# Consensus Reaching Process in Multi-stage Large-scale Group Decision-making Based on Social Network Analysis: Exploring the Implication of Herding Behavior

Xinlei Sun [ab], Jianjun Zhu [a*], Jiepeng Wang [c], Ignacio Javier Pérez [b], Francisco Javier Cabrerizo [b]

[a] *College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing, People's Republic of China*

[b] *Department of Computer Science and Artificial Intelligence, Andalusian Research Institute in Data Science and Computational Intelligence, University of Granada, Granada, Spain*

[c] *School of Economics and Management, Beihang University, Beijing, People's Republic of China*

* E-mail of corresponding author: zhujianjun@nuaa.edu.cn

**Abstract:** Multi-stage large-scale group decision-making refers to a decision-making system with a large number of democratic evaluations provided by decision-makers and a multi-stage dynamic decision-making process. Researchers can obtain the evaluation values of different decision-makers at heterogeneous stages, collect dynamic and complex decision-making information, and obtain objective decision-making results. In this paper, we consider the large-scale group decision-making in the context of social network, and develop a consensus reaching process based on herding behavior. Decision-makers are identified based on the characteristics of information gradient dissemination, risk aversion, and authority obedience, and are divided into different groups according to the varying degree of herding behavior. Guided by the referenced preferences obtained from a recommendation mechanism, the modification model considering adjustment willingness and the minimum adjustment cost optimizes the preferences of low-consensus decision-makers in the strong herding group and in the no herding group. Then, the punishment model, aiming at the minimum degree of group consensus that satisfies the consensus threshold condition, optimizes the weight of low-consensus decision-makers in the weak herding group. Finally, we present an illustrative example of the emergency generation selection for the Spanish energy crisis to verify the rationality and soundness of the proposed multi-stage large-scale group decision-making approach.

**Keywords:** Social network; Cloud model; Multistage large-scale group decision making; Herding behavior; Consensus reaching process

## 1. Introduction

In recent years, with the development of computer technology and social media, it has become possible for a large number of individuals to participate in decision-making processes such as major strategic decisions of governments and industries, or the management of large enterprises [1]. These strategic-level issues involve extensive, long-term dynamic decision-making processes requiring the participation of many decision-makers (DMs) in the decision-making process, and the support of scientific and efficient group decision-making technology (system) [2]. In order to solve large group decision-making (LGDM) problems with a long process, researchers usually adopt multi-stage over the decision-making process to gather expert evaluation values and obtain an optimal solution. Therefore, due to its ability to cover more dynamic and multi-source information, multi-stage large group decision-making (MSLGDM) has been widely studied in various contexts such as optimal investment [3], new product evaluation [4], supplier selection [5], evaluation of social credit system [6], evaluation of a power distribution network [7], etc.

MSLGDM refers to a decision-making system with a multi-stage dynamic decision-making process and a large number of DMs for democratic evaluation. In LGDM, researchers can gather the expertise, experience and wisdom of DMs in static environment to make scientific decisions. Since major strategic decision-making problems have the characteristics of complex information and long-time process [8], the evolution of the decision object has a significant impact on the efficiency of the selection [6]. Compared with the static LGDM, MSLGDM collects decision information of multiple stages to evaluate the performance of a limited set of alternatives, which can capture the objective status in time, and infer the development characteristics of the decision environment in the whole process. In addition, DMs can fully understand the decision-making problem in the long-time process, unify the evaluation standards, and give accurate information that is in line with the decision-making requirements.

However, MSLGDM still confronts some challenges. As the decision-making proceeds, the amount of information grows exponentially. Vast amounts of information fully describe the attributes of alternatives and inevitably it brings about some problems, such as incompleteness, uncertainty, inefficiency, and difficulty in aggregation [1]. In addition, experts usually come from relevant areas of specialization [9]. DMs frequently interact and exchange information based on the topological structure of the social network, which has a non-negligible impact on the decision-making results [10]. To study such impact, social network group decision-making (SNGDM) has become a hot issue in recent years, including trust relationships [11-13], interest interference [14, 15], subgroup division [2, 16] and manipulative behavior [17, 18]. Notably, SNGDM with dynamic evolution characteristics becomes complex [19]. In MSLGDM, the information that changes in a certain stage will directly affect the decision-making process of the next stage [17, 20]. At present, researchers mainly use clustering algorithms to alleviate the problem of information overload and interaction frequency, which are based on preference similarity [20], trust relationships [11] or interest factors [15]. In the consensus reaching process (CRP), subgroup consensus is achieved first, and then group consensus is reached. However, the CRP in this manner is an adjustment at the subgroup level, focusing on “subgroup behavior” rather than “individual behavior”, ignoring individual behavioral characteristics and increasing the risk of conflict and polarization between subgroups [11]. Undertake the above considerations, we dig deeper into the individual behavioral characteristics of DMs in a multi-stage context, i.e., herding behavior, and explore the consensus process and the decision-making process with this influence.

Herding behavior was originally used to study group selection dynamics [21-24]. Bon, the founder of group psychology, believes that individuals in groups will lose their rationality and sense of responsibility due to psychological factors such as anonymity, infection, and obedience, exhibiting impulsive and other extreme behaviors [25]. At this time, individuals are more easily influenced by others, especially those they trust. Sociologists believe that due to the incomplete information, individuals show extreme imitation and gregarious phenomena in the crowd [21, 26, 27]. Psychologists believe that the herd effect stems from human-beings’ avoidance of social pressure [28, 29]. Economists explain that herding behavior comes from the authority formed in society from the limited rationality of economic subjects [30, 31]. Summarizing the previous studies, the factors that trigger herding behavior mainly come from the following aspects: incomplete information, social pressure and obeying authority.

Herding behavior is common in MSLGDM. In the dynamic decision-making process, DMs may not collect complete information. At this time, if DMs are worried about the consequences of being different with other people's preferences or tend to refer to the opinions of authority figures, they are more likely to lose part of their self-judgment and exhibit herding behavior. On the one hand, herding behavior makes DMs evaluate irrationally. On the other hand, DMs with herding behavior are willing to absorb opinions of others for the sake of scientific and correct decision-making. Therefore, we have the opportunity to artificially guide consensus through herding behavior in decision-making groups. For DMs with high degree of consensus, since their preferences overlap with the group, their herding behavior will not have a major impact on the decision-making results. For the low-consensus DMs with herding behavior, we can explore their willingness to modify preferences by the varying degree of herding behavior, and provide targeted and personalized consensus strategies. The CRP process of MSLGDM considering herding behavior has the following key issues: consensus measurement, recommendation mechanism and consensus strategy construction.

In previous studies, consensus level generally comes from preference similarity among DMs [32-34]. By comparing the evaluation values between two DMs, the preference similarity matrix can be obtained. The higher the element value in the matrix, the higher the degree of consensus. However, most researchers only focus on the average value generated by the aggregation of elements in the matrix, while ignoring their distribution characteristics. When the element means are the same, the level of consensus between DM pairs with lower element dispersion should be better than that of DM pairs with higher element dispersion [20]. Therefore, the average value of the elements in the preference similarity matrix is not enough to fully reflect the consensus situation, because it cannot capture the dispersion characteristics. When defining the consensus level, we should incorporate the discreteness of the elements in the preference similarity matrix into the calculation, i.e., the fuzziness of the consensus level.

Since MSLGDM is an LGDM event that occurs in a multi-stage process, there is a phenomenon of consensus evolution. At each stage, DMs have the opportunity to interact, causing preferences to be influenced by others. Researchers mostly catch this interactive influence to design recommendation mechanisms and guide the evolution of group preferences towards consensus. DeGroot model is a basic method to obtain the low-consensus DM's referenced preference [35]. Dong et al. proposed a DeGroot model based on social networks that fully considers the influence of the interaction relationship between DMs on their preferences [36]. The referenced preference can come from the linear weighting of the trust people, and the linear weight is the edge weight in the social network [37]. However, DMs vary in their willingness to be influenced by the preferences of others. For DMs with low confidence, they tend to draw on the opinions of credible people to provide evaluation information that is more easily accepted by others. For more confident DMs, they stick to their own opinions without interference from others. In MSLGDM, the DM gives the evaluation value at each stage. Therefore, we can obtain the degree of influence through the dynamic changes of the evaluation information of DMs, so as to obtain the referenced preferences of low consensus DMs.

After identifying low-consensus DMs and obtaining their referenced preferences, researchers will construct a corresponding consensus strategy: recommend that the identified low-consensus DMs revise their evaluations under the guidance of referenced preferences to improve the group consensus level [37]. Currently, among the studies that consider the influence of behavioral characteristics, the issue of cooperation and non-cooperation in DM is a mainstream direction of CRP. For example, the management of non-cooperative behavior based on social network [18, 38], the analysis of DM's preferences to detect non-cooperative behavior [13, 39, 40], the consensus based on non-cooperative behavior of subgroups [41], or the definition of different non-cooperative types to carry out CRP [12, 42]. Indeed, the management of cooperative behavior is a judgment of the DM's willingness to modify preferences [34]. Based on the adjustment willingness of DMs, researchers can establish a modification model with minimum cost to retain the original preference information as much as possible [43-46]. However, due to the complexity and variability of the decision-making environment in MSLGDM, the adjustment willingness of some low-consensus DMs is indeterminable. In this scenario, it is inappropriate to construct a minimal modification model to adjust their preferences. Therefore, we consider a punishment model that reduces the weight of their decisions and ensures that the group reaches a consensus.

Summarizing the above motivations, we aim to develop a MSLGDM consensus model under the influence of herding behavior. According to the three factors of herding behavior, i.e., incomplete information, social pressure and obeying authority, we introduce a corresponding quantitative method to identify DMs with herding behavior. For DMs with different degrees of herding behavior, we propose a personalized consensus reaching strategy, which includes a modification model for preference optimization and a punishment model for weight optimization. The main decision-making methodology proposed in this paper is based on the research into the following four key areas:

(1) Modeling three characteristics of herding behavior to classify decision-makers;

(2) Obtaining consensus level with discrete feature in the form of cloud droplets to generate cloud model;

(3) Determining the influence degree and deriving the referenced preference through a recommendation mechanism;

(4) Developing a CRP that minimizes the modification cost considering the adjustment willingness, including the modification model and the punishment model.

The main contributions of the proposed consensus model in this paper can be summarized as follows:

(1) Three characteristics of herding behavior are modeled and DMs with different degrees of herding behavior are classified. We innovatively model information gradient propagation characteristics, risk aversion characteristics and authority obedience characteristics to describe the three factors of herding behavior, based on which we identify and classify DMs with different degrees of herding behavior.

(2) Consensus level is obtained by generating a cloud model through cloud drops. We innovatively use the expectation in the cloud model to represent the traditional mean of preference similarity, use entropy and hyper-entropy to describe the dispersion of preference similarity, i.e., the three digital characteristics of the cloud model to comprehensively evaluate the consensus level.

(3) The degree of influence of DM at each stage is fitted using least squares to obtain referenced preference for that with low consensus and strong herd behavior. We innovatively use the least squares method to fit the influence degree set and stage set, deduce the influence degree of the final stage, and

obtain the referenced preferences of DMs with low consensus and strong herding behavior.

(4) A modification model and a punishment model are built to optimize the DM's preferences and weights. We innovatively determine the preference modification willingness based on the degree of DM's herding behavior, and propose a corresponding modification model to optimize the DM's preferences. Then, a punishment model is innovatively constructed to bring the group consensus level pass the threshold condition with minimal adjustment.

The remainder of this paper is organized as follows. Some basic concepts of MSLGDM, social network, CRP and normal cloud model analysis are introduced in Section 2. In Section 3, we identify the three characteristics of herding behavior as information gradient propagation characteristics, risk aversion characteristics and authority obedience characteristics. We construct the modification model and punishment model to steer consensus based on the identification and classification of DMs with herd behavior in Section 4, and summarize the decision-making steps in Section 5. A numerical example is given in Section 6 for the selection of emergency generation methods during the Spanish energy crisis. Finally, the paper is concluded in Section 7.

## 2. Preliminaries

Before introducing the consensus model for MSLGDM, some basic knowledge of MSLGDM, social network, CRP and normal cloud model analysis needs to be recalled briefly in this section.

### *2.1. Multistage large scale group decision making framework*

In group decision-making systems, the attribute set, the alternative set and the stage set are donated as $C=\{c_1,\cdots,c_n,\cdots,c_N\}$, $A=\{A_1,\cdots,A_l,\cdots,A_L\}$ and $T=\{t_1,\cdots,t_\lambda,\cdots,t_T\}$. The attribute weights are $\tilde{\omega}=\{\omega_1,\cdots,\omega_n,\cdots,\omega_N\}$ satisfying $\omega_n\in(0,1)$, $\sum_{n=1}^{N}\omega_n=1$. According to the decision-making problem, DMs $Dset=\{d_1,\cdots,d_m,\cdots,d_M\}$ in relevant fields are invited to form a decision-making group. When $M>20$, it is considered as a large group decision-making [1]. All the symbols and their meanings involved in this paper are summarized in Appendix Table A.1.

Fuzzy preference relations (FPR) provide a way to construct a decision matrix for pairwise comparisons based on numeric values given by experts [47]. DMs can focus on only two options at a time, which facilitates they express their preferences more accurately than when using non-pairwise methods. Since FPR reflects the pairwise comparison of preferences, many CRPs are mainly proposed based on FPRs [48]. With the advantages of information representation and consensus measure, the FPRs are used to express DMs' opinions in this study.

DEFINITION 1. ([16, 49]) A FPR on $A=\{A_1,\cdots,A_l,\cdots,A_L\}$ is a fuzzy set on the product set $A\times A$ characterized by a membership function: $u_F:A\times A\to[0,1]$. Then the FPR is $F=\{f_{ll'}\}_{L\times L}$, where $u_F(A_l,A_{l'})=f_{ll'}$ is interpreted as the preference degree of the alternative $A_l$ over $A_{l'}$, and fulfilling $f_{ll'}+f_{l'l}=1$. Generally, if $Dset=\{d_1,\cdots,d_m,\cdots,d_M\}$ is the set of DMs in the decision-making process and $F_n^{m-t_\lambda}=\left\{f_{ll'-n}^{m-t_\lambda}\right\}_{L\times L}$ $(l,l'=1,2,\cdots,L)$ is the FPR on the set $A=\{A_1,\cdots,A_l,\cdots,A_L\}$ of DM $d_m$ on attribute $c_n$ in stage $t_\lambda$, then, the FPR matrix of $d_m$ can be represented as:

$$F_n^{m-t_\lambda}=\begin{Bmatrix} 0.5 & \cdots & f_{1l'-n}^{m-t_\lambda} & \cdots & f_{1L-n}^{m-t_\lambda} \\ \cdots & 0.5 & \cdots & & \cdots \\ f_{l1-n}^{m-t_\lambda} & \cdots & 0.5 & \cdots & f_{lL-n}^{m-t_\lambda} \\ \cdots & & \cdots & 0.5 & \cdots \\ f_{L1-n}^{m-t_\lambda} & \cdots & f_{Ll'-n}^{m-t_\lambda} & \cdots & 0.5 \end{Bmatrix}_{L\times L} \tag{1}$$

where $f_{ll'-n}^{m-t_\lambda}=u_{F_n^{m-t_\lambda}}\left(A_l,A_{l'}\right)$ and $f_{ll'-n}^{m-t_\lambda}+f_{l'l-n}^{m-t_\lambda}=1$.

Based on the FPRs, Herrera-Viedma et al. proposed the similarity matrix based on the FPRs to determine the consensus matrix for CRP [50]. The definition of the similarity matrix is as follows.

DEFINITION 2. ([50, 51]) If two DMs $d_i$ and $d_j$ gave their FPRs for attribute $c_n$ in stage $t_\lambda$ as $F_n^{i-t_\lambda}=\left\{f_{ll'-n}^{i-t_\lambda}\right\}_{L\times L}$ and $F_n^{j-t_\lambda}=\left\{f_{ll'-n}^{j-t_\lambda}\right\}_{L\times L}$, respectively, then, we can obtain the similarity matrix between $d_i$ and $d_j$ about the attribute $c_n$ in stage $t_\lambda$ as:

$$SM_n^{ij-t_\lambda}=\begin{Bmatrix} - & \cdots & sm_{1l'-n}^{ij-t_\lambda} & \cdots & sm_{1L-n}^{ij-t_\lambda} \\ \cdots & & \cdots & & \cdots \\ sm_{l1-n}^{ij-t_\lambda} & \cdots & - & \cdots & sm_{lL-n}^{ij-t_\lambda} \\ \cdots & & \cdots & & \cdots \\ sm_{L1-n}^{ij-t_\lambda} & \cdots & sm_{Ll'-n}^{ij-t_\lambda} & \cdots & - \end{Bmatrix}_{L\times L} \tag{2}$$

where $sm_{ll'-n}^{ij-t_\lambda}=1-\left|f_{ll'-n}^{i-t_\lambda}-f_{ll'-n}^{j-t_\lambda}\right|$, $sm_{ll'-n}^{ij-t_\lambda}\in[0,1]$.

### 2.2. Social network and clustering analysis

During the decision-making process, there is a social network based on cooperative relationships among DMs, which is represented as an undirected weighted graph $G=(V,E,W)$, where $V=(v_1,\cdots,v_m,\cdots,v_M)$ represent DMs, and $E=\left\{e_{ij}\,\middle|\,i,j\le M\right\}$ is the cooperative relationships between DMs. The edge weights $W=\left\{w_{ij}\,\middle|\,i,j\le M\right\}$ in social network are obtained by the cooperation strength between DMs.

In this paper, the construction of social network comes from the cooperative relationship between DMs, i.e., the historical cooperation level. As the decision-making process evolves, the cooperative relationship between DMs becomes complex and constantly changing, and the assessment of historical cooperation is often fuzziness [15]. Therefore, we extend the linguistic distribution (LD) to undirected weighted graph, and use the informational form of LD to represent the strength of cooperation in social networks.

DEFINITION 3 ([52]): If $H=\left\{h^k\,\middle|\,k=0,1,\cdots,K\right\}$ is an established linguistic term set (LTS), $h^k$ represents a possible value for a linguistic variable, then the LD can be defined as: $H(\sigma)=\left\{h^k\left(\sigma^k\right)\,\middle|\,h^k\in H,k=0,1,\cdots,K\right\}$, where $h^k\left(\sigma^k\right)$ is the linguistic term $h^k$ with respect to the symbolic proportion $\sigma^k$ satisfying $\sigma^k \geq 0$ and $\sum_{k=0}^{K} \sigma^k = 1$. The expectation of $H(\sigma)$ can be defined as $E(H(\sigma)) = \sum_{k=0}^{K} h^k \sigma^k$ .

Then, the edge weights are defined as follows.

DEFINITION 4 ([15]): If there is a cooperative relationship between DM $d_i$ and DM $d_j$, DMs evaluate the cooperative relationship by LTS $H = \{h^k | k = 0,1,\cdots,K\}$ . After $T$ stages of evaluation, the cooperation strength of $d_i$ rate $d_j$ is expressed as $h_{i-j}(\sigma_{i-j}) = \{h^k(\sigma_{i-j}^k) | k = 0,1,\cdots,K\}$, while $d_j$ rate $d_i$ is $h_{j-i}(\sigma_{j-i}) = \{h^k(\sigma_{j-i}^k) | k = 0,1,\cdots,K\}$. Herein, $\sigma_{i-j}^k$ is the probability that $d_i$ rates the cooperative relationship with $d_j$ as $h^k$, i.e., the ratio of times $d_i$ evaluates the cooperative relationship as $h^k$ over the total number of stages $T$. Then the edge weight between $d_i$ and $d_j$ is defined as:

$$w_{ij}(\sigma_{ij}) = \{h_{ij}^1(\sigma_{ij}^1), h_{ij}^2(\sigma_{ij}^2)\} \tag{3}$$

where $h_{ij}^1 = E(h_{i-j}(\sigma_{i-j}))$ , $\sigma_{ij}^1 = Ent_{j-i} / (Ent_{i-j} + Ent_{j-i})$ , $h_{ij}^2 = E(h_{j-i}(\sigma_{j-i}))$ , $\sigma_{ij}^2 = Ent_{i-j} / (Ent_{i-j} + Ent_{j-i})$, $\sigma_{ij}^1 + \sigma_{ij}^2 = 1$, $Ent_{i-j} = -\sum_{k=0}^{K} \sigma_{i-j}^k \ln \sigma_{i-j}^k$ , $Ent_{j-i} = -\sum_{k=0}^{K} \sigma_{j-i}^k \ln \sigma_{j-i}^k$ .

The degree and degree centrality of nodes are mainly used to estimate the importance and influence of nodes in the social network, so we give the definition of degree and degree centrality.

DEFINITION 5 ([53]): If $G = (V,E,W)$ is an undirected weighted graph, then the degree $d_i$ is the number of all adjacent nodes of node $v_i$, which is defined as $D_i = \sum_{j=1}^{M} |e_{ij}|$, and the degree centrality of node $v_i$ is defined as $W_i = \sum_{j=1}^{M} E(w_{ij}(\sigma_{ij}))$, where $|e_{ij}| = \begin{cases} 1, & e_{ij} \in E \\ 0, & e_{ij} \notin E \end{cases}$, $E(w_{ij}(\sigma_{ij})) = h_{ij}^1 \sigma_{ij}^1 + h_{ij}^2 \sigma_{ij}^2$.

In order to reduce the group size and simplify group information, cluster analysis is required to explore the subgroup of social networks. Modularity is a measurement to evaluate the division of a social network [54]. Considering the influence of fuzzy edge information, Sun and Zhu proposed the elastic modularity based on linguistic distribution entropy, and explored the EMCDA algorithm to determine the subgroup [15].

DEFINITION 6 (elastic modularity): If $G = (V,E,W)$ is an undirected weighted graph, then the edge weights are expressed in the form of LDs $w_{ij}(\sigma_{ij}) = \{h_{ij}^1(\sigma_{ij}^1), h_{ij}^2(\sigma_{ij}^2)\}$, and the expectation of the weight is expressed as $\tilde{h}_{ij}$. Then the elastic modularity of the community is defined as

$$Y = \frac{1}{2W} \sum_{i,j} \left( \tilde{h}_{ij} - \frac{W_i W_j}{2W} \right) \tilde{E}_{ij} \tag{4}$$

where $\tilde{h}_{ij}=E\left(w_{ij}\left(\sigma_{ij}\right)\right)$, $W=\sum_{i=1}^{M}\sum_{j=1,j\neq i}^{M}\tilde{h}_{ij}/2$ is the sum of weights corresponding to edges in the network $G$, $W_i=\sum_{j=1}^{M}E\left(w_{ij}\left(\sigma_{ij}\right)\right)$ is the degree centrality of $v_i$. $\tilde{E}_{ij}=\begin{cases}1-\eta Ent_{ij}, & e_{ij}\in E\\ 0, & else\end{cases}$ is the certainty degree of $e_{ij}$, $Ent_{ij}=-\sum_{k=1}^{2}\sigma_{ij}^{k}\ln\sigma_{ij}^{k}$ is the linguistic distribution entropy of edge $e_{ij}$, $\eta\in[0,1]$.

### *2.3. Consensus method and opinion evolution*

Consensus method is proposed to obtain a decision result accepted by all DMs. This is often an iterative process in which DMs reason, discuss, and revise their preferences to reach agreement. In real decision-making processes, people's emotions, thoughts, or behaviors can be changed through interactions with others [18, 37]. DeGroot model is one of the classic models in opinion dynamics.

DEFINITION 7 ([35]): $Dset=\{d_1,\cdots,d_m,\cdots,d_M\}$ is the set of DMs, and $f_{ll'-n}^{i-t_\lambda}$ is the DM $d_i$'s opinion of alternative $A_l$ to $A_{l'}$ on attribute $c_n$ in stage $t_\lambda$. Let $\delta_{ij}$ be the weight that $d_i$ gives $d_j$, where $\delta_{ij}>0$ and $\sum_{j=1}^{M}\delta_{ij}=1$. Then, the evolution of opinion of DM $d_i$ can be expressed as

$$f_{ll'-n}^{i-t_{\lambda+1}}=\delta_{i1}f_{ll'-n}^{1-t_\lambda}+\delta_{i2}f_{ll'-n}^{2-t_\lambda}+\cdots+\delta_{iM}f_{ll'-n}^{M-t_\lambda} \tag{5}$$

In a decision-making process based on social networks, Dong et al. proposed the DeGroot model under the social network and introduced the following definition [36].

DEFINITION 8: Let $\theta_i\in[0,1]$ be the influence degree for DM $d_i$'s opinion of alternative $A_l$ to $A_{l'}$ on attribute $c_n$ in stage $t_\lambda$. DMs' self-weights are expressed as: $\delta_{ii}=1-\theta_i$ $(i=1,\cdots,M)$. Then, the fixed weight matrix $\Delta=\{\delta_{ij}\}_{M\times M}$ are determined by:

$$\delta_{ij}=\frac{\theta_i E\left(w_{ij}\right)}{\sum_{j=1}^{M}E\left(w_{ij}\right)} \tag{6}$$

where $d_i,d_j\in Dset$, $E\left(w_{ij}\right)$ is the expectation of the edge weight $w_{ij}\left(\sigma_{ij}\right)=\left\{H_{ij}^{1}\left(\sigma_{ij}^{1}\right),H_{ij}^{2}\left(\sigma_{ij}^{2}\right)\right\}$. When $i=j$, $\delta_{ii}=1-\theta_i$. Based on Eq. (5), the opinion evolution for $d_i\in Dset$ in the SNDG model is

$$f_{ll'-n}^{i-t_{\lambda+1}}=\sum_{j=1,j\neq i}^{M}\delta_{ij}f_{ll'-n}^{j-t_\lambda}+\delta_{ii}f_{ll'-n}^{i-t_\lambda} \tag{7}$$

### *2.4. Normal cloud model analysis*

The normal cloud model generates quantitative conversion values of qualitative concepts through a specific structure generator composed of expectation, entropy and hyper-entropy, which relaxes the prerequisites for forming a normal distribution. Therefore, it is more generally applicable to describe the fuzziness and uncertainty of concepts.

DEFINITION 9 ([55, 56]): Suppose $U$ is the quantitative universe expressed by exact numerical values, and $\tilde{Z}$ is the qualitative concept on $U$. If $z\in U$ is a random realization of $\tilde{Z}$ that satisfies

$z \sim N\left(Ex, En'^2\right)$, $En' \sim N\left(En, He^2\right)$, the membership of $z$ related to $\tilde{Z}$ is a random number that satisfies

$$u(z) = \exp\left(-\frac{(z-Ex)^2}{2(En')^2}\right) \tag{8}$$

where $u(z) \in [0,1]$. The distribution of $z$ on universe $U$ is called the normal cloud model donated as $Z = (Ex, En, He)$, and each $z$ is called a cloud droplet. Through the three digital features of expectation $Ex$, entropy $En$ and hyper-entropy $He$, the cloud model effectively integrates the randomness and fuzziness of qualitative concepts.

DEFINITION 10 (cloud score value [57]): If $Z = (Ex, En, He)$ is a normal cloud with $n$ generated cloud drops, and the variance of $n$ cloud drops can be computed as $var = En^2 + He^2$, then, the standard deviation of $n$ cloud drops is $sd = \sqrt{En^2 + He^2}$. Therefore, the score value of $Z = (Ex, En, He)$ can be defined as

$$sc = Ex - \varepsilon \cdot sd \tag{9}$$

where $\varepsilon \in [0,1]$ is a coefficient to capture the attitude toward the standard deviation.

DEFINITION 11 (cloud-weighted arithmetic averaging operator (CWAA) [58]): In a set of cloud models $\tilde{P} = \left\{P_i\left(Ex_i, En_i, He_i\right) \middle| i = 1, 2, \cdots, n\right\}$, the mapping $CWAA$: $\tilde{P}^n \to \tilde{P}$ is defined as

$$CWAA\left(P_1, \cdots, P_n\right) = \left(\sum_{i=1}^{n_i} w_i Ex_i, \sqrt{\sum_{i=1}^{n_i} w_i En_i^2}, \sqrt{\sum_{i=1}^{n_i} w_i He_i^2}\right) \tag{10}$$

where $w = \left(w_1, \cdots, w_n\right)$ is the corresponding weight vector of $\tilde{Z}$ satisfying $w_i \in [0,1]$ $(i = 1, \cdots, n)$ and $\sum_{i=1}^{n} w_i = 1$. Therefore, the result obtained by CWAA is still a cloud model [59].

## 3. Determination of herd behavior characteristics

In this section, we provide methods for identifying three characteristics of herding behavior, i.e., information gradient propagation characteristics, risk aversion characteristics and authority obedience characteristics.

### *3.1. Opinion leader identification considering fuzzy relationship*

Due to the complex practical problems, DMs often have different understandings and evaluation standards for decision-making alternatives. DMs usually interact with their trusted experts to break through the limitations of ability and experience, so as to adjust their evaluation standards in time and make objective decisions. Among these trusted experts, DMs care more about those with good reputation and great influence. We usually refer to such influential DMs as "opinion leaders". Opinion leaders (OLs) have information dissemination speed 10 times faster than ordinary DMs, which is significant in social networks [60]. After interacting with OLs, the preferences of general DMs may be affected, resulting in a phenomenon of tendency toward OLs, exhibiting a degree of "herd behavior". Therefore, to distinguish the

DMs with herd behavior, we should identify the OLs of the group.

In previous studies, the identification of OLs is often equated with the identification of key nodes in a social network. There are many methods to evaluate the importance of nodes, such as degree centrality, betweenness centrality and closeness centrality [61]. However, these methods require comprehensive global information and are computationally intensive. Therefore, it is more significant to explore a method calculating node's importance via local information. Du et al. learned network representations from the social network topologies to find OLs, ignoring network weight information [60]. Zhu et al. proposed a structural hole influence matrix to evaluate and identify key nodes in complex networks based on the topology of social networks, ignoring the influence of bridge nodes [62]. Based on the above analysis, we believe that the identification of OLs should consider the local influence of nodes and bridge nodes in the social network. In addition, as DMs come from different areas of specialization, they have different analytical perspectives and judgment criteria. It means there will be more than one OL in the social network. OLs have greater influence within their local subgroups, and general DMs with herd behavior also tend to follow their identified OLs. Meanwhile, there is some fuzziness in the DM's judgment of the cooperative relationship in actual decision-making. Identifying OL should consider the influence of fuzziness in cooperative relationship. Therefore, we determine OL based on the local influence with fuzziness characteristics.

DIL method is a tool for assessing the importance of nodes in social networks. It is based on degree value and line importance, and only needs to use local features to evaluate the importance of nodes, while taking into account the influence of bridge nodes [63]. Compared with methods that use global social network information, DIL has relatively low computational complexity, which is more suitable for large-scale social networks. However, in decision-making contexts, social network has fuzziness due to the complexity and the limited capacity of DMs. The DIL method obtains the node importance only based on the social network structure in the ideal case, which fails to perfectly adapt to the fuzziness of social network nodes evaluation relationship weights in real problems. Therefore, we propose a DIL with fuzziness to measure the importance of nodes in social network and determine the OL in each subgroup.

We first cluster the social network into a series of subgroups $Q=\{G_1,\cdots,G_q\}$ according to the EMCDA algorithm [15]. Then, we give the degree and the importance of lines (DIL) considering fuzzy features to calculate the local influence of nodes in each subgroup, and thus obtain the OLs of subgroups.

DEFINITION 12: If $G=(V,E,W)$ is an undirected weighted graph, then the importance of edge between $v_i$ and $v_j$ is defined as

$$I_{ij}=\frac{U_{ij}}{\rho}\tilde{E}_{ij} \tag{11}$$

where $U_{ij}=(D_i-p_{ij}-1)(D_j-p_{ij}-1)$ is the connection strength of $e_{ij}$, $D_i$ is the degree of $v_i$, $p_{ij}$ is the number of triangles containing edge $e_{ij}$. $\rho$ is the alternative index of $e_{ij}$, which is defined as $\rho=(p_{ij}/2)+1$. $\tilde{E}_{ij}$ is the certainty value of the edge $e_{ij}$.

Then, the contribution of node to edge and the importance of node $v_i$ are defined as follows:

DEFINITION 13: If $G=(V,E,W)$ is an undirected weighted graph, then the importance of edge between $v_i$ and $v_j$ is $I_{ij} = \frac{U_{ij}}{\rho}\tilde{E}_{ij}$. Then the contribution of $v_i$ to edge $e_{ij}$ can be defined as:

$$Con_{ij} = I_{ij} \cdot \frac{D_i - 1}{D_i + D_j - 2} \tag{12}$$

And the importance of node $v_i$ can be expressed as:

$$I_i = W_i + \sum_{v_j \in N_i \cap G_q} Con_{ij} \tag{13}$$

where $N_i$ is the set of neighbors of $v_i$, $G_q$ is the subgroup to which $v_i$ belongs, $W_i = \sum_{v_j \in G} \tilde{h}_{ij}$ is the degree centrality of $v_i$.

We calculate the importance of all nodes in the social network based on the subgroup structure and select the most important node $\{d_1^*, d_2^*, \cdots, d_q^*\}$ in each subgroup as the OL, their corresponding importance is $\{I_1^*, I_2^*, \cdots, I_q^*\}$.

### *3.2. Information gradient propagation characteristics*

In the initial decision stage, some DMs have limited access to information and are pressed for time to make decisions, so their understanding of alternatives or attributes are biased. These DMs have an inaccurate grasp of decision information and prefer to communicate with others during the decision-making process. They observe the behavior of trusted people and imitate their preferences and evaluation standards [23]. As decision-making proceeds, their rating values gradually approach their trusted people. Furthermore, these trusted people will imitate their trusted ones. DMs may exhibit herd behavior if they tend to imitate the decisions of others rather than basing on their own judgment [21]. Therefore, we can further determine whether DMs have herding behavior by judging whether they have the information gradient propagation characteristics according to their stage preference trends.

In order to identify DMs with herd behavior, we first give the preference similarity between DMs and OLs in the same subgroup based on Eq. (2). Then, we fit this preference similarity at each stage according to the least square method, and obtain the development trend of the preference similarity between DMs and OLs.

If the similarity between the DM's preferences and those of its OL becomes more apparent as the stage progresses, we can say that the DM satisfies the information gradient propagation characteristics. Therefore, to obtain the tendency of the preference similarity between DM and OL, we fit the preference similarity values $sm_{ll'-n}^{iq*-t_\lambda}$ and each stage $t_\lambda$ as a linear function, where the stage $t_\lambda$ is the independent variable and the similarity $sm_{ll'-n}^{iq*-t_\lambda}$ is the dependent variable. The definition of this linear function is shown as follow.

DEFINITION 14: If $SMS_{ll'-n}^{iq*} = \left\{sm_{ll'-n}^{iq*-t_1}, \cdots, sm_{ll'-n}^{iq*-t_\lambda}, \cdots, sm_{ll'-n}^{iq*-t_T}\right\}$ is the set of similarity between the preference of DM $d_i$ $(d_i \in G_q)$ and OL $d_q^*$ on the $c_n$ attribute $A_l$ over $A_{l'}$, $T = \{t_1, \cdots, t_\lambda, \cdots, t_T\}$ is the set of decision stages, then there exists a binary equation $y = a_{ll'-n}^{iq*}x + b_{ll'-n}^{iq*}$ satisfying

$$f\left(a_{ll'-n}^{iq*}, b_{ll'-n}^{iq*}\right) = \min \sum_{\lambda=1}^{T} \left[sm_{ll'-n}^{iq*-t_\lambda} - \left(a_{ll'-n}^{iq*}\lambda + b_{ll'-n}^{iq*}\right)\right]^2 \tag{14}$$

where $sm_{ll'-n}^{iq*-t_\lambda}=1-\left|f_{ll'-n}^{i-t_\lambda}-f_{ll'-n}^{q*-t_\lambda}\right|$, $a_{ll'-n}^{iq*}$ can reflect the trend of preference similarity between DM $d_i$ and OL $d_q^*$ on $c_n$ attribute $A_l$ over $A_{l'}$. When $a_{ll'-n}^{iq*}>0$, $y=a_{ll'-n}^{iq*}x+b_{ll'-n}^{iq*}$ is an increasing function, the preference similarity of $d_i$ for $d_q^*$ increases as the decision stage progresses, i.e., the preference level of $d_i$ is getting closer to the preference value of $d_q^*$. When $a_{ll'-n}^{iq*}<0$, $y=a_{ll'-n}^{iq*}x+b_{ll'-n}^{iq*}$ is a decreasing function, the preference similarity of $d_i$ for $d_q^*$ decreases as the decision stage progresses, i.e., the preference level of $d_i$ is getting farther from the preference value of $d_q^*$. We use the weighted average operator (WA) to gather the gradient $a_{ll'-n}^{iq*}$ corresponding to each similarity set $SMS_{ll'-n}^{iq*}$ to obtain the comprehensive gradient $A^{iq*}$ of $d_i$ and $d_q^*$ in all preference values.

DEFINITION 15: If the set of preference similarity gradients of $d_i$ for OL $d_q^*$ is $\left\{\left\{a_{ll'-1}^{iq*}\right\}_{L\times L},\cdots,\left\{a_{ll'-n}^{iq*}\right\}_{L\times L},\cdots,\left\{a_{ll'-N}^{iq*}\right\}_{L\times L}\right\}$, then the comprehensive gradient of $d_i$ and $d_q^*$ is

$$A^{iq*}=\frac{1}{NL(L-1)}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}a_{ll'-n}^{iq*} \tag{15}$$

$A^{iq*}\in[-1,1]$ reflects the tendency of preference similarity from $d_i$ to $d_q^*$. When $A^{iq*}>0$, the preference similarity of $d_i$ for $d_q^*$ increases with the progression of the decision stage, i.e., the preference level of $d_i$ is getting closer to the preference value of $d_q^*$, thus $d_i$ satisfies the information gradient propagation characteristics. When $A^{iq*}\leq 0$, the preference similarity of $d_i$ for $d_q^*$ is constant or decreasing with the progression of decision stages, i.e., the preference level of $d_i$ is flat or getting farther from the preference value of $d_q^*$, thus $d_i$ does not satisfy the information gradient propagation characteristics.

### *3.3. Risk aversion characteristics*

In multi-stage decision-making, DMs can understand other's evaluation standards and evaluation values by interacting with these people. DMs may experience decision-making pressure if their own evaluations differ significantly from those of people they trust. For risk-seeking DMs, their ability to resist pressure is strong, which makes them more confident in the evaluation value given by themselves. For risk-aversion DMs, their stress tolerance is low and they are vulnerable to the reputational risks that are inconsistent with mainstream views [64]. In addition, risk-aversion DMs are more cautious. They are willing to integrate the wisdom of others and revise their original evaluation for accurate decision. Therefore, risk-aversion DMs are more likely to be influenced by social pressure, exhibiting herd behavior. Based on the above analysis, we will choose risk aversion characteristics as one of the indicators for identifying herding behavior.

At different stages, the distance of preference value between the DM and his trusted people reflects his risk degree at this stage. The DM whose preference value is greater than that of the neighbor nodes is more inclined to affirm some attributes of the alternative, has an optimistic attitude towards the current state of the alternative attributes, and shows the characteristics of risk-seeking; while the DM whose preference value is smaller than the neighbor nodes are more inclined to deny some attributes of the alternative, have a pessimistic attitude towards the status quo of the alternative, showing the characteristics of risk-aversion. In addition, the neighbor nodes trusted by the DMs are not all in the same subgroup. If the trusted nodes are distributed in another subgroups, the preferences of these trusted people will evolve in different directions according to the information gradient propagation characteristics, which is unfavorable to the judgment of the risk characteristics of the DM. Therefore, we define the risk index of the DM and the trusted people in the same subgroup for the purpose of determination the risk characteristics of the DM relative to the subgroup he belongs to.

We first give a definition of the risk index between the DM and those he/she trusts, and then we give an idea of the risk characteristics of the DM related to his/her subgroup.

DEFINITION 16 (risk index (RI)): If $d_i$ and one of his/her trusted DMs $d_j$ $\left(d_j \in N_i\right)$ gave FPRs for attribute $c_n$ in stage $t_\lambda$ as $F_n^{i-t_\lambda} = \left\{f_{ll'-n}^{i-t_\lambda}\right\}_{L\times L}$ and $F_n^{j-t_\lambda} = \left\{f_{ll'-n}^{j-t_\lambda}\right\}_{L\times L}$, respectively, then, we define the risk index of $d_i$ related to $d_j$ on attribute $c_n$ of $A_l$ rate $A_{l'}$ in stage $t_\lambda$ as:

$$r_{ll'-n}^{ij-t_\lambda} = f_{ll'-n}^{i-t_\lambda} - f_{ll'-n}^{j-t_\lambda} \tag{16}$$

Then we give the definition of relative risk index (RRI) to determine the risk level of DM related to other people.

DEFINITION 17 (relative risk index (RRI)): If $r_{ll'-n}^{ij-t_\lambda} = f_{ll'-n}^{i-t_\lambda} - f_{ll'-n}^{j-t_\lambda}$ is the risk index of $d_i$ related to $d_j$ on attribute $c_n$ of $A_l$ to $A_{l'}$ in stage $t_\lambda$, then, we can obtain the RRI of $d_i$ over $d_j$ as:

$$r_{ij} = \frac{1}{TNL(L-1)} \sum_{l=1}^{L} \sum_{l'=1, l'\neq l}^{L} \sum_{\lambda=1}^{T} \sum_{n=1}^{N} \left( f_{ll'-n}^{i-t_\lambda} - f_{ll'-n}^{j-t_\lambda} \right) \tag{17}$$

$r_{ij} \in [-1,1]$ reflects the risk level of $d_i$ related to $d_j$. When $r_{ij} \geq 0$, compared with $d_j$, $d_i$ tends to affirm certain performances of attributes, which has a risky evaluation style. When $r_{ij} = 0$, $d_i$ and $d_j$ have no difference. $r_{ij} < 0$ means that $d_i$ tends to negate certain performances of the attribute and has a more conservative evaluation style than $d_j$.

Based on the RRI, we obtain the comprehensive risk index (CRI) $R_i$ of DM $d_i$ as:

$$R_i = \frac{1}{\left|N_i \cap G_i\right|} \sum_{d_j \in N_i \cap G_i} r_{ij} \tag{18}$$

where $N_i$ is the set of people trusted by $d_i$, $G_i$ is the subgroup to which $d_i$ belongs, and $N_i \cap G_i$ is the set of people trusted by $d_i$ in the same subgroup of $d_i$.

$R_i \in [-1,1]$ reflects the risk characteristics of $d_i$. $R_i > 0$ means $d_i$ has the risk seeking characteristic, $R_i = 0$ imply that that $d_i$ does not show obvious risk tendency. When $R_i < 0$, $d_i$ has the risk aversion characteristic. From Eq. (18), we obtain the CRI of each DM as $\{R_1, R_2, \cdots, R_N\}$.

### *3.4. Authority obedience characteristics*

During the decision-making process, DMs usually listen partially to the person they trust and update their own preferences to make a more objective and reasonable evaluation [19]. Affected by incomplete information and social pressure, some DMs may blindly trust and obey others, leading to herding behavior. Authoritative people generally have the characteristics of comprehensive information, thorough analysis of problems, and accurate prediction of situations, which are more likely to trigger large-scale superstitious obedience behavior, thus leading to the herd behavior in the group. Therefore, we can judge whether a DM has herding behavior by whether he/she has the authoritative obedience characteristics to others.

Generally speaking, if the trust value of $d_i$ rate to $d_j$ is greater than that of $d_j$ to $d_i$, then $d_j$ is authoritative to $d_i$ and $d_i$ is more willing to interact with $d_j$. In this case, we can consider that DM $d_i$ has obedience to $d_j$. By analogy, if DM $d_i$ has obedience to the DMs he/she trusts in the same subgroup, it can be said that the $d_i$ has obedience to the subgroup which it belongs. At this point, we believe that the DM $d_i$ satisfies the authority obedience characteristic.

In order to determine whether the DM has authority obedience characteristics, we firstly give the definition of net trust value (NTV) as follows to evaluate the authority degree of the DM to its neighbor nodes in social network.

DEFINITION 18 (net trust value (NTV)): If $G=(V,E,W)$ is an undirected weighted graph, the edge weights are expressed as the form of LDs $w_{ij}(\sigma_{ij})=\left\{h_{ij}^1(\sigma_{ij}^1),h_{ij}^2(\sigma_{ij}^2)\right\}$, then, the net trust value of $d_i$ rate $d_j$ is defined as:

$$Ntv_{ij}=h_{ij}^1\sigma_{ij}^1-h_{ij}^2\sigma_{ij}^2 \tag{19}$$

When $Ntv_{ij}>0$, $d_i$ has a higher authority evaluation on $d_j$, and $d_i$ has obedience to $d_j$. $Ntv_{ij}=0$ means they have an equal relationship with each other, so there is no obedience between $d_i$ and $d_j$. When $Ntv_{ij}<0$, the authoritative evaluation of $d_i$ rate $d_j$ is lower, $d_i$ does not have obedience to $d_j$. At this time, it can be deduced that $Ntv_{ji}>0$, i.e., $d_j$ has a high authority evaluation on $d_i$, and $d_j$ has obedience to $d_i$.

Then, we gather the NTVs of DM to his/her neighbor nodes in the same subgroups and obtain the net trust degree (NTD) of the DMs to their subgroups, which is used as the identification of whether DM has the authoritative obedience characteristic.

DEFINITION 19 (net trust degree (NTD)): If $G=(V,E,W)$ is an undirected weighted graph, the edge weights are expressed as the form of LDs $w_{ij}(\sigma_{ij})=\left\{\left(h_{ij}^1(\sigma_{ij}^1),h_{ij}^2(\sigma_{ij}^2)\right)\middle|h^k\in H,k=1,2\right\}$, then, the net trust degree of $d_i$ $(d_i\in G_i)$ rate $G_i$ is defined as:

$$Ntd_i=\frac{1}{|N_i\cap G_i|}\sum_{d_j\in N_i\cap G_i}Ntv_{ij} \tag{20}$$

where $N_i$ is the set of people trusted by $d_i$, $G_i$ is the subgroup to which $d_i$ belongs, $N_i\cap G_i$ is the set of people trusted by $d_i$ in the same subgroup as $d_i$.

From the above formula, we obtain the NTD of each DM as $\{Ntd_1, Ntd_2, \cdots, Ntd_M\}$. $Ntd_i \in [-1,1]$ can reflect the obedience degree of DM $d_i$ to the belonging subgroup $G_q$. When $Ntd_i > 0$, the NTD of $d_i$ to the neighbor nodes in the subgroup $G_q$ is high, and $d_i$ has the characteristic of authoritative obedience to the belonging subgroup $G_q$. When $Ntd_i = 0$, there is no obedience relationship between $d_i$ and $G_q$. When $Ntd_i < 0$, $d_i$ is more authoritative than trusted neighbor nodes in the same subgroup $G_q$, so $d_i$ has no authoritative obedience characteristic for the subgroup $G_q$.

In order to show the state change process of the three herd behavior characteristics in MSLGDM, we set up a 9-person decision-making group for illustration, as shown in Example 1 and Figure 1.

EXAMPLE 1: The social network relationship of the group at each stage and its clustering results are shown in "Social network" in Figure 1. Among them, DM $d_3$ and $d_6$ marked with crowns are the opinion leaders in the subgroups. ⓘ→ⓙ represents $A^{ij*} > 0$ in "Comprehensive gradient of DM", $r_{ij} < 0$ in "Relative risk index between DMs", and $Ntv_{ij} > 0$ in "Net trust value between DMs". The nodes marked with colors represent the corresponding characteristics that DM has identified at the current stage. We can see that DM's status relative to others may change at each stage (color-marked edges), which will also lead to changes in DM's herding behavior characteristics. For example, $d_7$ meets all the characteristics of herding behavior in stage $t_{\lambda-1}$, but in the subsequent two stages, his information gradient propagation characteristics and risk aversion characteristics have changed.

From EXAMPLE 1 we can see that DM's herding behavior characteristics change dynamically. Therefore, the proposed method to characterize the three characteristics of herd behavior can update the status of the DM based on real-time information. Combined with the model proposed in Section 4, it is achievable to obtain the decision-making results that are most in line with the current situation in a timely manner.

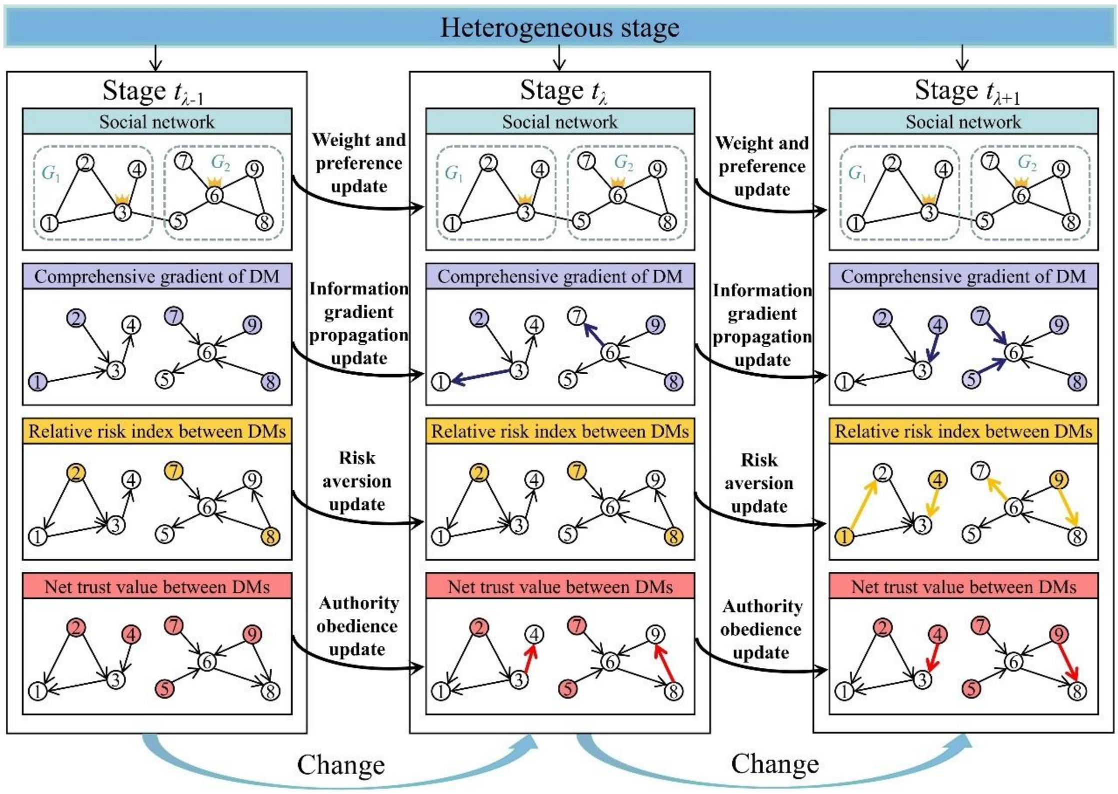


Figure 1. The state update of the herd behavior characteristics within 9 DMs

## 4. Consensus reaching process with varying herd behavior

In this section, based on the identification and classification of DMs with herd behavior with the use of three characteristics mentioned in Section 3, the consensus measurement, the recommendation mechanism and the consensus strategy including modification model and punishment model are proposed in the consensus reaching process for MSLGDM.

### *4.1. Consensus measurement*

In previous studies, the consensus achieved by DMs was often obtained from the preference similarity of DMs. Wu et al. used the mean of the elements in the similarity matrix as the consensus level of DMs [48]. Zhang et al. took the average of the difference between the subgroup preference matrix and the elements of the corresponding positions of the individual preference matrix in the subgroup as the consensus level of the subgroup [38]. Each element in the preference similarity matrix affects the consensus level of the corresponding DM pair. The higher the value of the element, the higher the consensus level. However, the elements in the preference similarity matrix obtained by the comparison of different alternative pairs are not the same. When having the same mean value of the preference similarity matrix, the consensus preference level between DM pairs with lower discrete elements should be better than that of DM pairs with higher dispersion. Therefore, the mean value of the elements in the preference similarity matrix is not sufficient to reflect the level of agreement of DM pairs because it does not reflect the dispersion of the elements in the preference similarity matrix. When defining the consensus level of each DM pair, we should include the dispersion of the elements in the preference similarity matrix in the calculation of the consensus level, i.e., the fuzziness of the consensus level.

Considering entropy and hyper-entropy to characterize the fuzziness of consensus level, we give the calculating formula of the individual consensus in stage $t_T$.

DEFINITION 20: If two DMs $d_i$ and $d_j$ gave their FPRs for attribute $c_n$ in stage $t_T$ as $F_n^{i-t_T}=\left\{f_{ll'-n}^{i-t_T}\right\}_{L\times L}$ and $F_n^{j-t_T}=\left\{f_{ll'-n}^{j-t_T}\right\}_{L\times L}$, the similarity measures of $f_{ll'-n}^{i-t_T}$ and $f_{ll'-n}^{j-t_T}$ is $sm_{ll'-n}^{ij-t_T}$, then the individual consensus between $d_i$ and other DMs in $t_T$ can be obtained as:

$$CD^{i-t_T}=\left(ex^{i-t_T},en^{i-t_T},he^{i-t_T}\right) \tag{21}$$

where $ex^{i-t_T}=\dfrac{1}{MNL(L-1)}\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}sm_{ll'-n}^{ij-t_T}$, $en^{i-t_T}=\dfrac{\sqrt{\pi/2}}{MNL(L-1)}\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}\left|sm_{ll'-n}^{ij-t_T}-ex^{i-t_T}\right|$,

$he^{i-t_T}=\sqrt{\dfrac{\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}\left(sm_{ll'-n}^{ij-t_T}-ex^{i-t_T}\right)^2}{MNL(L-1)-1}-\left(en^{i-t_T}\right)^2}$.

As a result, we obtain the individual consensus score value of $d_i$ in stage $t_T$ as:

$$sc\left(CD^{i-t_T}\right)=ex^{i-t_T}-\varepsilon\sqrt{\left(en^{i-t_T}\right)^2+\left(he^{i-t_T}\right)^2} \tag{22}$$

where $CD^{i-t_T}\in[0,1]$, $sc\left(CD^{i-t_T}\right)\in[0,1]$, $\varepsilon\in[0,1]$ is the scaling factor used to adjust the entropy and hyper-entropy weight.

When $sc\left(CD^{i-t_T}\right)\geq\gamma$, the consensus level of DM $d_i$ is high, $d_i$ does not need to adjust his/her preferences. All DMs with high consensus level form group $HC=\left\{d_i\left|sc\left(CD^{i-t_T}\right)\geq\gamma,d_i\in Dset\right.\right\}$. When $sc\left(CD^{i-t_T}\right)<\gamma$, the consensus level of DM $d_i$ is low, and he/she needs to adjust his preference to reach the group consensus. All DMs with low consensus level form group $LC=\left\{d_i\left|sc\left(CD^{i-t_T}\right)<\gamma,d_i\in Dset\right.\right\}$. Thus, $HC\cup LC=Dset$.

Based on DEFINITION 20 and Eq. (10), we obtain the group consensus in stage $t_T$ considering the fuzziness:

DEFINITION 21: If the individual consensus of DM $d_i$ in stage $t_T$ is $CD^{i-t_T}=\left(ex^{i-t_T},en^{i-t_T},he^{i-t_T}\right)$, then the group consensus in stage $t_T$ can be obtained as:

$$CM^G=\left(Ex^G,En^G,He^G\right) \tag{23}$$

where $Ex^G=\dfrac{1}{\sum_{d_i\in Dset}w_i}\sum_{d_i\in Dset}w_i ex^{i-t_T}$, $En^G=\dfrac{1}{\sqrt{\sum_{d_i\in Dset}w_i}}\sqrt{\sum_{d_i\in Dset}w_i\left(en^{i-t_T}\right)^2}$,

$He^G=\dfrac{1}{\sqrt{\sum_{d_i\in Dset}w_i}}\sqrt{\sum_{d_i\in Dset}w_i\left(he^{i-t_T}\right)^2}$, $w_i$ is the individual weight of DM $d_i$.

As a result, we obtain the group consensus score value in $t_T$ as:

$$sc\left(CM^G\right)=Ex^G-\varepsilon\sqrt{\left(En^G\right)^2+\left(He^G\right)^2} \tag{24}$$

where $CM^G\in[0,1]$, $sc\left(CM^G\right)\in[0,1]$, $\varepsilon\in[0,1]$.

### *4.2. Recommendation mechanism*

In large group decision-making, since DMs come from various fields, there may be differences in the understanding of alternative attributes, resulting in the summary results of evaluation values failing to meet most people's expectations. In order to obtain the consensus optimal decision-making alternative, DMs with low consensus often need to modify their preferences. In the case of retaining part of their own preferences, low-consensus DMs will absorb the preferences of people they trust and have a high degree of consensus, so that group decision-making can evolve towards consensus.

In multi-stage decision-making process, DMs in each stage can interact with each other, and such interaction may affect the evaluation value of DMs in next stage. However, DMs vary in the degree to which they are willing to be influenced by others' preferences. For DMs with low decision-making confidence, they will heavily draw on the opinions of trusted people in order to provide a more objective and recognized evaluation value. For DMs with greater confidence, they stick to their views and not be interfered by other people. In order to obtain the degree of DM's willingness to accept other people's opinions, we use the change of DM's preference in each stage to predict the influence degree of DM in the final stage.

We first identify the DMs with low individual consensus, and take the preference values of people they trust with high consensus as the evolution direction. Since the preference information of DMs evolves with the development of the decision-making process, the latest information is closer to the status quo of the program and has higher authenticity and credibility. Therefore, we then select the consensus degree in the last stage $t_T$ to determine the group consensus. We assume that the preference of DMs in each stage is influenced by other DMs in the previous stage, so as to obtain the influence degree and referenced preference.

DEFINITION 22 (influence degree (ID)): Let DMs be nodes in a social network $G=(V,E,W)$. The expectation of edge weights are $E\left(w_{ij}\right)=\sum_{k=1}^{2}h_{ij}^{k}\sigma_{ij}^{k}$ . Each DM gives decision preference $\{P_1,\cdots,P_m,\cdots,P_M\}$ to select the optimal alternative, $P_m=\left\{F_n^{m-t_\lambda}\right\}_{N\times T}$ , $F_n^{m-t_\lambda}=\left\{f_{ll'-n}^{m-t_\lambda}\right\}_{L\times L}$ $(l,l'=1,2,\cdots,L)$. Then, the influence degree $\theta_{ll'-n}^{i-t_\lambda}$ of $d_i$ in $t_\lambda$ stage satisfies the following formula:

$$f_{ll'-n}^{i-t_{\lambda+1}}=\theta_{ll'-n}^{i-t_\lambda}\sum_{j=1}^{M}E\left(w_{ij}\right)f_{ll'-n}^{j-t_\lambda}+\left(1-\theta_{ll'-n}^{i-t_\lambda}\right)f_{ll'-n}^{i-t_\lambda} \tag{25}$$

where, $\theta_{ll'-n}^{i-t_\lambda}\in[0,1]$ represents the $d_i$'s willingness to absorb the opinions of trust people in $t_\lambda$ stage $A_l$ related to $A_{l'}$ on $c_n$. When $\theta_{ll'-n}^{i-t_\lambda}=0$, $d_i$ is not influenced by other people, and only recognizes its own preferences. $\theta_{ll'-n}^{i-t_\lambda}=1$ means that $d_i$'s preference fully considers other people's opinions, and his/her own opinion in $t_{\lambda+1}$ stage have been covered up.

Since the preference value of each stage is known, according to Eq. (25), we can obtain the influence degree set $\theta set_{ll'-n}^{i} = \left\{\theta_{ll'-n}^{i-t_1}, \cdots, \theta_{ll'-n}^{i-t_\lambda}, \cdots, \theta_{ll'-n}^{i-t_{T-1}}\right\}$ of $d_i$ in stages set $T_{t-1} = \{t_1, \cdots, t_\lambda, \cdots, t_{T-1}\}$. Then, we use the linear least squares method to fit the influence degree set and partial stage set.

DEFINITION 23: If $\theta set_{ll'-n}^{i} = \left\{\theta_{ll'-n}^{i-t_1}, \cdots, \theta_{ll'-n}^{i-t_\lambda}, \cdots, \theta_{ll'-n}^{i-t_{T-1}}\right\}$ is the influence degree set of DM $d_i$ on the $c_n$ attribute $A_l$ related to $A_{l'}$, and $T_1 = \{t_1, \cdots, t_\lambda, \cdots, t_{T-1}\}$ is the partial stage set excluding the last stage $t_T$, then there exists a binary equation $y = a_{ll'-n}^{i} x + b_{ll'-n}^{i}$ satisfying

$$f\left(a_{ll'-n}^{i}, b_{ll'-n}^{i}\right) = \min \sum_{\lambda=1}^{T-1} \left[\theta_{ll'-n}^{i-t_\lambda} - \left(a_{ll'-n}^{i} \lambda + b_{ll'-n}^{i}\right)\right]^2 \tag{26}$$

In DEFINITION 23, $a_{ll'-n}^{i}$ can reflect the tendency of $d_i$'s preference being influenced. When $a_{ll'-n}^{i} > 0$, $y = a_{ll'-n}^{i} x + b_{ll'-n}^{i}$ is an increasing function, the influence degree of $d_i$ increases with the progress of the decision-making stage, i.e., $d_i$ is more inclined to listen to the opinions of others. When $a_{ll'-n}^{i} < 0$, $y = a_{ll'-n}^{i} x + b_{ll'-n}^{i}$ is a decreasing function, the influence degree decreases as the decision-making stage progresses, i.e., $d_i$ is less affected by other people and sticks to its own evaluation opinions.

DEFINITION 24: If $y = a_{ll'-n}^{i} x + b_{ll'-n}^{i}$ is the fitting function of influence degree set $\theta set_{ll'-n}^{i} = \left\{\theta_{ll'-n}^{i-t_1}, \cdots, \theta_{ll'-n}^{i-t_\lambda}, \cdots, \theta_{ll'-n}^{i-t_{T-1}}\right\}$ and stage set $T_1 = \{t_1, \cdots, t_\lambda, \cdots, t_{T-1}\}$, then the influence degree of $d_i$ in the final stage $t_T$ is calculated as $\theta_{ll'-n}^{i-t_T} = a_{ll'-n}^{i} T + b_{ll'-n}^{i}$, and the referenced preference of $d_i$ is defined as

$$f_{ll'-n}^{i-re} = \theta_{ll'-n}^{i-t_T} \sum_{d_j \in N_i \cap G_i} E\left(w_{ij}\right) c_j^{*} f_{ll'-n}^{j-t_T} + \left(1 - \theta_{ll'-n}^{i-t_T}\right) f_{ll'-n}^{i-t_T} \tag{27}$$

where $c_j^{*} = \begin{cases} 1, & sc\left(CD^{j-t_T}\right) \geq \gamma \\ 0, & else \end{cases}$, $N_i$ is the set of DMs trusted by $d_i$, $G_i$ is the subgroup to which $d_i$ belongs, $N_i \cap G_i$ is the set of DMs trusted by $d_i$ in the same subgroup as $d_i$. $c_j^{*}$ and $N_i$ can effectively control the evolution of referenced preference toward consensus.

### *4.3. Herding behavior classification and modification model*

In fact, the identification of herd behavior is a complex process. DMs with herd behavior generally have the above three characteristics, and DMs who do not possess or cannot recognize some of these characteristics due to objective conditions may also have herding behavior. Therefore, we divide groups into three categories according to the above three characteristics: strong herding group (SG), weak herding group (WG) and no herding group (NG).

When $A^{iq*} > 0$, $R_i < 0$, $Ntd_i > 0$, i.e., all the three characteristics mentioned above are met, the DM shows obvious herd behavior, so it is classified as a strong herding group: $SG = \left\{d_i \middle| A^{iq*} > 0, R_i < 0, Ntd_i > 0\right\}$. When $A^{iq*} \leq 0$, $R_i \geq 0$, $Ntd_i \leq 0$, i.e., the above three characteristics are not satisfied, the DM does not exhibit herding behavior, so it is classified as a no herding group: $NG=\left\{d_i \middle| A^{iq*}\le 0, R_i \ge 0, Ntd_i \le 0\right\}$. When $A^{iq*}>0$, $R_i<0$, $Ntd_i \le 0$, or $A^{iq*}\le 0$, $R_i<0$, $Ntd_i>0$, or $A^{iq*}>0$, $R_i \ge 0$, $Ntd_i>0$, or $A^{iq*}>0$, $R_i \ge 0$, $Ntd_i \le 0$, or $A^{iq*}\le 0$, $R_i<0$, $Ntd_i \le 0$, or $A^{iq*}\le 0$, $R_i \ge 0$, $Ntd_i>0$, i.e., when no more than two or no less than one condition is met, the DM shows a certain degree of herding, so it is classified as a weak herding group: $WG = Dset - SNG$ $\left(SNG = SG \cup NG\right)$.

Based on the classification of DMs with different degrees of herding behavior, we design feedback adjustment strategies for low-consensus DMs. For DMs with strong herding behavior, when they realize that their individual consensus level is low, they tend to listen to the opinions of trusted DMs with high consensus for a more scientific decision-making process. Their preference adjustment willingness is high, and their individual willingness favors achieving group consensus. Thus, we will look for the modified preferences of low-consensus DMs with strong herding behavior closer to the referenced preference. For the low-consensus DMs without herding behavior, they would rather retain their own preference than help to pass the consensus threshold. Their willingness to adjust their preferences is low, and their individual willingness tends to retain the original preferences. Thus, we will look for the modified preference of the low-consensus DM without herding behavior closer to the original preference.

Since the change of preference will generate a modification cost, we tend to model the minimum distance between the modified preferences and referenced preferences of low-consensus DMs with strong herding behavior or between the modified preferences and original preferences of low-consensus DMs without herding behavior, to minimize the modification cost. Both objectives try to find the minimum value, so we merge them into one objective function. We first combine the individual consensus level to extract DM who meet the following classification conditions: low-consensus DMs with strong herding behavior $SGL=\left\{d_i \middle| d_i \in SG \cap LC\right\}$, low-consensus DMs with weak herding behavior $WGL=\left\{d_i \middle| d_i \in WG \cap LC\right\}$, and low-consensus DMs without herding behavior $NGL=\left\{d_i \middle| d_i \in NG \cap LC\right\}$. Then, we build the following modification model (Model (28)) to obtain the modified preferences of DMs whose consensus degree does not reach the threshold in the strong herding group and the no herding group. Since the most recent preference information is the closest to the rational preference and the status quo of the alternatives, we only use the original preferences in the final stage $t_T$. In the initial state, each DM contributes equally to the group consensus, so we set $w_i = 1$.

$$f\left(y_{ll'-n}^{v}, y_{ll'-n}^{k}\right)=\min\left(\sum_{d_v\in SGL}\left|f_{ll'-n}^{v-re}-y_{ll'-n}^{v}\right|+\sum_{d_k\in NGL}\left|f_{ll'-n}^{k-t_T}-y_{ll'-n}^{k}\right|\right)$$

$$s.t.\begin{cases}
Ex^{y}-\varepsilon\sqrt{\left(En^{y}\right)^{2}+\left(He^{y}\right)^{2}}\geq\gamma & (28-1)\\
Ex^{y}=\dfrac{1}{\sum_{d_i\in SNG}w_i}\sum_{d_i\in SNG}w_i ex^{i-y} & (28-2)\\
En^{y}=\dfrac{1}{\sqrt{\sum_{d_i\in SNG}w_i}}\sqrt{\sum_{d_i\in SNG}w_i\left(en^{i-y}\right)^{2}} & (28-3)\\
He^{y}=\dfrac{1}{\sqrt{\sum_{d_i\in SNG}w_i}}\sqrt{\sum_{d_i\in SNG}w_i\left(he^{i-y}\right)^{2}} & (28-4)\\
ex^{i-y}=\dfrac{1}{MNL\left(L-1\right)}\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}sm_{ll'-n}^{ij-y} & (28-5)\\
en^{i-y}=\dfrac{\sqrt{\pi/2}}{MNL\left(L-1\right)}\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}\left|sm_{ll'-n}^{ij-y}-ex^{i-y}\right| & (28-6)\\
he^{i-y}=\sqrt{\dfrac{\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}\left(sm_{ll'-n}^{ij-y}-ex^{i-y}\right)^{2}}{MNL\left(L-1\right)-1}-\left(en^{i-y}\right)^{2}} & (28-7)\\
sm_{ll'-n}^{ij-y}=1-\left|f_{ll'-n}^{i-y}-f_{ll'-n}^{j-y}\right| & (28-8)\\
f_{ll'-n}^{i-y}=\begin{cases}y_{ll'-n}^{i}, & d_i\in SGL\cup NGL\\ f_{ll'-n}^{i-t_T}, & d_i\in SNG\setminus\left(SGL\cup NGL\right)\end{cases} & (28-9)\\
f_{ll'-n}^{j-y}=\begin{cases}y_{ll'-n}^{j}, & d_j\in SGL\cup NGL\\ f_{ll'-n}^{j-t_T}, & d_j\in SNG\setminus\left(SGL\cup NGL\right)\end{cases} & (28-10)\\
y_{ll'-n}^{v}\in\left[\min\left(f_{ll'-n}^{v-re}, f_{ll'-n}^{v-t_T}\right),\max\left(f_{ll'-n}^{v-re}, f_{ll'-n}^{v-t_T}\right)\right] & (28-11)\\
y_{ll'-n}^{k}\in\left[\min\left(f_{ll'-n}^{k-re}, f_{ll'-n}^{k-t_T}\right),\max\left(f_{ll'-n}^{k-re}, f_{ll'-n}^{k-t_T}\right)\right] & (28-12)\\
w_i=1 & (28-13)
\end{cases}\qquad(28)$$

The goal of the modification model is to minimize the modification cost while considering the individual willingness of low-consensus DM with strong herd behavior or without herd behavior. The decision variables are the modified preferences $y_{ll'-n}^{v}$, $y_{ll'-n}^{k}$ $\left(d_v\in SGL, d_k\in NGL\right)$. For $d_v\in SGL$, as low-consensus DMs with strong herding behavior, they are willing to accept the opinions of others to reach a consensus, so the feedback strategy is to modify the preference as close as possible to the referenced preference $f_{ll'-n}^{v-re}$. For $d_k\in NGL$, as low-consensus DMs who do not have herding behavior, they are more inclined to retain their original preferences to the greatest extent, so the feedback strategy is to modify the preference as close as possible to the original preference $f_{ll'-n}^{k-t_T}$ in the final stage. We first retrieve the preference similarity (condition (28-8)) between DMs with strong herding behavior and no herding behavior based on the modified preferences of DMs (conditions (28-9) and (28-10)). Then, we use the cloud model to gather the preference similarities between DMs in strong herding group and no herding group, and obtain the individual consensus degrees of DMs in these group (conditions (28-5)- (28-7)). Based on this, according to Eq. (10), we gather the individual consensus of DMs in the strong herding group and no herding group to obtain the group consensus cloud model of the combined set of strong herding group and no herding group (conditions (28-2)- (28-4)). Condition (28-1) means that the group consensus scores of the combined set need to be greater than the consensus threshold. Conditions (28-11) and (28-12) mean that the modified preference should be in the range between the referenced preference and the original preference. Condition (28-13) is the setting of related parameters.

The modification model is a single-objective nonlinear programming model. Conditions (28-2)- (28-10) are the derivation formula of condition (28-1), and condition (28-1) is the group consensus threshold limit. The conditions (28-11)- (28-12) are the boundary limits of decision variables. According to the extension of Weierstrass' theorem, the feasible region is non-empty and bounded and the objective function is lower semicontinuous, so Model (28) has an optimal solution [53].

### *4.4. Punishment model*

After solving the above modification model, we obtain the modified preferences of DMs in the strong herding group and the no herding group that meet the consensus threshold. At this time, the new preference of DMs $d_i$ in decision-making group can be expressed as $f_{ll'-n}^{i-New} = \begin{cases} y_{ll'-n}^{i}, & d_i \in SGL \cup NGL \\ f_{ll'-n}^{i-t_T}, & d_i \in Dset \setminus (SGL \cup NGL) \end{cases}$, and the new individual consensus of DMs are defined as:

DEFINITION 25: If the new similarity between $d_i$ and $d_j$ on the attribute $c_n$ of $A_l$ related to $A_{l'}$ is $sm_{ll'-n}^{ij-New} = 1 - \left| f_{ll'-n}^{i-New} - f_{ll'-n}^{j-New} \right|$, where $f_{ll'-n}^{i-New} = \begin{cases} y_{ll'-n}^{i}, & d_i \in SGL \cup NGL \\ f_{ll'-n}^{i-t_T}, & d_i \in Dset \setminus (SGL \cup NGL) \end{cases}$, $f_{ll'-n}^{j-New} = \begin{cases} y_{ll'-n}^{j}, & d_j \in SGL \cup NGL \\ f_{ll'-n}^{j-t_T}, & d_j \in Dset \setminus (SGL \cup NGL) \end{cases}$, then the new individual consensus between $d_i$ and other DMs can be obtained as:

$$CD^{i-New} = \left( ex^{i-New}, en^{i-New}, he^{i-New} \right) \tag{29}$$

where $ex^{i-New} = \dfrac{1}{MNL(L-1)} \sum_{j=1}^{M} \sum_{l=1}^{L} \sum_{l'=1, l' \neq l}^{L} \sum_{n=1}^{N} sm_{ll'-n}^{ij-New}$,

$$en^{i-New} = \frac{\sqrt{\pi/2}}{MNL(L-1)} \sum_{j=1}^{M} \sum_{l=1}^{L} \sum_{l'=1, l' \neq l}^{L} \sum_{n=1}^{N} \left| sm_{ll'-n}^{ij-New} - ex^{i-New} \right|,$$

$$he^{i-New} = \sqrt{ \frac{ \sum_{j=1}^{M} \sum_{l=1}^{L} \sum_{l'=1, l' \neq l}^{L} \sum_{n=1}^{N} \left( sm_{ll'-n}^{ij-New} - ex^{i-New} \right)^2 }{ MNL(L-1) - 1 } - \left( en^{i-New} \right)^2 }.$$

From above, we obtain the new individual consensus score value as:

$$sc\left( CD^{i-New} \right) = ex^{i-New} - \varepsilon \sqrt{ \left( en^{i-New} \right)^2 + \left( he^{i-New} \right)^2 } \tag{30}$$

Based on the new individual consensus, we can calculate the new group consensus by Eq. (10):

DEFINITION 26: If the new individual consensus of DM $d_i$ is $CD^{i-New} = \left( ex^{i-New}, en^{i-New}, he^{i-New} \right)$, then the new group consensus can be obtained as:

$$CM^{G-1} = \left( Ex^{G-1}, En^{G-1}, He^{G-1} \right) \tag{31}$$

where $Ex^{G-1} = \frac{1}{\sum_{d_i \in Dset} w_i} \sum_{d_i \in Dset} w_i ex^{i-New}$, $En^{G-1} = \frac{1}{\sqrt{\sum_{d_i \in Dset} w_i}} \sqrt{\sum_{d_i \in Dset} w_i \left(en^{i-New}\right)^2}$, $He^{G-1} = \frac{1}{\sqrt{\sum_{d_i \in Dset} w_i}} \sqrt{\sum_{d_i \in Dset} w_i \left(he^{i-New}\right)^2}$, $w_i$ is the individual weight of DM $d_i$.

As a result, we obtain the new group consensus score value as:

$$sc\left(CM^{G-1}\right) = Ex^{G-1} - \varepsilon\sqrt{\left(En^{G-1}\right)^2 + \left(He^{G-1}\right)^2} \tag{32}$$

where $CM^{G-1} \in [0,1]$, $sc\left(CD^{G-1}\right) \in [0,1]$, $\varepsilon \in [0,1]$.

After the modification model optimizes the preferences of low-consensus DMs in strong herding group and no herding group, if the group consensus fails to pass the threshold, then we will take the optimization for the weak herding group. Low-consensus DMs with weak herding behavior have a willingness to adjust their preferences that is intermediate between strong herding and no herding groups, and thus they are willing to pay some price for consensus achievement. However, we can only infer that low-consensus DMs with weak herding behavior have an individual willingness to reach group consensus, but we cannot know the direction of their preference adjustment, and thus we cannot build the modification model for them. In addition, the weak herding group is a large group with intermediate willingness. If we try to obtain their specific preference adjustment willingness through other in-depth methods, it will lead to huge time investment cost and preference modification cost.

Based on the above considerations, we propose a method of weight punishment by giving lower weights to low-consensus DMs with weak herding behavior. We construct the punishment model (Model (33)) to set the minimum consensus level that satisfies the threshold limit, and optimize the individual weights of the low-consensus DMs in weak herding group.

The goal of punishment model is to minimize the consensus level satisfying the threshold limit. The decision variables are weights $\{\iota_1, \cdots, \iota_i, \cdots\}$ of DMs in $WGL$. We first update the group preference values (conditions (33-9) and (33-10)) according to the modified preferences obtained in modification model, so as to retrieve the preference similarity among all DMs (condition (33-8)). Then, we aggregate the preference similarities between DMs in a cloud model to obtain individual consensus (conditions (33-5)- (33-7)). Based on this, we gather the individual consensus of all DMs according to Eq. (10), and obtain the consensus degree cloud model of the decision-making group (conditions (33-2)- (33-4)). Condition (33-1) means that the consensus score of the decision-making group needs to be greater than the consensus threshold. Condition (33-11) sets the weight of the weak herding group as the decision variable. Condition (33-12) is the prior information of the decision variable.

Punishment model is a single-objective nonlinear programming model. If the feasible region is non-empty and bounded, then model must have an optimal solution [53]. In the Model (33), conditions (33-2)- (33-10) are the derivation formula of conditions 1, and conditions 1 is the group consensus threshold limit. The conditions (33-11)- (33-12) are the settings and boundary conditions of decision variables. For Model (33), the feasible region formed is non-empty and bounded, model has an optimal solution.

We continue the 9-person decision-making group mentioned in Example 1 in Section 3.4, and show the proposed consensus reaching process in Example 2 and Figure 2.

$$f\left(\iota_i\right)=\min\left(Ex^{New}-\varepsilon\sqrt{\left(En^{New}\right)^2+\left(He^{New}\right)^2}\right)$$

$$s.t.\begin{cases}
Ex^{New}-\varepsilon\sqrt{\left(En^{New}\right)^2+\left(He^{New}\right)^2}\geq\gamma & (33-1)\\
Ex^{New}=\dfrac{1}{\sum_{d_i\in Dset}w_i^{New}}\sum_{d_i\in Dset}w_i^{New}ex^{i-New} & (33-2)\\
En^{New}=\dfrac{1}{\sqrt{\sum_{d_i\in Dset}w_i^{New}}}\sqrt{\sum_{d_i\in Dset}w_i^{New}\left(en^{i-New}\right)^2} & (33-3)\\
He^{New}=\dfrac{1}{\sqrt{\sum_{d_i\in Dset}w_i^{New}}}\sqrt{\sum_{d_i\in Dset}w_i^{New}\left(he^{i-New}\right)^2} & (33-4)\\
ex^{i-New}=\dfrac{1}{MNL(L-1)}\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}sm_{ll'-n}^{ij-New} & (33-5)\\
en^{i-New}=\dfrac{\sqrt{\pi/2}}{MNL\left(L-1\right)}\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}\left|sm_{ll'-n}^{ij-New}-ex^{i-New}\right| & (33-6)\\
he^{i-New}=\sqrt{\dfrac{\sum_{j=1}^{M}\sum_{l=1}^{L}\sum_{l'=1,l'\neq l}^{L}\sum_{n=1}^{N}\left(sm_{ll'-n}^{ij-New}-ex^{i-New}\right)^2}{MNL\left(L-1\right)-1}-\left(en^{i-New}\right)^2} & (33-7)\\
sm_{ll'-n}^{ij-New}==1-\left|f_{ll'-n}^{i-New}-f_{ll'-n}^{j-New}\right| & (33-8)\\
f_{ll'-n}^{i-New}=\begin{cases}y_{ll'-n}^{i}, & d_i\in SGL\cup NGL\\ f_{ll'-n}^{i-t_T}, & d_i\in Dset\setminus\left(SGL\cup NGL\right)\end{cases} & (33-9)\\
f_{ll'-n}^{j-New}=\begin{cases}y_{ll'-n}^{j}, & d_j\in SGL\cup NGL\\ f_{ll'-n}^{j-t_T}, & d_j\in Dset\setminus\left(SGL\cup NGL\right)\end{cases} & (33-10)\\
w_i^{New}=\begin{cases}\iota_i, & d_i\in WGL\\ 1, & else\end{cases} & (33-11)\\
\iota_i\in\left[0,1\right] & (33-12)
\end{cases}\qquad(33)$$

EXAMPLE 2: In Figure 2, it is assumed that DM $d_2$ and $d_9$ have strong herding behavior in stage $t_T$, $d_2$ has high consensus and $d_9$ has low consensus. The classification of other DMs is shown in "Classification of DMs". Through the Preference modify of the modification model, $d_9$ is optimized for high consensus, while $d_6$ is not optimized for high consensus. This can be understood in the way that not all low-consensus DMs in $SNG$ need to pass the consensus threshold level, as long as $sc\left(CM^{SNG}\right)\geq\gamma$ is satisfied. At this time, the consensus level of the entire decision-making group has not exceeded the threshold. Thus, we perform the punishment model process to optimize the weight of the low-consensus DM in $WG$ so that the group consensus passed the threshold.

From the demonstration and analysis of the CRP in EXAMPLE 2, we find that the modification model minimizes the preference adjustment cost of low-consensus DMs in $SNG$. The punishment model minimizes the cost of weight adjustment for low-consensus groups in $WG$. The adjustment costs of the two models do not interfere with each other, achieving a targeted adjustment process.

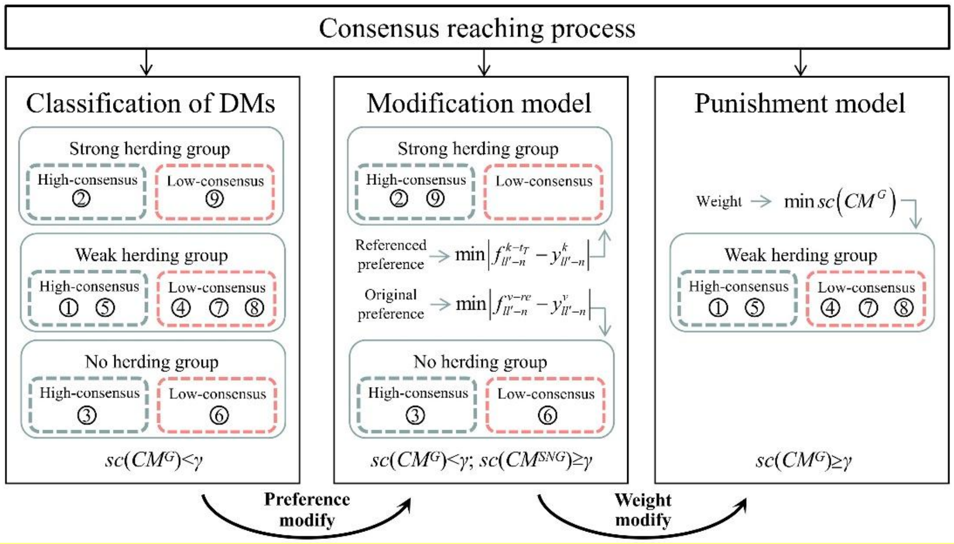


Figure 2. The consensus reaching process with 9 DMs

## 5. The main procedures for the multistage large scale group decision making method

In a MSLGDM system, the social network formed by the cooperative relationship between DMs evolves with the decision-making stage, and the derived herding behavior will affect the degree of consensus and decision-making results. In order to use herding behavior to improve the degree of group consensus, we propose a method that describes three characteristics of herding behavior, i.e., information gradient propagation, risk aversion, and authority obedience, to identify and classify the low-consensus DMs with varying degree of herding behavior. Based on this, we propose different feedback adjustment strategies for different types of low-consensus DMs. The decision-making steps of the proposed method are:

**Step 1:** Determination of OL in each subgroup. We cluster the decision-making groups by EMCDA algorithm, and identify the OLs of each subgroup based on the extended DIL.

**Step 2:** Identification of information gradient propagation characteristics. We fit the preference similarity sets and the stage sets by linear least squares method, and obtain the fitting linear functions. We use the gradients of linear functions to judge whether the DMs have the characteristics of information gradient propagation.

**Step 3:** Identification of risk aversion characteristics. We calculate the RIs, RRIs, and CRIs of DMs, and judge whether the DMs have the characteristics of risk aversion.

**Step 4:** Identification of authority obedience characteristics. We calculate the NTVs and NTDs of DMs, and judge whether the DMs have the characteristics of authority obedience.

**Step 5:** Classification of DMs with herding behavior. According to whether DMs satisfy the three characteristics of herding behavior, we divide decision-making groups into strong herding group, weak herding group and no herding group.

**Step 6:** Acquisition of individual consensus. According to the formulas Eq. (21) and Eq. (22), we obtain the individual consensus DMs, and divide them into high consensus group and low consensus group. Then we calculate the group consensus by the formulas Eq. (23) and Eq. (24).

**Step 7:** Classification of low-consensus DMs with herding behavior. Combined with the measurement of individual consensus in Step 6, we extract DMs with strong herding behavior, weak herding behavior and no herding behavior among the low-consensus DMs.

**Step 8:** Aggregation of influence degree and acquisition of referenced preference. We used the least squares method to obtained the influenced degree of DMs in the final stage. Then, we calculate the referenced preferences of the low-consensus DMs according to the influence degree.

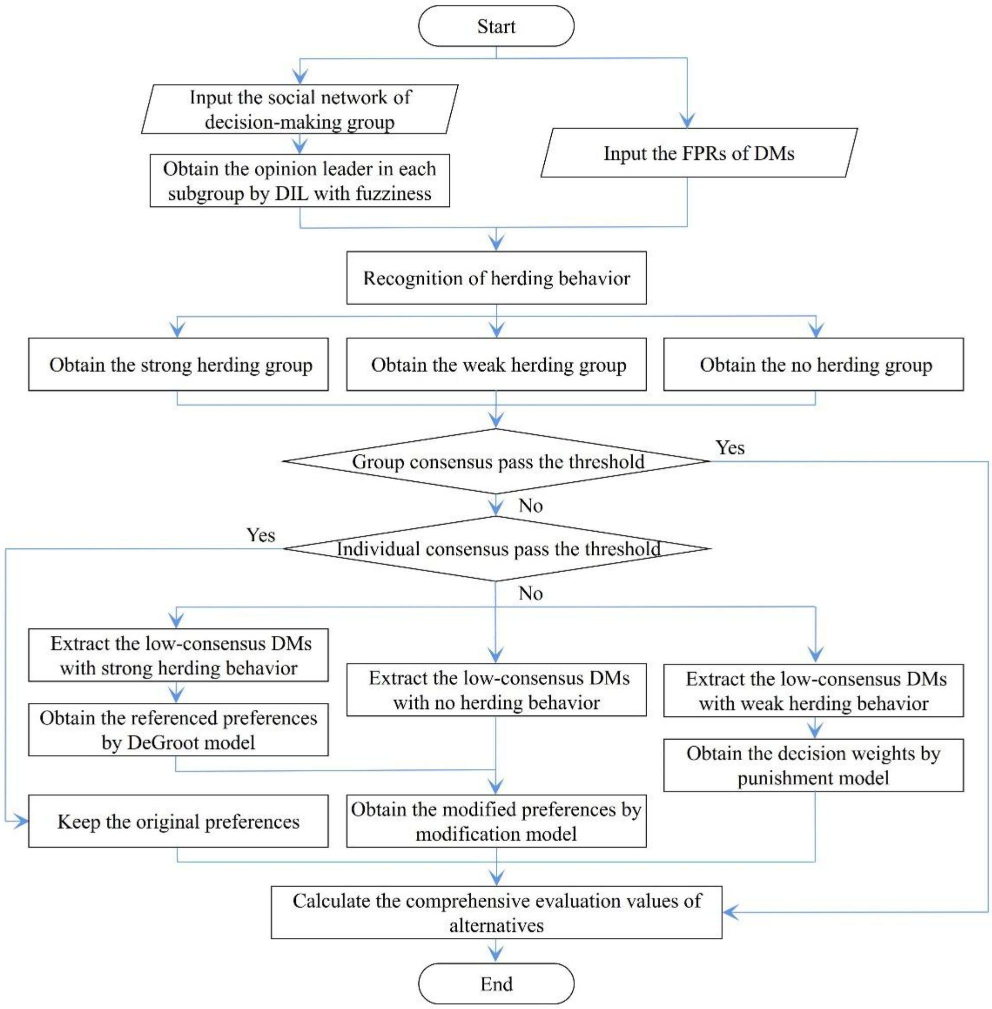


Figure 3. The general framework of the proposed MSLGDM model

**Step 9:** Construction of modification model and acquisition of modified preferences. Based on the classification of low-consensus DMs with varying degree of herding behavior in Step 7, we establish a modification model to obtain the modified preferences of low-consensus DMs in strong herding group and no herding behavior.

**Step 10:** Construction of punishment model and alternative selection. We establish a punishment model to optimize the decision weights of low-consensus DMs with weak herding behavior. Based on the modified preferences optimized by the modification model and the individual weights optimized by the punishment model, we gather preference information and obtain decision results.

We first obtain the evaluation information of each DM after attribute aggregation as:

$$y_{ll'}^{i} = \sum_{n=1}^{N} \omega_n f_{ll'-n}^{i-New} \tag{34}$$

where $f_{ll'-n}^{i-New} = \begin{cases} y_{ll'-n}^{i}, & d_i \in SGL \cup NGL \\ f_{ll'-n}^{i-t_T}, & d_i \in Dset \setminus \left(SGL \cup NGL\right) \end{cases}$. Then we gather the evaluation information of each

DM on each alternative as:

$$y_l^i = \sum_{\substack{l'=1 \\ l' \neq l}}^{L} y_{ll'}^i \tag{35}$$

Finally, we gather the evaluation values of the DMs for the alternatives based on individual weights to obtain the comprehensive evaluation value of each alternative:

$$P(A_l) = \frac{1}{\sum_{d_i \in Dset} w_i^{New}} \sum_{d_i \in Dset} w_i^{New} y_l^i \tag{36}$$

where $w_i^{New} = \begin{cases} \iota_i, & d_i \in WGL \\ 1, & else \end{cases}$.

We sort the comprehensive evaluation values of the alternatives according to Eq. (36) and select the optimal alternative.

According to the above decision-making steps, we draw the decision-making framework as shown in Figure 3.

## 6. Illustrative example

In order to show the application of the proposed MSLGDM method, the selection of emergency power generation methods during the energy crisis in Spain is implemented in this section, followed with some sensitivity analysis and comparative analysis.

### *6.1. Example description*

Affected by epidemic disasters and geopolitical factors, Europe experienced an energy crisis in June 2022, which continues up to now. It has disrupted the economic and social development of Europe, not only tested the EU's political unity and rescue ability, but also had a direct impact on China-EU economic and trade cooperation. The European energy crisis has frustrated the process of carbon neutrality in Europe, and energy transition has given way to energy security. In response to the energy crisis, the European Commission has adopted a series of measures such as increasing natural gas reserves, promoting energy conservation, and finding alternatives to natural gas, making maintaining European energy security a top priority. Some countries in Europe have restarted once-shuttered fossil-fuel power plants in response to the crisis. But Spanish Prime Minister Pedro Sánchez Pérez-Castejón insisted that European countries should not stop their efforts to transition to clean energy.

At present, the emergency power generation methods adopted to deal with the energy crisis mainly include: renewable energy power generation ($A_1$), fossil fuel power generation ($A_2$), nuclear power generation ($A_3$) and imported liquefied natural gas power generation ($A_4$). In order to adjust the emergency power generation measures in time according to the current energy crisis, based on the MSLGDM method proposed in this paper, we evaluate the corresponding attributes of the above-mentioned power generation alternatives in different natural gas energy crisis stages, so as to dynamically predict the energy crisis response strategies in the near future. We invited 200 people including experts in intelligent decision-making and environmental engineering, relevant staff of the Spanish government, senior managers of natural gas power plants, managers of former fossil fuel power plants, and managers of new energy power plants. We requested all the experts to score the relevant attributes of power generation alternatives on a monthly basis from July 2022 to February 2023 (8 stages $T=\{t_1,t_2,\cdots,t_8\}$ in total), to obtain the evaluation information of experts in different crisis periods. The decision-making information was summarized in March 2023, so that the optimal power generation plan for the period from March to April can be obtained. We select six attributes including unit construction cost ($C_1$), operation and management cost ($C_2$), technology development cost ($C_3$), environmental protection degree ($C_4$), resource adequacy degree ($C_5$) and emergency power generation benefit ($C_6$) to evaluate the above alternatives. Their weights are $\tilde{\omega}=\{0.15,0.2,0.2,0.15,0.1,0.2\}$ respectively.

At the same time, in these 8 stages, DMs also evaluate each other's cooperative relationship with linguistic variables $H=\{h^0,h^1,h^2,h^3,h^4,h^5,h^6\}$, where $h^0=extremelylow$, $h^1=slightlylow$, $h^2=low$, $h^3=medium$, $h^4=high$, $h^5=slightlyhigh$, $h^6=extremelyhigh$, among which the numerical value corresponding to the linguistic variables is $H=\{1,2,3,4,5,6,7\}$. The social network formed by DMs based on cooperative relations is shown in Figure 4. There are 991 edges in Figure 4, and each node in the social network has at least one edge connected to it, reflecting the strong linkages among DMs.

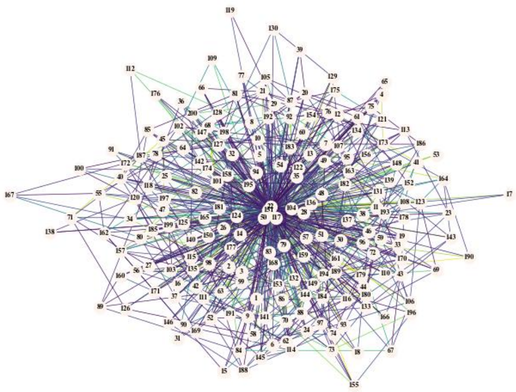

Figure 4. The social network among DMs

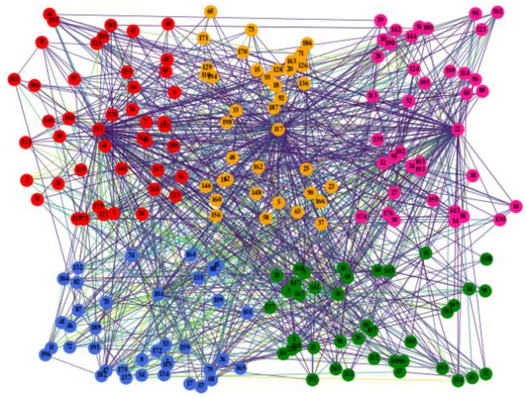

Figure 5. The subgroups of social network

The energy crisis situation is constantly changing with the development of the external environment. Under different energy crisis stages, power generation strategies also have different optimal choices. Therefore, the decision-making model proposed in this paper is suitable for dynamic and changeable power generation strategy selection problems. In the decision-making of such a major strategic issue as energy selection, it is necessary to gather the wisdom, knowledge and experience of experts in many related fields to ensure the soundness and accuracy of the decision-making results. Therefore, the interactive relationship between experts and their derivative behavior in multi-stage large group decision-making is an important research content that cannot be ignored in the decision-making process. Based on the social network relationship, the MSLGDM method proposed in this paper explores the interactive relationship between experts and its derived behavior - herding behavior, and studies its impact on the decision-making process and the assembly result. Therefore, the MSLGDM method proposed in this paper is suitable for dynamic, complex and changeable major strategic decision-making problems.

### *6.2. Select the best alternative*

We use Gurobi 9.5.0 (win64) to solve the decision-making problem in the example and verify the proposed MSLGDM method. The specific steps are as follows:

**Step 1:** Determination of OL in each subgroup. Through the EMCDA algorithm $(\eta = 1)$, we cluster the decision-making groups in Figure 4, and obtain the distribution of subgroups as shown in Figure 5. It can be seen from Figure 5 that the decision-making group is divided into five subgroups $G_1 = \{45 \text{ experts}\}$, $G_2 = \{40 \text{ experts}\}$, $G_3 = \{39 \text{ experts}\}$, $G_4 = \{38 \text{ experts}\}$, $G_5 = \{38 \text{ experts}\}$, which are represented by five different colors. The size of the five subgroups is similar, indicating that the selection of DMs is relatively balanced, without focusing on a certain group of people, and the decision results will be more objective and soundness. Then, we identify OLs in each subgroup according to the importance of nodes as: $d_1^* = d_{151}$, $d_2^* = d_{50}$, $d_3^* = d_{22}$, $d_4^* = d_{104}$, $d_5^* = d_{117}$.

**Step 2:** Identification of information gradient propagation characteristics. We first obtain the preference similarity between DMs and OLs of their subgroups at each stage by Eq. (2). Then, we extract the preference similarity sets between DMs and OLs at all stages on different attributes of $A_l$ relative to $A_{l'}$ as $SMS_{ll'-n}^{iq*} = \left\{ sm_{ll'-n}^{iq*-t_1}, \cdots, sm_{ll'-n}^{iq*-t_\lambda}, \cdots, sm_{ll'-n}^{iq*-t_T} \right\}$, and fit them with the stage set $T = \{t_1, \cdots, t_\lambda, \cdots, t_T\}$ by the linear least square method. The gradient of the obtained fitting function is aggregated on the attribute dimension according to Eq. (15), with the result shown in Figure 6.

As shown in Figure 6, the preferences of $130$ DMs gradually approached the preferences of the OLs. The preference of $70$ DMs gradually moved away from their OLs. Among them, the comprehensive gradients of DMs $d_{61}$, $d_{124}$ and $d_{141}$ all exceed $0.80$, indicating that they satisfy the gradient propagation characteristics of information to a large extent. The comprehensive preference gradients of DMs $d_6$, $d_{135}$ and $d_{184}$ are lower than $-0.70$, indicating that they hardly have the gradient propagation of information. The number of DMs who prefer to be close to OLs is greater than the number of DMs who prefer to be far away from OLs, indicating that most people satisfy the information gradient propagation characteristics in the decision-making process.

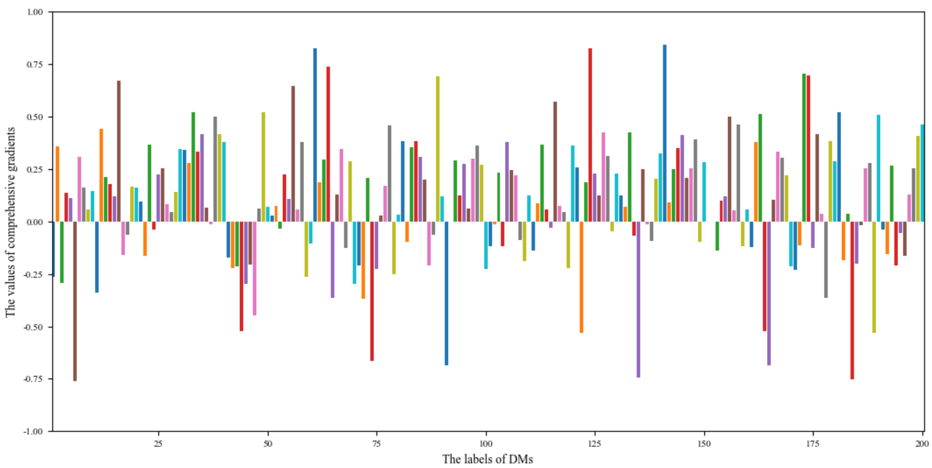


Figure 6. The comprehensive gradients between DMs and the OLs

**Step 3:** Identification of risk aversion characteristics. We first obtain the RI of the DM relative to the neighbor nodes in the same subgroup on attribute $c_n$ of $A_l$ relative to $A_{l'}$ according to the formula Eq. (16). Then we aggregate the RI to obtain the RRI by Eq. (17). Finally, we aggregate the relative risk index with the use of Eq. (18) to determine CRI of DMs relative to their subgroups, and the results are shown in Figure 7.

From Figure 7, we can observe that $126$ experts have more aggressive scoring preferences than other experts in their subgroup, indicating that these $126$ experts have risk-seeking characteristics. The other $74$ experts had scoring preferences that were more conservative than the experts in the subgroup to which they belong. Therefore, these $74$ experts have risk aversion characteristics. Among them, the risk factor value of $d_{49}$ exceeds $0.80$, which is more risk-seeking. The risk factor value of $d_{181}$ is lower than $-0.60$, which has a greater degree of risk aversion characteristics. From the above analysis, it can be seen that the number of DMs with risk-seeking characteristics is greater than that with risk-avoiding characteristics, indicating that most people in the decision-making group score more aggressively and have more confidence in the performance of alternative attributes.

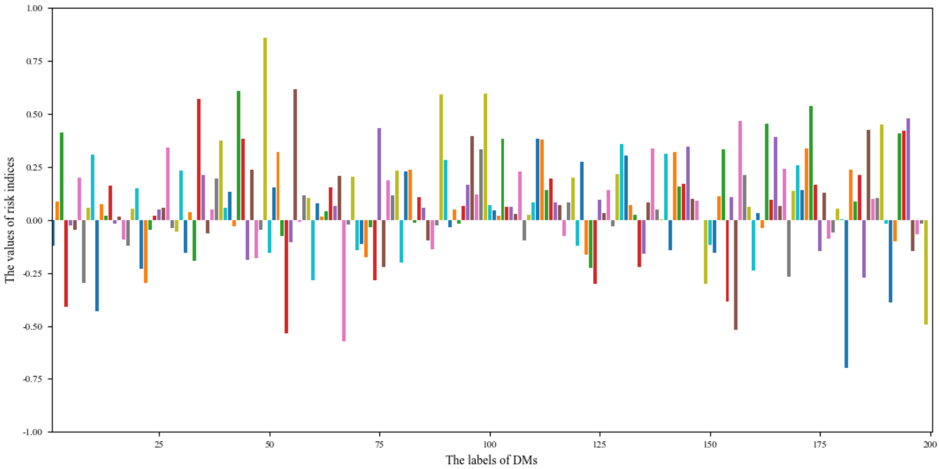


Figure 7. Comprehensive risk index of DMs relative to their subgroups

**Step 4:** Identification of authority obedience characteristics. According to the defined net gap of trust degree, we obtain the authoritative evaluation $Ntv_{ij}$ of DMs on their neighbor nodes. Then, according to Eq. (20), we gather the authoritative evaluation values of the DMs on the neighbor nodes belonging to the same subgroup to obtain the authoritative evaluation $Ntd_i$ of the DMs related to the subgroup to which they belong. The results are shown in Figure 8.

As it can be seen from Figure 8, there are $130$ DMs with a positive net trust value related to their subgroup, indicating that these $130$ DMs have the characteristics of authoritative obedience to their subgroup. At the same time, there are $70$ DMs with a negative net trust value relative to their subgroup, indicating that these $70$ DMs do not have the characteristics of authoritative obedience to their subgroups. Among them, the net trust degree of $d_{42}$, $d_{57}$, $d_{64}$ and $d_{77}$ related to their subgroups are all greater than $0.80$, indicating that these experts have strong authority obedience characteristics. The net trust degree of $d_{166}$ and $d_{174}$ related to the subgroup they belong to is lower than $-0.60$, indicating that these two experts have weaker authority obedience characteristics. Overall, the number of DMs with authority obedience characteristics is greater than those without authority obedience characteristics.

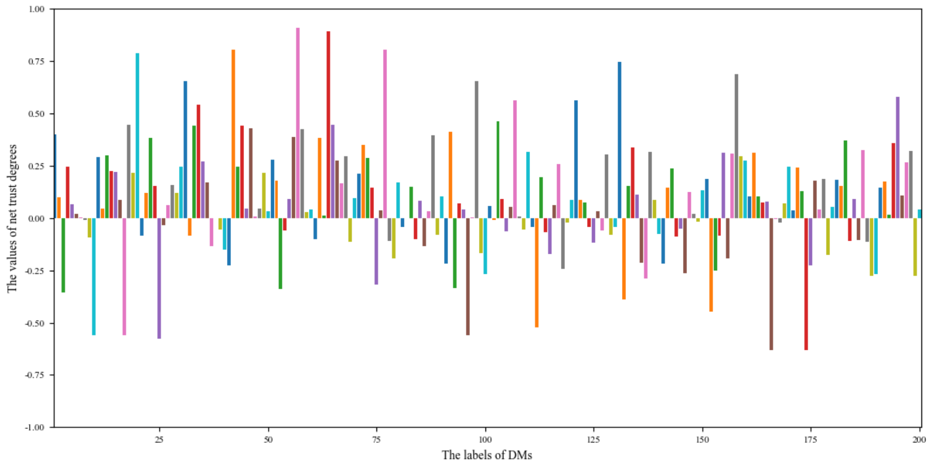


Figure 8. Net trust degree of DMs relative to their subgroups

**Step 5:** Classification of DMs with herding behavior. By combining the identification results of Step 2-Step 4, we can identify DMs with herd behavior in the decision-making group. According to whether the DMs have the above behavioral characteristics, we divide the decision-making group into strong herding group, weak herding group and no herding group, as shown in Figure 9.

In Figure 9, there are $61$ people with strong herding behavior, $150$ people with weak herding behavior, and only $19$ people with no herding behavior. From this, we can deduce that, affected by the complexity of decision-making problems and limited decision-making ability, most DMs have varying degrees of herd behavior. Furthermore, the number of DMs with strong herding behavior is relatively small, indicating that most DMs still maintain a certain degree of rationality and personal judgment, they are not easily influenced by others in the face of complex decision-making problems. In addition, there are a small number of $19$ DMs without herding behavior, which shows that there are very few DMs who are completely unaffected by others.

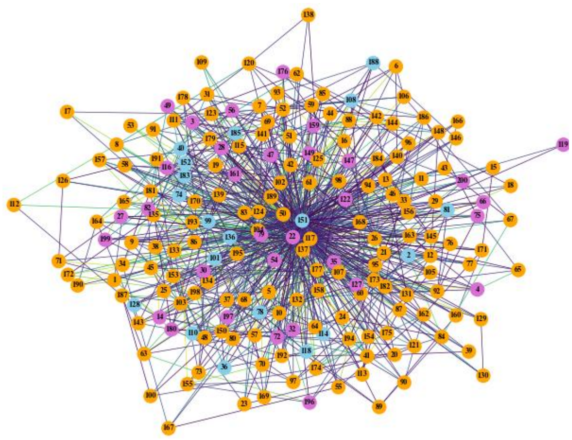

Figure 9. Classification results of DMs with varying degrees of herding behavior (Purple: SG; Orange: WG; Blue: NG)

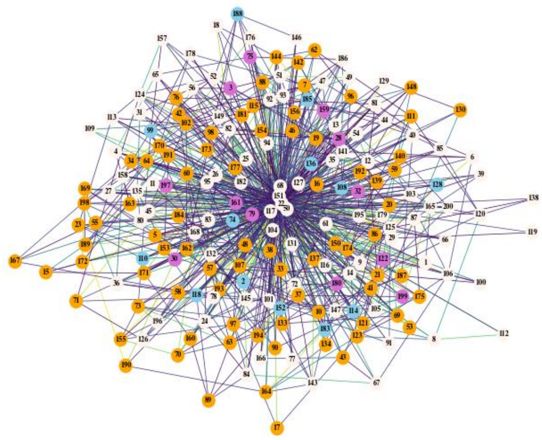

Figure 10. Classification results for low-consensus DMs with herding behavior (Purple: SGL; Orange: WGL; Blue: NGL; White: Others

**Step 6:** Acquisition of individual consensus degree. According to the calculation formulas Eq. (21) and Eq. (22), we obtain the expectation, entropy, hyper-entropy and score value of the individual consensus. Then, we divide the DMs into high consensus group and low consensus group by judging whether the individual consensus score of the DM passes the consensus threshold $(\gamma = 0.8)$ or not, as shown in Figure 11. Finally, by using Eq. (23) and Eq. (24), we gather the obtained individual consensus to obtain the expectation, entropy and hyper-entropy of the group consensus as $CM^{G}=(0.817,0.026,0.0002)$, and thus calculate the group consensus score value $sc(CM^{G})=0.791$. We also obtain the consensus score value of strong herding group and no herding group as $sc(CM^{SNG})=0.796$ $(CM^{SNG}=(0.821,0.025,0.0002))$. Therefore, the group consensus fails to pass the consensus threshold condition $(sc(CM^{G})<\gamma)$, and the decision preference information needs to be adjusted by feedback mechanism.

In Figure 11, we set the individual consensus that passes the consensus threshold as blue, and that fails the consensus threshold as red. It can be seen from Figure 11 that 92 DMs have passed the consensus threshold, and another 108 DMs have not reached the consensus threshold. It shows that affected by domain expertise and professional experience in various fields, the preferences of DMs are different, and the evaluation values given are not the same. The consensus degree of decision-making groups is concentrated between $(0.70,0.90)$, indicating that the preferences of DMs have a certain degree of similarity, and the selection of DMs is reasonable and scientific.

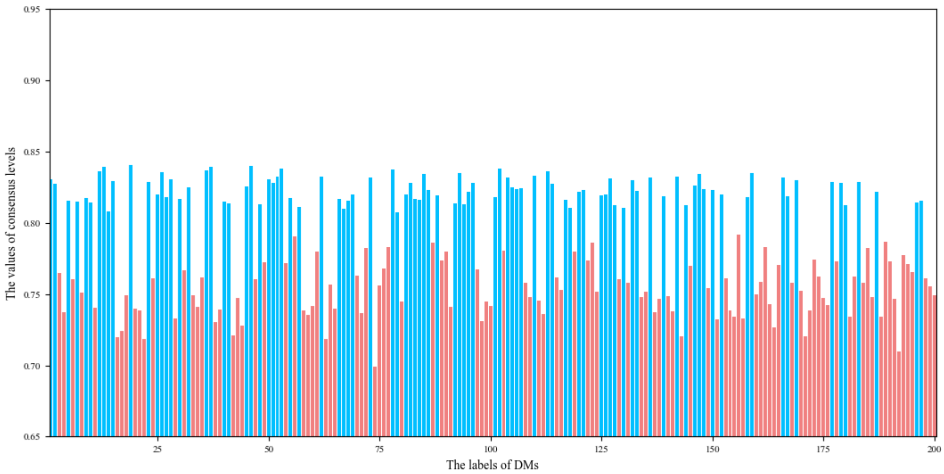


Figure 11. The individual consensus score value of DMs

**Step 7:** Classification of low-consensus DMs with herding behavior. Based on the DMs with herding behavior identified in Step 5, combined with the measurement of individual consensus in Step 6, we extract the DMs with low consensus degree who have strong herding behavior, weak herding behavior and no herding behavior, the result are shown in Figure 10.

From Figure 10, we can see that there are 12 low-consensus DMs with strong herding behavior, 83 low-consensus DMs with weak herding behavior, and 13 low-consensus DMs without herding behavior. Among the DMs with low consensus, the number of which with strong herding behavior and weak herding behavior accounted for 87.96%. It shows that most DMs with low consensus have herd behavior, and whether they have herd behavior or not has a great influence on the individual consensus.

**Step 8:** Aggregation of influence degree and acquisition of referenced preference. We fitted the influence degree set $\theta set^{i}_{ll'-n}=\{\theta^{i-t_1}_{ll'-n},\cdots,\theta^{i-t_\lambda}_{ll'-n},\cdots,\theta^{i-t_{T-1}}_{ll'-n}\}$ and the partial stage set $T_1=\{t_1,\cdots,t_\lambda,\cdots,t_{T-1}\}$ by the least square method, and obtained the influenced degree $\theta^{i-t_T}_{ll'-n}$ in the final stage $t_T$. We combined the influence degree to gather the preferences of trusted DMs with high consensus, so as to obtain the referenced preferences of low-consensus DMs with strong herding behavior. We aggregate the influence degree of

DMs on each attribute of each alternative by $\theta^{i-t_T}=\frac{2}{NL(L-1)}\sum_{l=1}^{L-1}\sum_{l'=l+1}^{L}\sum_{n=1}^{N}\theta_{ll'-n}^{i-t_T}$, and thus obtain the comprehensive influence degree of each DM, which are shown in Table 1.

It can be seen from Table 1 that among all the 12 low-consensus DMs with strong herding behavior, only $d_{30}$, $d_{79}$, $d_{122}$ and $d_{197}$ have a comprehensive influence degree exceeding 0.50. This shows that in the decision-making process, $d_{30}$, $d_{79}$, $d_{122}$ and $d_{197}$ are more likely to listen to the opinions of prestigious DMs or OLs, so as to optimize their decision-making preferences. Therefore, the evaluation values of $d_{30}$, $d_{79}$, $d_{122}$ and $d_{197}$ are greatly affected by herd behavior. Among them, $d_{30}$ has the largest comprehensive influence degree, and he is most influenced by herd behavior in the decision-making process. In addition, the comprehensive influence degree of most DMs does not exceed 0.50, indicating that although most DMs have herd behavior, they still maintain a certain level of self-confidence in their decision-making process. Among them, the comprehensive influence level of $d_{159}$ is the smallest, and it is least affected by herd behavior.

Table 1. The influence degree of low-consensus DMs with strong herd behavior

| DMs | $d_3$ | $d_{28}$ | $d_{30}$ | $d_{32}$ | $d_{75}$ | $d_{79}$ | $d_{122}$ | $d_{159}$ | $d_{161}$ | $d_{180}$ | $d_{197}$ | $d_{199}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID | 0.467 | 0.402 | 0.556 | 0.367 | 0.463 | 0.529 | 0.527 | 0.341 | 0.441 | 0.420 | 0.521 | 0.464 |

**Step 9:** Construction of modification model and acquisition of modified preferences. We recalculate the individual consensus of each DM after the preference modification, and the results are shown in Figure 12. At this point, the group consensus score value is $sc\left(CM^{G-1}\right)=0.798$ $\left(CM^{G-1}=(0.824,0.026,0.0002)\right)$, and the consensus score value of strong herding group and no herding group is $sc\left(CM^{SNG-1}\right)=0.832$ $\left(CM^{SNG-1}=(0.854,0.022,0.0002)\right)$. Next, we reclassified low-consensus DMs with strong herding behavior, low-consensus DMs with weak herding behavior, and low-consensus DMs without herding behavior. The DMs whose individual consensus score value passed the threshold after optimization in the modification model were collectively recorded as $CDP=\left\{d_i \middle| CD^{i-t_T}<\gamma, CD^{i-New}\geq\gamma\right\}$, and the classification results are shown in Figure 13.

From the consensus results of $sc\left(CM^{G}\right)=0.791$ to $sc\left(CM^{G-1}\right)=0.798$ and that of $sc\left(CM^{SNG}\right)=0.796$ to $sc\left(CM^{SNG-1}\right)=0.832$, it can be seen that the optimization effect of the modification model is significant. From Figure 11 and Figure 12, we can see that the individual consensus of most DMs has improved, including those who have passed the consensus threshold from the beginning. As can be seen from Figure 13, after the modification model optimizes the modified preferences of low-consensus DMs in strong herding group and no herding group, $d_{136}$, $d_{174}$, $d_{175}$, $d_{181}$ and $d_{183}$ that originally did not exceed the consensus threshold exceeded the consensus threshold after modification model adjusted. Among them, $d_{174}$, $d_{175}$ and $d_{181}$ belong to the weak herding group, while $d_{136}$ and $d_{183}$ belong to the no herding group, which is shows that when the modification model optimizes the modified preferences of DMs in $SGL$ and $NGL$, it also has an impact on the individual consensus of DMs in $WGL$. At this time, compared with the 92 DMs at the beginning, there are currently 97 DMs who have passed the consensus threshold. Therefore, after the optimization of the modification model, even though the consensus passing number of $SGL$ has not increased, the consensus passing rate of the whole decision-making group and the group consensus level have improved.

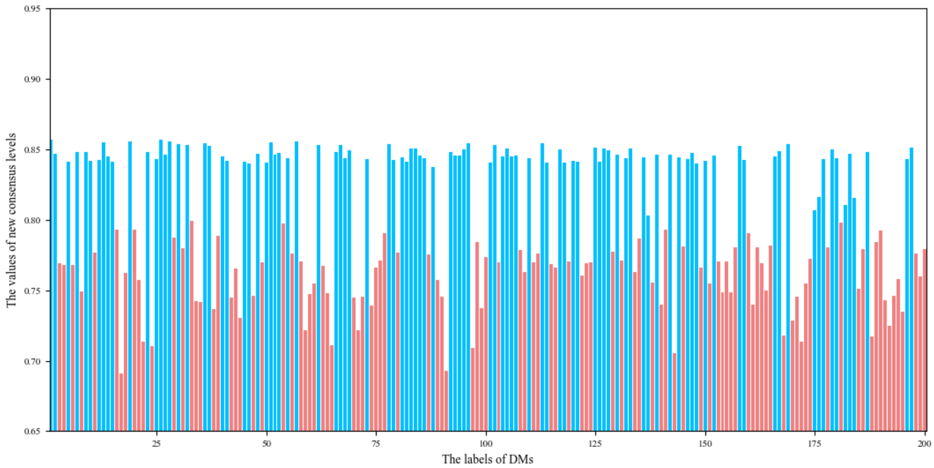


Figure 12. The individual consensus score value of DMs after modification model optimization

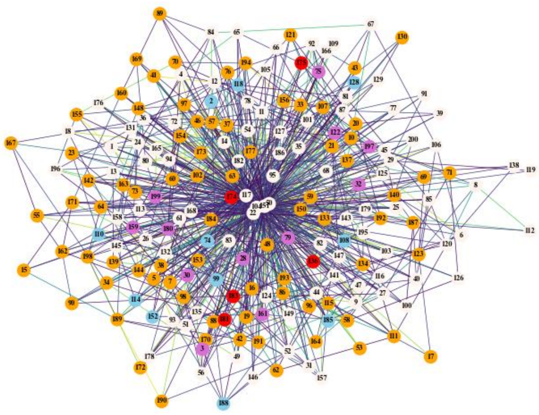

Figure 13. Classification results of DMs with varying degrees of herding behavior after modification model optimization (Purple: SGL; Orange: WGL; Blue: NGL; Red: CDP; White: Others)

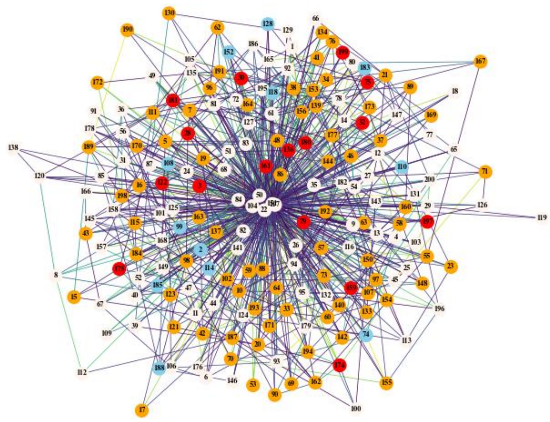

Figure 14. Classification results of DMs with varying degrees of herding behavior after modification model optimization by Ding method

**Step 10:** Construction of punishment model and alternative selection. Based on the modified preferences obtained in Step 9, we establish a punishment model to optimize the DMs' weights of low-consensus DMs with weak herding behavior. After optimization, the decision weights of DMs are $w_i^{New} = \begin{cases} 0.848, & i=16 \\ 1, & else \end{cases}$.

At this time, the group consensus score value is $sc\left(CM^{New}\right)=0.8$, and the group consensus passes the consensus threshold.

From the consensus results of $sc\left(CM^{G-1}\right)=0.798$ to $sc\left(CM^{New}\right)=0.8$, it can be seen that the optimization effect of the punishment model is significant. The cost of consensus result optimization is only to change the weight of $d_{16}$, which shows that the punishment model saves more modification costs and retains more original preference information because it does not involve preference adjustment.

We obtain the decision result according to the DM's preference and DM's weight at this time. First, we combine attribute weights to aggregate the modified preferences obtained in modification model of Step 9 and calculate the FPRs of various DMs after attribute aggregation by Eq. (34). Then we gather the FPRs of the DMs to obtain the overall evaluation values of the DMs for each alternative by Eq. (35), as shown in Figure 15. Finally, we gather the evaluation values of the DMs for the alternatives based on individual weights to obtain the comprehensive evaluation values of alternatives as $P(A_1)=1.838$, $P(A_2)=2.004$, $P(A_3)=2.044$, $P(A_4)=2.053$. We rank the comprehensive evaluation values of the alternatives as: $A_4 \succ A_3 \succ A_2 \succ A_1$, obviously the optimal solution for group decision-making is $A_4$.

It can be seen from Figure 15 that 31 DMs think $A_1$ is the optimal solution, 35 DMs think $A_2$ is the best solution, 71 DMs think $A_3$ is the best solution, and 63 DMs think $A_4$ is the best solution. In contrast, 121 DMs believe that $A_1$ is the worst solution, 21 DMs think that $A_2$ is the worst solution, 27 DMs think that $A_3$ is the worst solution, and 31 DMs think that $A_4$ is the worst solution. Therefore, the evaluation values of $A_1$ and $A_2$ alternatives are generally low, and they are easier to exclude from the candidates. It is worth noting that 80 DMs consider $A_4$ to be the second best solution, while only 69 DMs consider $A_3$ to be the second best solution. Therefore, even if the number of people who think $A_3$ is the best is more than the number of people who think $A_4$ is the best, the overall evaluation value of the alternatives are still satisfy $P(A_4) > P(A_3)$, i.e., $A_4 \succ A_3$.

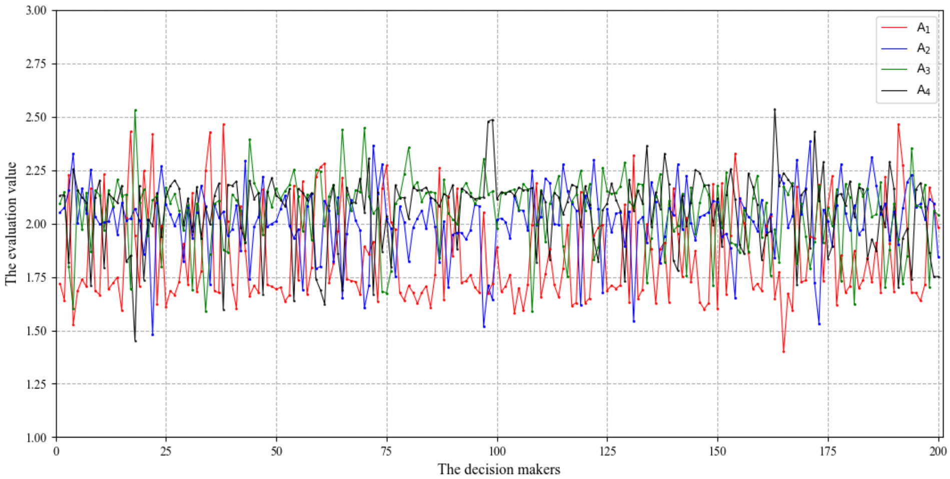

Figure 15. The comprehensive evaluation value of each alternative by each DM

From the decision results of this case, we can draw the following conclusions:

(1) Most DMs in the decision-making group have herd behavior, and herd behavior has a great influence on the group consensus. From Figure 9, we can know that in the multi-stage decision-making system with 200 DMs, there are 181 DMs with herd behavior, accounting for 90.50%. It shows that in the multi-stage large group decision-making system, the DMs are closely connected and interact frequently. They are easy to be influenced by other people's decision-making preferences in current stage, so they can change their preference information in the next stage. And it can be seen from Figure 10 that 87.96% of DMs who fail to pass the consensus threshold have herd behavior. It shows that most of the DMs with low consensus have strong or weak herding behavior.

(2) The dispersion degree of group preference has a great influence on the level of group consensus. In Step 6, the initial group consensus level is $Ex^G = 0.817$, and the consensus score after considering the influence of entropy and hyper-entropy is $sc(CM^G) = 0.791$. If the fuzziness of group preferences is not

considered, the group consensus passes the consensus threshold condition $(\gamma = 0.8)$ at the beginning. If it directly enters the decision-making stage at this time, there may be deviations in the comprehensive evaluation values of some alternative attributes, and ultimately the decision-making results cannot meet the wishes of more people. However, the group consensus after considering the influence of entropy and hyper-entropy did not pass the consensus threshold condition at the beginning. Therefore, in the subsequent feedback process, through the acquisition of referenced preferences and modified preferences, the dispersion of DMs' preferences will gradually decrease, the degree of group consensus will also increase. Finally, the decision-making results will meet the requirements of more people.

(3) The modification model and the punishment model retain more original decision-making information and save more modification costs on the premise of satisfying the consensus. From Step 9, only 5 DMs' consensus pass status has changed, indicating that modification model has largely retained the DMs' original preferences while adjusting their preferences to reach a consensus. From Step 10, we found that under the optimization of the punishment model, the decision-making system only adjusts the decision-making weight of DM $d_{16}$ to make the group consensus reach the threshold, which does not involve preference changes. Therefore, optimizing group consensus in the form of a combination of modification model and punishment model is a method that can quickly and efficiently bring the decision-making group to reach the consensus threshold.

### *6.3. Sensitivity analysis*

In order to find out the influence of $\eta \in [0,1]$ in trust-clustering algorithm, $\varepsilon \in [0,1]$ in cloud model score value and consensus threshold $\gamma \in [0,1]$, we make a sensitivity analysis on these three parameters based on the proposed numerical experiment.

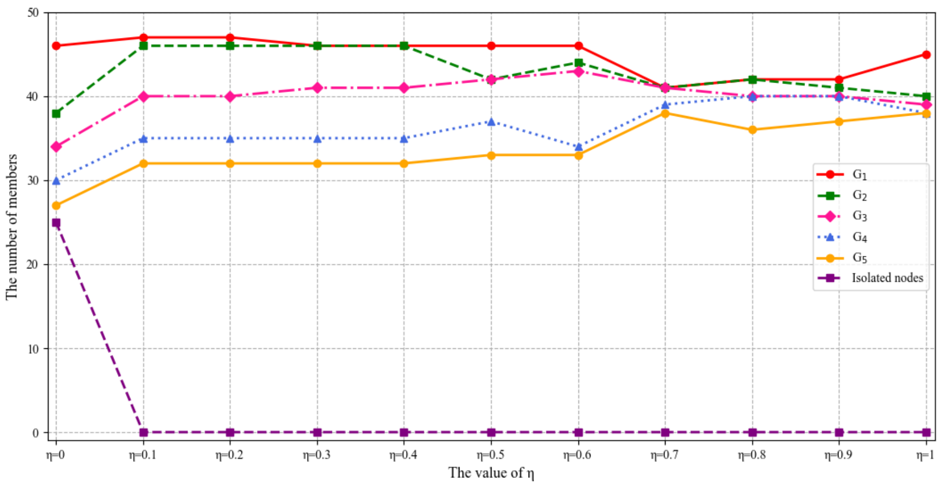


Figure 16. Clustering result of social network with different $\eta$

(1) $\eta$ in CDC. $\eta \in [0,1]$ is the scaling factor used to adjust the entropy weight. We set $\eta$ changing from 0 to 1 according to $step(\eta) = 0.1$. The results with different coefficients $\eta$ are shown in Figure 16. The X -axis represents the change in the entropy coefficient, and the Y -axis represents the number of people in each subgroup.

By observing Figure 16, the following two points are worth noting. 1) When $\eta = 0$, the effect of entropy value is 0, the decision-making group is clustered into 5 subgroups and 25 outliers. It can be deduced that the social network in the above example does not fully satisfy the clustering condition of classical modularity maximization. 2) When $\eta \in [0.10,1]$, entropy has effect on elastic modularity. The decision-making group is completely divided into 5 subgroups and the number of people in the five communities is getting closer. From this, we can conclude that DMs are full of uncertainty about the cooperative relationship with each other. Compared with the classic modularity maximization clustering, the EMCDA algorithm considering entropy disturbance is more suitable for the real social network structure.

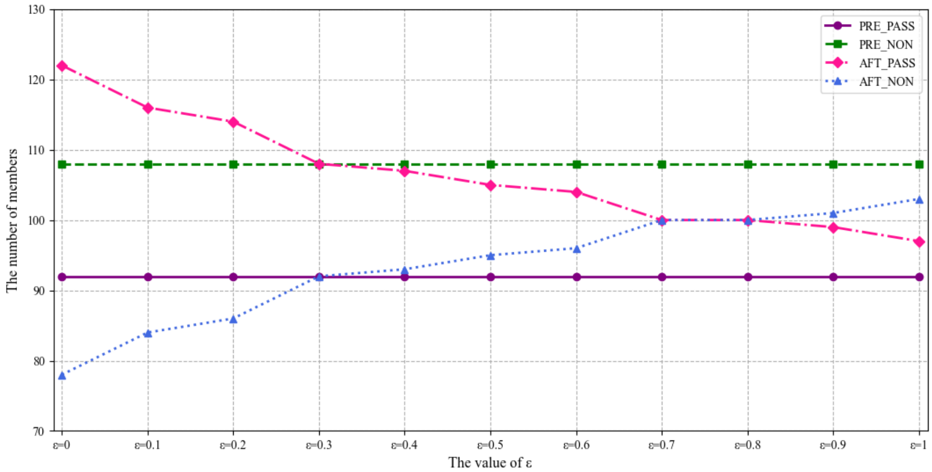


Figure 17. The number of DMs who pass and fail the consensus threshold before and after the adjustment under different $\varepsilon$

(2) $\varepsilon \in [0,1]$. $\varepsilon$ is the parameter to adjust the entropy and hyper-entropy weights in the individual consensus cloud score formula. We set $\varepsilon$ to change from 0 to 1 with $step(\varepsilon) = 0.10$, and observe the consensus results under different $\varepsilon$ values, the results are shown in Figure 17. The X-axis represents the change of $\varepsilon$ value, and the Y-axis represents the number of people reaching the consensus threshold and the number of people not reaching the consensus threshold $(\gamma = 0.80)$ before and after modification model adjustment (We set the number of DMs passed or failed to pass the consensus threshold before adjustment as PRE_PSS or PRE_NON respectively, the number of DMs passed or did not pass the consensus threshold after adjustment as AFT_PSS and AFT_NON respectively).

By observing Figure 17, the following two points are worth noting. 1) As the weight of entropy and hyper-entropy increases, the optimization effect of modification model is more and more affected by entropy and hyper-entropy. The value of AFT_PSS was greater than that of AFT_NON in the beginning $(\varepsilon \in [0,0.70))$, and then the two values gradually leveled off $(\varepsilon \in [0.70,0.80])$. Finally, the number of people who passed after optimization was smaller than the number of people who failed after optimization $(\varepsilon \in (0.80,1])$, so it is necessary to be re-optimized with the help of the punishment model. 2) In the whole period, the number of people whose original individual consensus passes the consensus threshold has not changed, indicating that the entropy and hyper-entropy will not affect the original individual consensus of the DMs, while it has a greater impact on the consensus passing degree of the referenced preferences optimized by the modification model.

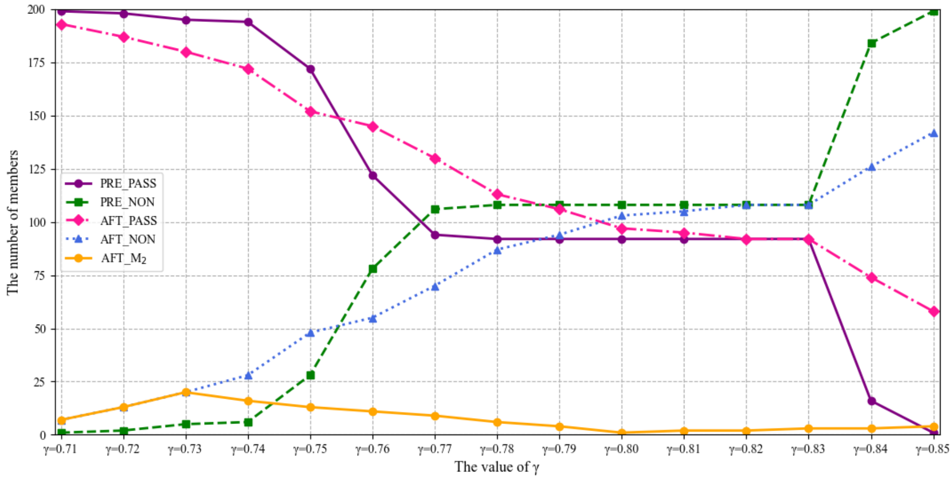


Figure 18. The number of DMs who pass and fail the consensus threshold before and after the adjustment under different $\gamma$

(3) $\gamma \in [0,1]$. $\gamma$ is the consensus threshold of the decision-making group. In order to study the impact of the value of the consensus threshold on consensus and decision-making results, we set $\gamma$ to vary from 0 to 1, and observe the consensus situation and decision-making results under different $\gamma$ values.

When $\gamma \in [0,0.70]$ or $\gamma \in (0.85,1]$, as shown in Figure 11, all DMs reach a consensus at the beginning, or all DMs did not reach a consensus at the beginning. Therefore, in both cases, we go straight to the decision-making step. We obtained the overall evaluation value of the decision-making group as: $P(A_1)=1.843$, $P(A_2)=2.009$, $P(A_3)=2.045$, $P(A_4)=2.057$. The ranking of the alternatives is consistent with the decision-making results of the proposed method. It shows that when the consensus threshold is not greater than $0.70$ or not less than $0.85$, the consensus results and decision-making results are not affected. When $\gamma \in [0,0.70]$ or $\gamma \in (0.85,1]$, the decision-making group is not sensitive to the consensus threshold.

When $\gamma \in (0.70,0.85]$, we set $\gamma$ to change with $step(\gamma)=0.01$ to obtain the consensus pass rate and decision-making results under different consensus thresholds, as shown in Figure 18. The X-axis represents the change of $\gamma$ value, and the Y-axis represents the number of people reaching the consensus threshold (We set the number of DMs passed or failed to pass the consensus threshold before adjustment as PRE_PSS or PRE_NON respectively, the number of DMs passed or did not pass the consensus threshold after adjustment as AFT_PSS or AFT_NON respectively, and the number of people in AFT_NON that have been adjusted by the punishment model as AFT_$M_2$).

By observing Figure 18, the following four points are worth noting. 1) When $\gamma \in [0.71,0.75]$, the value of AFT_$M_2$ is firstly lower than the value of AFT_PSS, indicating that the punishment model does not need to optimize the weights of all DMs who fail the consensus threshold. 2) When $\gamma \in [0.76,0.78]$, The value of PRE_PSS drops significantly, as does the value of AFT_NON, which shows that since more DMs need to adjust their preferences through the modification model, the number of DMs who needs to be adjusted by the punishment model is reduced. 3) When $\gamma \in [0.79,0.83]$, the value of PRE_PSS does not change, and the value of AFT_PSS declines slowly, which indicate the optimization efficiency of the modification model is the highest, and the optimization effect is the best in this period. 4) When $\gamma \in (0.83, 0.85]$, the value of PRE_PSS drops sharply, and the value of AFT_PSS also drops sharply. However, the value of AFT_PSS is still greater than the value of PRE_PSS, and the value of AFT_M2 is still at a low level. It shows that after the adjustment of the modification model, the degree of group consensus is still at a high level near the consensus threshold, and the modification model is still valid at this period.

### *6.4. Comparative analysis*

In order to verify the rigor and applicability of the proposed method, we conduct a comparative analysis based on the following three aspects: the comparison of different consensus methods, the comparison of different influence degree methods, and the comparison of consensus and decision results considering herd behavior or not.

(1) Comparison of different consensus methods.

In general, two methods are adopted in group decision-making to calculate the degree of consensus: calculating the similarity between individual preferences and collective preferences, and calculating the similarity between each pair of DMs. We choose the methods of [65] and [66] to conduct a comparative analysis of consensus methods based on the similarity between individual preferences and collective preferences, and select the methods of [34] and [67] to conduct a comparative analysis of consensus methods based on the similarity between each pair of individual preferences. Liu's method judges whether the DMs are in consensus based on whether the expectations corresponding to individual preferences are within the acceptable range of the group preference cloud model [65]. Zhang's method defines a new consensus measurement method based on the distance between the DM's preference and the group consensus preference [66]. According to the definition of similarity between DMs for each attribute of each alternative, Tan's method gathers the similarity to obtain a consensus measurement method between individuals [34]. Xiao's method first calculates the comprehensive distance between DMs, and then defines the consensus measurement method to obtain the consensus level among individuals [67]. In order to verify the rigor and soundness of the consensus calculation method based on the cloud model, we compare the above consensus measurement methods. We calculate the degree of individual consensus based on the above four methods respectively using the proposed illustrative example. The results are shown in Table 2.

Table 2. Consensus pass numbers for the five consensus measurement methods

| | Liu's method | Zhang's method | Tan's method | Xiao's method | Proposed Method |
|---|---|---|---|---|---|
| Pass | 86 | 72 | 92 | 94 | 92 |
| Not Pass | 114 | 128 | 108 | 106 | 108 |

By observing Table 2, the following points are worth noting: 1) The number of people who failed the threshold measured by the five methods in the table is more than the number of people who passed the threshold, and the error between the five methods does not exceed 10%. This shows that the results of the five methods for measuring the degree of individual consensus are similar, which proves the rationality of the proposed method. 2) In comparison, the results of Tan's method and Xiao's method are more like our proposed consensus measurement method, and the results of Liu's method and Zhang's method are quite different from our proposed consensus measurement method. It shows that the Tan's method, Xiao's method and proposed method all belong to the method of describing the consensus between individuals, so their final measurement results of the individual consensus will be closer.

(2) Comparison of different influence degree methods.

In order to verify the rigor and soundness of the influence degree calculation method obtained by the least squares fitting, we compare the influence degree proposed by Ding et al [68]. In [68], Ding et al. studied the influence of the DMs' confidence level and node degree on the consensus opinion formation and consensus convergence speed in the social network based DeGroot model, and concluded that when the DMs confidence level and node degree satisfy $\theta_i = 1 - D_i / \sum_{i=1}^{M} D_i$, the self-confidence level and node degree in the social network are balanced, and the consensus convergence speed is faster.

Therefore, we use Ding's method to obtain the influence degree of DMs in the proposed example and compare the consensus level and decision-making results. We first obtain the influence degree of low-consensus DMs with strong herding behavior, which is shown in Table 3. Then we obtain the referenced preferences under this influence degree and obtain the modified preferences by the modification model. We recalculate the individual consensus of each DM after the preference modification. The results are shown in Figure 19. We reclassify low-consensus DMs in strong herding group, weak herding group, and no herding group, which is shown in Figure 14. The group consensus score value is $sc\left(CM^{G-D-1}\right) = 0.807$, and the group consensus score value except for DMs with weak herding behavior is $sc\left(CM^{SNG-D-1}\right) = 0.847$. Since the group has reached a consensus, we directly gather the preferences of the DMs to obtain the final decision evaluation value as: $P_D\left(A_1\right) = 1.827$, $P_D\left(A_2\right) = 2.006$, $P_D\left(A_3\right) = 2.061$, $P_D\left(A_4\right) = 2.066$, and the optimal solution is $A_4$.

Table 3. The influence degree of Ding's method

| DM | $d_3$ | $d_{28}$ | $d_{30}$ | $d_{32}$ | $d_{75}$ | $d_{79}$ | $d_{122}$ | $d_{159}$ | $d_{161}$ | $d_{180}$ | $d_{197}$ | $d_{199}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ding's ID | 0.996 | 0.996 | 0.997 | 0.996 | 0.997 | 0.996 | 0.995 | 0.997 | 0.996 | 0.995 | 0.996 | 0.997 |

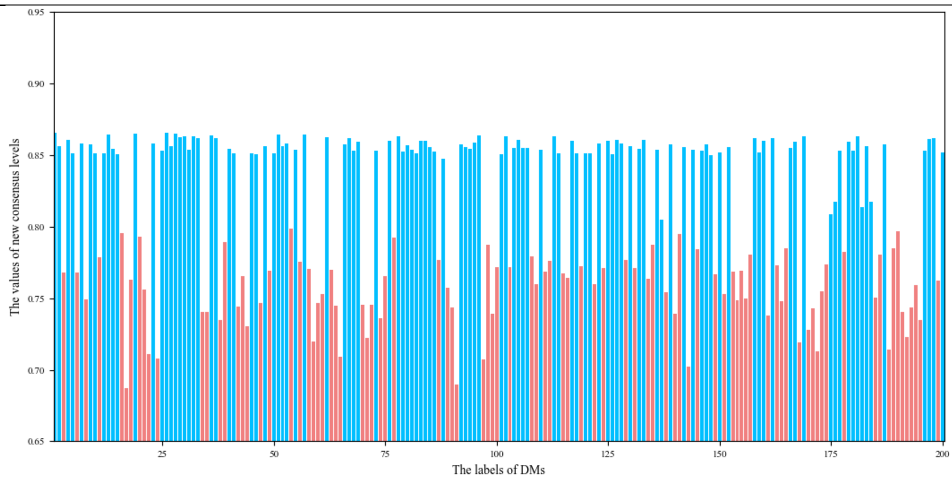


Figure 19. The individual consensus score value of DMs after modification model optimization by Ding method

The relevant results are discussed as follows: 1) From the consensus results $sc\left(CM^{G-D-1}\right) = 0.807$ and $sc\left(CM^{SNG-D-1}\right) = 0.847$, it can be seen that the optimization effect of the modification model on the referenced preference obtained by the Ding's influence degree is still obvious. 2) From Figure 14 and Figure 19, we can see that after the modification model optimizes the modified preferences of low-consensus DMs in strong herding group and no herding group, $d_3$, $d_{28}$, $d_{30}$, $d_{32}$, $d_{75}$, $d_{79}$, $d_{122}$, $d_{136}$, $d_{159}$, $d_{161}$, $d_{174}$, $d_{175}$, $d_{180}$, $d_{181}$, $d_{197}$, and $d_{199}$ who had not previously reached the consensus threshold condition all exceeded the consensus threshold condition after this round of adjustment. Among them, $d_3$, $d_{28}$, $d_{30}$, $d_{32}$, $d_{75}$, $d_{79}$, $d_{122}$, $d_{159}$, $d_{161}$, $d_{180}$, $d_{197}$, and $d_{199}$ belong to the strong herding group, $d_{174}$, $d_{175}$, and $d_{181}$ belong to the weak herding group, and $d_{136}$ belongs to the no herding group. Now, $109$ DMs have passed the consensus threshold. 3) After the modification model is optimized, the group has reached a consensus, the punishment model is not needed for optimization. Therefore, comparing the consensus decision-making results obtained by the proposed method, it can be shown that the consensus convergence effect of influence degree calculated by Ding's method is better. 4) The comparison of Table 3 and Table 1 shows that the influence value obtained by Ding's method is much larger than that obtained by the proposed method, indicating that in Ding's method, most of the referenced preferences come from DMs' trusted people, while their own self-confidence is low. This phenomenon is contradictory to reality. Under the premise of group consensus, the proposed method retains more original preference information of DMs and gathers the wisdom of more experts, so the proposed method is more scientific and applicable.

(3) Comparison of consensus and decision results considering herd behavior or not.

In order to verify the rationality and superiority of the feedback mechanism obtained by considering the herding behavior in this paper, we compare the degree of consensus, preference feedback process and decision-making results of the group that considered and did not consider the effects of herding behavior.

In the decision-making system, when a DM has a higher degree of individual consensus, the preference similarity between him/her and other DMs will also be higher. Since the trust between DMs will be affected by the similarity of their preferences, when a DM's individual consensus is high, it means that he/she has established trust relationships with more people in the decision-making group [19]. DMs are more willing to accept the opinions of people they trust to make preference adjustments than that of unfamiliar DMs [12]. Summarizing these points, we can infer that high-consensus DMs have a higher degree of preference adjustment willingness. Therefore, we divide DMs that have not reached consensus into the following three categories according to the degree of individual consensus to adapt our proposed model. $CDL\_a = \left\{ d_i \middle| 0.76 \le sc\left(CD^{i-t_T}\right) \le 0.8, d_i \in Dset \right\}$ is the higher consensus group in the low consensus group, and $CDL\_c = \left\{ d_i \middle| sc\left(CD^{i-t_T}\right) < 0.75, d_i \in Dset \right\}$ is the lower consensus group in the low consensus group. These two groups of people are optimized by the modification model. $CDL\_b = \left\{ d_i \middle| 0.75 \le sc\left(CD^{i-t_T}\right) < 0.76, d_i \in Dset \right\}$ is the general high-consensus group in the low-consensus group, and this group of people will be optimized through the punishment model.

After the optimization of the modification model, the result of the individual consensus of DMs is shown in Figure 20. Now, the group consensus score value is $CM^{G-NH-1} = 0.796$, and the group consensus score value except $CD\_b$ is $CM^{SNG-NH-1} = 0.812$. After the punishment model optimization process, the decision weights of $d_{90}$ is $w_{90}^{New} = 0.423$, the decision weight of $d_{96}$ is $w_{96}^{New} = 0.001$, the decision weight of $d_{114}$ is $w_{114}^{New} = 0.001$, and the weights of other DMs are all $1$. At this point, the group consensus score reaches $CM^{New-NH} = 8.0$, and the group consensus passes the consensus threshold. We use the DM's weight obtained from the punishment model to gather the evaluation value of the alternative by DMs, and obtain the comprehensive evaluation value of the alternatives by the decision-making group no considering the herding behavior as: $P_{NH}\left(A_1\right)=1.822$, $P_{NH}\left(A_2\right)=2.005$, $P_{NH}\left(A_3\right)=2.033$, $P_{NH}\left(A_4\right)=2.047$. The optimal solution of group decision-making is still $A_4$.

The relevant results are discussed as follows: 1) Comparing the modification model optimization effect that did not consider the herding behavior $CM^{G-NH-1}=0.796$ and $CM^{SNG-NH-1}=0.812$, the consensus result value after considering the herding behavior is closer to the consensus threshold ($CM^{G-1}=0.798$, $CM^{SNG-1}=0.832$). This shows that after considering the herding behavior, the consensus convergence of decision-making information is better. 2) Compared with the punishment model that optimizes the weights of the three DMs $d_{90}$, $d_{96}$, and $d_{114}$ when the herd behavior is not considered, the punishment model only optimizes the weight of $d_{16}$ when the herd behavior is considered. It shows that considering the herd behavior for consensus adjustment can preserve more original decision information and lower the cost of model optimization. 3) In the case of considering herd behavior or not, $A_4$ is the optimal solution, which shows that considering the herd behavior in the group to make a decision is in line with the reality. In summary, it can be shown that herd behavior is common in decision-making groups, and it has an impact that cannot be ignored on consensus results and decision-making results. Therefore, the CRP in MSLGDM proposed in this paper considering the implication of herding behavior are scientific and reasonable.

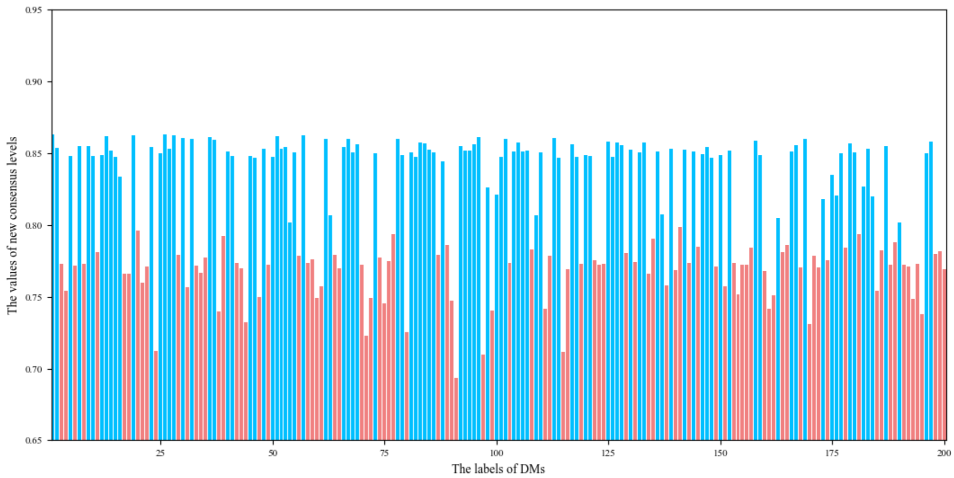


Figure 20. The individual consensus score value of DMs after modification model optimization without considering herding behavior

## 7. Conclusions and future studies

For the complex decision-making problem of MSLGDM considering social networks, we have proposed a series of concepts and definitions, explored the behavioral characteristics of DMs, determined the consensus strategy of group preferences, and achieved a highly consistent ranking of alternative solutions.

The characteristics of herding behavior in large group decision-making have been explored, which reflects the individual's irrational mentality. For a DM with a high degree of consensus, even if he/she has herding behavior, his/her decision-making process will not have a great impact on the decision-making result. Therefore, we have focused on DMs with low consensus levels and herding behavior. Through social network and preference information, according to the three causes of herding behavior (incomplete information, social pressure, and obedience to authority), we have proposed three quantitative methods for the corresponding characteristics (information gradient propagation characteristics, risk aversion characteristics, and authority obedience characteristics), for judging and categorizing DMs with varying degrees of herd behavior. We have determined DMs' preference adjustment willingness according to their degree of herding behavior, which is not only reasonably grasp the willingness of DMs to adjust preferences and provide targeted preference adjustment strategies, but also transform the adverse effects of herd behavior on group decision making into factors that can be used to avoid consequence such as the evolution of decentralized consensus.

We have established a modification model to adjust the preferences of DMs in strong herding group and non-herding group, so that the consensus degree of these two groups passed the threshold. Under the premise of considering the individual willingness of DMs in strong herding group and non-herding group, the modified preference that minimizes the adjustment cost is obtained through the modification model. For weak herding groups that cannot judge the specific preference adjustment willingness, we have established a punishment model to reduce the weights of low-consensus DMs, so as to ensure that the entire decision-making group can pass the consensus threshold condition. The punishment model not only preserve the original preference of DM on the basis of the group consensus passing the threshold, but also save a lot of preference adjustment costs.

We have chosen the selection of emergency power generation methods adopted by the Spanish energy crisis, and we have provided an illustrative example of the proposed MSLGDM method. We have conducted three sensitivity analyses and three comparative analyses to obtain the following conclusions from the proposed illustrative example. 1) Most of the DMs in the decision-making group have herd behavior, and herd behavior has a great influence on the group consensus. 2) The dispersion degree of group preference has a great influence on the level of group consensus. 3) The modification model and the punishment model retain more original decision-making information and save more modification costs on the premise of satisfying the consensus. The above research conclusions can provide policy recommendations for the current Spanish government. The proposed model can also be used for other decision-making or prediction problems involving long-term dynamic processes of large groups, such as democratic elections, risk analysis, electronic markets, recommendation systems, and crowdfunding platforms.

Finally, we need to point out that only the herding behavior of individual DMs is considered in this paper. In fact, the psychology and behavior of DMs in MSLGDM are complex. In the future, we need more research on other behavioral characteristics to guide group consensus more efficiently. In addition, the herding behavior of DMs may divide the decision-making group into different subgroups. It is also a valuable research direction in the future to focus on the behavioral characteristics of subgroups and their impact on consensus and decision-making results.

## Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

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# Appendix

Table A.1. Symbols and Meanings

| Symbols | Meanings |
|---|---|
| $C=\{c_1,\cdots,c_n,\cdots,c_N\}$ | Attributes set |

| | |
|---|---|
| $A=\{A_1,\cdots,A_l,\cdots,A_L\}$ | Alternative set |
| $T=\{t_1,\cdots,t_\lambda,\cdots,t_T\}$ | Stage set |
| $\tilde{\omega}=\{\omega_1,\cdots,\omega_n,\cdots,\omega_N\}$ | Attribute weights |
| $Dset=\{d_1,\cdots,d_m,\cdots,d_M\}$ | Decision makers |
| $F_n^{m-t_\lambda}=\{f_{ll'-n}^{m-t_\lambda}\}_{L\times L}$ | FPR on the set $A=\{A_1,\cdots,A_l,\cdots,A_L\}$ of DM $d_m$ on attribute $c_n$ in stage $t_\lambda$ . |
| $SM_n^{ij-t_\lambda}=\{sm_{ll'-n}^{ij-t_\lambda}\}_{L\times L}$ | Similarity matrix between $d_i$ and $d_j$ about the attribute $c_n$ in stage $t_\lambda$ |
| $V=(v_1,\cdots,v_m,\cdots,v_M)$ | Decision makers in social network |
| $E=\{e_{ij}\|i,j\le M\}$ | Edges among DMs in social network |
| $W=\{w_{ij}\|i,j\le M\}$ | Edge weights |
| $E(w_{ij})=\sum_{k=1}^2 h_{ij}^k\sigma_{ij}^k$ | Expectation of edge weights |
| $h_{i-j}(\sigma_{i-j})=\{h^k(\sigma_{i-j}^k)\|k=0,1,\cdots,K\}$ | cooperation strength of $d_i$ rate $d_j$ |
| $w_{ij}(\sigma_{ij})=\{h_{ij}^1(\sigma_{ij}^1),h_{ij}^2(\sigma_{ij}^2)\}$ | Edge weight between $d_i$ and $d_j$ |
| $Q=\{G_1,\cdots,G_q\}$ | Subgroups in social network |
| $\{d_1^*,d_2^*,\cdots,d_q^*\}$ | Opinion leaders in subgroups |
| $\{I_1^*,I_2^*,\cdots,I_q^*\}$ | Importance of opinion leaders |
| $SMS_{ll'-n}^{iq*}=\{sm_{ll'-n}^{iq*-t_1},\cdots,sm_{ll'-n}^{iq*-t_\lambda},\cdots,sm_{ll'-n}^{iq*-t_T}\}$ | Set of similarity between the preference of DM $d_i$ $(d_i\in G_q)$ and opinion leader $d_q^*$ on the $c_n$ attribute $A_l$ over $A_{l'}$ , |
| $a_{ll'-n}^{iq*}$ | Slope of fitted function $y=a_{ll'-n}^{iq*}x+b_{ll'-n}^{iq*}$ |
| $A^{iq*}$ | Aggregation of $a_{ll'-n}^{iq*}$ |
| $N_i$ | Set of DMs trusted by $d_i$ |
| $r_{ll'-n}^{ij-t_\lambda}$ | Risk index of $d_i$ relative to $d_j$ on attribute $c_n$ of $A_l$ rate $A_{l'}$ in stage $t_\lambda$ |
| $r_{ij}$ | Relative risk index of $d_i$ relative to $d_j$ |
| $R_i$ | Comprehensive risk index of DM $d_i$ |
| $Ntv_{ij}$ | Net trust value of $d_i$ rate $d_j$ |
| $Ntd_i$ | Net trust degree of $d_i$ $(d_i\in G_i)$ rate $G_i$ |
| $CD^{i-t_T}=(ex^{i-t_T},en^{i-t_T},he^{i-t_T})$ | Individual consensus of $d_i$ in $t_T$ |
| $sc(CD^{i-t_T})$ | Individual consensus score value of $d_i$ in stage $t_T$ |
| $\gamma$ | Consensus threshold |
| $CM^G=(Ex^G,En^G,He^G)$ | Group consensus in stage $t_T$ |
| $sc(CM^G)$ | Group consensus score value in $t_T$ |
| $\theta set_{ll'-n}^i=\{\theta_{ll'-n}^{i-t_1},\cdots,\theta_{ll'-n}^{i-t_\lambda},\cdots,\theta_{ll'-n}^{i-t_{T-1}}\}$ | Influence degree set of $d_i$ on the $c_n$ attribute $A_l$ relative to $A_{l'}$ |
| $a_{ll'-n}^i$ | Slope of fitted function $y=a_{ll'-n}^i x+b_{ll'-n}^i$ |
| $f_{ll'-n}^{i-re}$ | Referenced preference of $d_i$ on the $c_n$ attribute $A_l$ relative to $A_{l'}$ |
| $c_j^*$ | Parameter control people with high consensus to participate in calculations |
| $SG$ | Strong herding group |
| $WG$ | Weak herding group |
| $NG$ | No herding group |
| $SNG$ | Union of $SG$ and $NG$ |
| $SGL$ | Group of low-consensus DMs with strong herding behavior |
| $WGL$ | Group of low-consensus DMs with weak herding behavior |
| $NGL$ | Group of low-consensus DMs with no herding behavior |
| $w_i$ | Decision-making weight of DM $d_i$ |
| $y_{ll'-n}^v$ | Modified preferences of $d_v\in SGL$ |
| $y_{ll'-n}^k$ | Modified preferences of $d_k\in NGL$ |
| $f_{ll'-n}^{i-New}$ | New preference of $d_i$ after modification model on the attribute $c_n$ of $A_l$ relative to $A_{l'}$ is |

| | |
|---|---|
| $sm_{ll'-n}^{ij-New}$ | New similarity between $d_i$ and $d_j$ on the attribute $c_n$ of $A_l$ relative to $A_{l'}$ |
| $CD^{i-New} = \left(ex^{i-New}, en^{i-New}, he^{i-New}\right)$ | New individual consensus of $d_i$ |
| $sc\left(CD^{i-New}\right)$ | New individual consensus score value of $d_i$ |
| $CM^{G-1} = \left(Ex^{G-1}, En^{G-1}, He^{G-1}\right)$ | New group consensus after modification model |
| $sc\left(CM^{G-1}\right)$ | New group consensus score value |
| $t_i$ | Decision-making weight of DM $d_i$ in $WG$ |
| $w_i^{New}$ | New decision-making weight after punishment model |
| $y_l^i$ | Evaluation information of DM $d_i$ |
| $P\left(A_l\right)$ | Comprehensive evaluation value of $A_l$ |
| $CM^{SNG} = \left(Ex^{SNG}, En^{SNG}, He^{SNG}\right)$ | Group consensus of $SNG$ in stage $t_T$ |
| $sc\left(CM^{SNG}\right)$ | Group consensus score value of $SNG$ in $t_T$ |
| $sc\left(CM^{G-D-1}\right)$ | New group consensus after modification model using Ding's method |
| $sc\left(CM^{SNG-D-1}\right)$ | Group consensus score value of $SNG$ after modification model using Ding's method |
| $P_D\left(A_l\right)$ | Comprehensive evaluation value of $A_l$ using Ding's method |
| $CDL\_a$ | Higher consensus group in the low consensus group |
| $CDL\_b$ | General high-consensus group in the low-consensus group |
| $CDL\_c$ | Lower consensus group in the low consensus group |
| $CM^{G-NH-1}$ | Group consensus score value without considering herding behavior |
| $CM^{SNG-NH-1}$ | Group consensus score value of $SNG$ without considering herding behavior |
| $P_{NH}\left(A_l\right)$ | Comprehensive evaluation value of $A_l$ without considering herding behavior |