. The combination of big data, AI technology, and LSGDM can transform the data advantage into the decision advantage, which will be a great leap in the development of LSGDM theory and method.

2) Large-scale group collaborative decision-making with public participation. With the democratization process and the increasing complexity of major social and economic decision-making issues, the public has become an important stakeholder in these complex decision-making issues, such as the project initiation and construction of major livelihood projects, the macro-strategic policies of government departments, the emergency decision-making of major natural disasters and mega emergencies, which involve the form of public participation, the degree of participation, feedback and coordination mechanisms and the effects of participation. In addition, Internet-based social networks provide many convenient conditions for the public to participate in the discussion and decision-making of various events, and the decision support system is more socialized.

3) With the rapid development of Internet technology and the increase of mobile terminal equipment, DMs come from different regions, which will have an increasing demand for distributed LSGDM platforms, such as mobile group decision-making application software. For example, in an epidemic situation, intelligent network decision-making can play an important role in efficient prevention and control deployment, etc. The application of distributed decision-making platform poses challenges to the network environment, such as how to provide high security, high fluency, and strong timeliness in the decision-making process. The emergence of blockchain technology can effectively solve these problems. How to apply blockchain technology to distributed LSGDM in the network environment will be a cutting-edge way.

5. **Conclusions.** As an important branch of the decision-making field, LSGDM provides scientific and reliable solutions to complex decision-making problems in economic and social development. This paper systematically reviews and summarizes the current situation of group preference structure analysis, trust network establishment, different forms of preference information fusion, group clustering, conflict detection, and behavior management, summarizes the current situation of LSGDM, analyzes the problems and challenges it faces, points out the future development directions in the field, and provides a useful reference for the majority of decision-making scientific research personnel.

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