

Article

A Hybrid Human–AI Consensus Model in Information Granularity-Based Large-Scale Group Decision-Making

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Abstract

Artificial intelligence (AI) helps people improve decision-making in uncertain environments. When there is an AI decision maker (DM) in a large-scale group, how can consensus be reached? We address this problem by developing a hybrid human–AI consensus model in this paper. First, a two-stage grouping mechanism is proposed: it divides DMs into human and AI at the first stage, then classifies human DMs into several subgroups via the fuzzy c-means (FCM) clustering algorithm based on their fuzzy preference relations (FPRs). Second, a proximity-aware subgroup weight determination method is introduced, considering the cohesion degree, scale, and distance from AI to determine subgroup weights. Then, an information granularity-based model for consensus optimization is proposed, where the objective function is designed to simultaneously minimize the sum of distances from each subgroup's collective matrix to the global group matrix and maximize the consistency indices of all subgroups. The particle swarm optimization (PSO) algorithm is employed to solve this model, enabling rapid and effective decision-making for large-scale group decision-making (LSGDM) problems in emergency management. A case study is conducted to elucidate the advantages of the developed model, where some comparisons are reported. The results show that human attitudes toward AI play an important role in reaching consensus in LSGDM involving an AI DM.

Keywords: human–AI consensus model; large-scale group decision-making; granular matrix; optimization model; particle swarm optimization (PSO)

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1. Introduction

Group decision-making (GDM) is a situation in which more than one expert discusses a decision problem from a range of feasible alternatives and attempts to reach a collective solution. There is a trend in which a whole army of experts is invited to participate in the decision-making process due to the quick expansion of societal and technological paradigms like e-government [1,2] and social networks [3–5]. As a result, large-scale group decision-making (LSGDM) is becoming increasingly popular and significant in the field of decision-making. According to the criterion proposed by Ref. [6], a GDM problem is defined as an LSGDM problem when it involves at least 20 experts.

Solving LSGDM problems in various environments has continued to attract the attention of many scholars in recent years. For example, in order to retain as much information as

possible, Rodriguez et al. [7] proposed a new adaptive consensus reaching process (CRP) model for handling LSGDM by using hesitant fuzzy sets to fuse expert subgroup preferences. Chao et al. [8] proposed a consensus reaching model to solve heterogeneous LSGDM with non-cooperative behaviors and discussed its application in inclusive finance. Generally speaking, DMs give preference information based on their background, professional knowledge, and habits when evaluating the optimal alternative. One of the popular and powerful tools for preference modeling in GDM is the reciprocal preference relation (RPR) [9]. Different types of RPRs have been presented, such as additive preference relations [10], multiplicative preference relations [11], linguistic preference relations [12], hesitant fuzzy preference relations [13], and others. For GDM problems with RPRs, three important aspects should be considered before reaching a final solution: (1) the consistency of individual preference relations; (2) the level of group consensus; (3) the selection process of the optimal alternative.

Unlike traditional LSGDM, where DMs are all human experts, recent years have witnessed the rapid development of AI and big data technologies, making hybrid Human–AI LSGDM a reality [6]. In a recent study, Zhang et al. [14] developed a minimum-cost consensus model for human–AI collaborative LSGDM, where experts are grouped by similarity–trust–attitude scores and heterogeneous unit adjustment costs are assigned based on their attitudes toward Generative Artificial Intelligence (GenAI) across three predefined interaction scenarios: decisive, equal, and auxiliary. However, their method relies on iterative feedback where preference modifications are bounded by unit costs, yet it does not explicitly address the optimization of individual consistency within the revised preferences. Existing well-established LSGDM methods still face non-trivial challenges when they are directly applied to hybrid Human–AI decision scenarios. Previous studies have rarely considered the involvement of an AI DM in LSGDM; therefore, how to develop consensus models that involve hybrid human and AI DMs is a problem worth investigating. Here, we expand on previous research to develop a hybrid human–AI consensus model in the context of LSGDM.

LSGDM faces more complexity due to the large number of experts with different backgrounds, expertise, and experience levels [15]. Therefore, a key procedure of LSGDM is the dimensionality reduction technique [16], which involves dividing a large group into several subgroups according to certain characteristics. Two important concerns in LSGDM are the methods of dimension reduction and weight determination. For the former, many clustering methods have been reported in LSGDM, such as the k-means clustering method [17] and the broad first searching neighbors method [18]. In the prevalent LSGDM models [5,19], all experts constitute a unified group, which is subsequently divided into distinct clusters by utilizing a clustering algorithm. However, it may be necessary to divide experts based on their roles before clustering in the scenario of hybrid human–AI decision-making. Therefore, this paper proposes a two-stage grouping mechanism. In the first stage, experts are categorized into human and AI experts, and in the second stage, inspired by Ref. [20], we apply the FCM clustering algorithm to the context of this study. For the latter, some weight determination methods have been proposed in LSGDM. Li et al. [21] used the majority principle to measure the weights of subgroups; the more experts in a subgroup, the higher the weight of the subgroup. This method only considers the size of the subgroup. Tang et al. [19] considered both subgroup size and cohesion to determine the weights of subgroups, where cohesion is measured by the silhouette coefficient. Li et al. [22] calculated the weight of a subgroup by combining its size and level of togetherness depicted by the deviation of a possibility distributed hesitant fuzzy linguistic term set (PDEHFLTS) of a subgroup. More recently, Trillo et al. [5] obtained the weight of the subgroups by considering four aspects: the number of the subgroup, the degree of aggressiveness of experts, the degree of positivity of experts, and the consensus of the subgroup. However, existing subgroup weighting methods ignore

the unique dynamics of Human–AI interaction, where a subgroup’s proximity to objective AI judgment may indicate higher decision quality, a consideration that guides our weighting design. Therefore, this paper also develops a novel method to obtain the weights of the subgroups by considering their cohesion degree, scale, and the distance from the AI.

Finally, to improve the level of group consensus, many studies have been conducted. For instance, Zhang et al. [23] proposed linear optimization models for addressing the individual consistency and group consensus problems of FPRs, respectively. Wu and Xu [24] developed a decision-making model where the individual consistency index and the group consensus index were inspired by the idea of a deviation between two matrices. Xu et al. [25] presented a distance-based consensus model predicated on fuzzy and multiplicative preference relations to advance the solutions for GDM problems. Li et al. [26] proposed a novel consensus reaching model in GDM with FPRs, where an optimization-based consensus rule was designed to ensure individual consistency across the consensus process. More recently, Liu et al. [27] presented a new CRP model that considered the reliability of experts to address the GDM problem involving hesitant fuzzy linguistic term sets. A complete distributed preference relation (DPR) model was proposed in Ref. [28] to assist GDM, where an automatic adjustment algorithm and an evidence reasoning algorithm were proposed to adjust and aggregate DPRs, thereby maximizing consensus among all experts. In particular, it is important to point out that the PSO algorithm has been employed to emulate the process of reaching consensus [29–31]. However, the aforementioned consensus models only considered a limited number of experts, potentially rendering them unsuitable for solving LSGDM problems due to significant adjustment expenses or time limitations [32]. Under time constraints during emergencies, conventional CRPs that rely on iterative interactions become prohibitively time-consuming, necessitating an automatic optimization mechanism that balances consensus and individual consistency within a flexible adjustment space, which leads to our adoption of information granularity [29–31,33,34] and an optimization model.

To bridge these gaps, this paper proposes a hybrid human–AI consensus model to solve LSGDM problems with FPRs. The main contributions to the literature are as follows:

- (1) A novel hybrid human–AI decision framework with a two-stage grouping mechanism is proposed. The first stage divides all DMs into human and AI DMs according to their roles, and the second stage further classifies human DMs into several subgroups based on their FPRs by using the FCM clustering algorithm.
- (2) A proximity-aware subgroup weighting mechanism considering human–AI interaction is proposed by considering each subgroup’s cohesion degree, scale, and the distance from the AI.
- (3) An information granularity-based consensus optimization model is proposed, and a rapid yet effective decision can be reached by performing the PSO algorithm for the given LSGDM problem.

The remainder of this paper is organized as follows. Section 2 presents several key concepts employed throughout this research, such as FPR, the consistency index, and FCM. Section 3 presents a novel hybrid human–AI consensus model for LSGDM, and the performance of the PSO algorithm is analyzed. In Section 4, a case study is provided to show the feasibility and effectiveness of the proposed model. Some comparisons and discussions are given in Section 5. Concluding remarks are presented in Section 6.

2. Preliminaries and Notations

In this section, we first present the notations used in this paper, as shown in Table 1, and then introduce the relevant concepts required for constructing the proposed model, namely FPR, the consistency index, and FCM.

Table 1. List of notations.

Notations	Meanings
$X = \{x_1, x_2, \dots, x_n\}$	A series of n alternatives
$E = \{e_1, e_2, \dots, e_m, e_{AI}\}$	m human decision makers and one AI decision maker
$P = \{P_1, \dots, P_m, P_{AI}\}$	Preference relations from human and AI decision makers
$P_{C_h} = (p_{ij}^{C_h})_{n \times n}$	The collective matrix of cluster C_h
P_H	The collective matrix of all human clusters $C_h, h \in \{1, \dots, N\}$
P_C	The collective matrix of all decision makers
$C_h, h \in \{1, \dots, N\}$	N clusters
$AICD(C_h)$	The average intra-cluster distance of C_h
CI	Consistency Index
$\overline{CI}$	The acceptable additive consistency threshold
Q_1	The average consistency level of subgroups
Q_2	The group consensus
c	Fuzziness degree parameter in the FCM
γ	The group consensus threshold
α	Information granule endowed to cluster C_h
η_{AI}	A parameter representing the degree of human trust in AI
δ	A parameter that trades off individual consistency and group consensus

2.1. FPR

Definition 1. An FPR on a set of alternatives X is defined by a fuzzy set on the Cartesian product $X \times X$, i.e., it is featured by a membership function $\mu_B : X \times X \rightarrow [0, 1]$. B is an $n \times n$ matrix whose elements b_{ij} satisfy $b_{ij} = \mu_B(x_i, x_j)$ ($\forall i, j \in \{1, \dots, n\}$) [10].

If it satisfies the condition $b_{ij} + b_{ji} = 1$ ($\forall i, j \in \{1, \dots, n\}$), the matrix B is called an RPR. In Definition 1, the element b_{ij} of B can be interpreted as the preference degree or intensity of the alternative x_i over the alternative x_j . Specifically, $b_{ij} = 0.5$ suggests indifference between x_i and x_j ($x_i \sim x_j$); $b_{ij} > 0.5$ suggests that x_i is preferred to x_j ($x_i \succ x_j$), and $b_{ij} < 0.5$ suggests that x_j is preferred to x_i ($x_i \prec x_j$). When the reciprocal property is considered, the DMs only need to give their estimated values of the upper triangular or lower triangular positions of the FPRs.

Definition 2. An FPR $B = (b_{ij})_{n \times n}$ is called additively consistent if the following relation holds [10]:

$$b_{ij} = b_{ik} + b_{kj} - 0.5, \forall i, j, k \in \{1, \dots, n\}. \quad (1)$$

However, it is hard to reach perfect additive consistency in real-life situations in view of the fact that the DMs have poor global cognition of the pairwise comparisons among all the alternatives. The DMs always provide an inconsistent FPR. In order to measure the degree of inconsistency of an FPR, Herrera-Viedma et al. [35] defined a consistency index as follows:

$$CI(B) = 1 - \frac{2}{3n(n-1)(n-2)} \sum_{i,k=1; i \neq k}^n \sum_{j=1, j \neq i, k}^n |b_{ij} + b_{jk} - b_{ik} - 0.5|. \quad (2)$$

When the value of $CI(B)$ is equal to 1, the matrix B is additively consistent. Let $\overline{CI}$ be the given threshold. If $CI(B) \geq \overline{CI}$, then the matrix B has acceptable consistency; otherwise, the DMs need to modify their preferences.

2.2. Fuzzy Clustering

Clustering involves the process of dividing a collection of data objects into multiple clusters, with the aim that those within the same cluster exhibit high similarity, whereas those in distinct clusters show significant differences. Fuzzy clustering methods based on fuzzy set theory [36] were proposed on the assumption that a data object may belong to multiple clusters with different membership degrees [37]. The FCM algorithm features an iterative optimization procedure that updates the cluster centroids and membership degrees until a local optimum is found, indicated by minimal changes in cluster membership between iterations. The principal procedures of the FCM algorithm, designed for the resolution of LSGDM challenges with FPRs, are summarized as follows:

Notes:

- (1) Considering the research objective of this paper, the collection of data objects consists of the preference relations from all experts, $P_1, \dots, P_m$; thus, P_1 is treated as a data object. Consequently, the cluster centroid $C_h, h \in \{1, \dots, N\}$ is likewise constructed from FPRs.
- (2) The fuzziness parameter c represents the fuzziness degree of clusters. The larger the c value, the higher the fuzziness degree of the clusters [38]. The most frequently used value for this parameter is $c = 2$.
- (3) The membership degree $\mu_{C_h}(P_i)$ is computed by employing similarity measures, which are based on the chosen distance metric.
- (4) The stopping criterion of the FCM algorithm used in this paper is described in the next section.

3. A Novel Hybrid Human–AI Method for LSGDM

In this section, we present a novel hybrid human–AI method for LSGDM, which consists of three parts: clustering of experts, determination of subgroup weights, and a new consensus optimization model.

3.1. Classification of Experts

In the first stage, we divide experts into human experts and an AI expert according to their roles. In the second stage, the human experts are divided into several subgroups based on their FPRs using the FCM algorithm. Several rules of this algorithm are described as follows:

- (1) In the FCM algorithm, the cluster number can be preset randomly. This paper sets the number of clusters to be the number of different alternatives, $C = \{C_1, \dots, C_N\}$, under the scenario-specific assumption that each subgroup reflects a representative preference for one alternative. It should be noted that this setting may not hold for general clustering tasks; in other practical applications, the number of clusters is usually determined by conventional clustering validity indices such as the Davies–Bouldin index or the silhouette coefficient.
- (2) A centroid symbolizes each cluster, denoted as c_i for i in the set $\{1, \dots, N\}$. The process of establishing the initial centroid can be performed randomly or by selecting a value from the data set, but the initialization significantly affects the convergence. In this regard, we adopt the method proposed in Ref. [39]. Initialize the collective preference relation P_c as the first cluster centroid c_1 . Then, the expert preference P_i that is farthest from P_c is selected as the second cluster centroid c_2 . For $c_h (h \geq 3)$, compute the minimum distance between the remaining experts' preferences and the two current centroids, and find the expert preference with the largest minimum distance and assign it to c_3 . Repeat this procedure until all N centroids are initialized.

- (3) The levels of membership $\mu_{c_{h,t}}(P_i)$ for clusters and the cluster centroid $c_{h,t}$ are iteratively updated, as shown in Algorithm 1.
- (4) For the purpose of calculating distances between preference relations, we use the following Minkowski distance measure [40]:

$$d(P_k, c_{h,t}) = \left(\frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1, i \neq j}^n |p_{ij}^k - c_{ijh,t}|^\lambda \right)^{1/\lambda}, \quad (3)$$

where $\lambda > 0$. In this paper, we set $\lambda = 2$, which corresponds to the Euclidean distance.

- (5) The termination condition in the FCM algorithm is triggered once all clusters have become stable. It happens when the variation in membership degrees from one iteration to the next approaches zero. To formalize, the termination criterion is defined as follows:

$$\frac{\sum_{k=1}^m \sum_{h=1}^N |\mu_{c_{h,t+1}}(P_k) - \mu_{c_{h,t}}(P_k)|}{m \cdot N} \leq \varepsilon, \quad (4)$$

where ε is a threshold value tending to zero used to verify the termination condition. Here, following the well-established practice in Ref. [19], we set ε to 0.001.

Algorithm 1 FCM Algorithm used for experts' FPRs

- 1: Set the number of clusters $N (N \geq 2)$, and fuzziness degree of a cluster c .
- 2: Initialize the centroids of N clusters $C_h, h \in \{1, \dots, N\}$.
- 3: **while** the stopping criterion is not met. **do**
- 4: Calculate the membership degree between each preference relation P_i and each cluster centroid $c_{h,t}, \mu_{c_{h,t}}(P_i) \in [0, 1]$, where t is the number of iterations, as follows:

$$\mu_{c_{h,t}}(P_i) = \frac{(1/d(P_i, c_{h,t}))^{1/(c-1)}}{\sum_{\mu=1}^N (1/d(P_i, c_{\mu,t}))^{1/(c-1)}}. \quad (5)$$

- 5: Update the cluster centroids $c_{h,t}$:

$$c_{h,t} = \frac{\sum_{i=1}^m \mu_{c_{h,t}}(P_i) P_i}{\sum_{i=1}^m \mu_{c_{h,t}}(P_i)}. \quad (6)$$

- 6: **end while**
-

3.2. Weight Determination for Subgroups

After dividing the experts into multiple subgroups, it is necessary to compute the importance degree of individual experts and subgroups. For the former, the opinions of experts within each subgroup are similar, so we think that the weight of each expert in the same subgroup is equal. For the latter, it includes the following elements:

- The number of experts and the degree of cohesion of the subgroup.
- The distance between the subgroup and the AI.

Unlike existing weight determination methods [5,19,21,22], this paper introduces a new element, namely, the distance from the subgroup to the AI, and contends that those subgroups closer to the AI should be assigned higher weights, on the grounds that the AI provides a distinct, data-calibrated perspective that serves as an external referent during the decision-making process. Human experts in LSGDM are inevitably subject to cognitive biases, bounded rationality, or emotional factors, particularly in emergency scenarios. Although AI is subject to its own limitations, such as biases in training data, it generates preferences through data-driven algorithms that draw on far more information than any single group of experts could access on its own. It is therefore posited that a subgroup

whose preferences are closer to those of the AI better reflects this externally derived, data-informed perspective. This indicates that the subgroup is less influenced by subjective biases, suggesting higher decision quality and thus meriting a greater weight.

To compute the first element, let $P_{C_h} = (p_{ij}^{C_h})_{n \times n}$ be the collective FPR of the cluster C_h , which can be obtained by integrating all the individual FPRs of experts in C_h . We can employ Equation (3) to compute the distance between the FPR $P_i^{C_h}$ of $e_i^{C_h}$ in C_h and P_{C_h} , where $e_i^{C_h} \in C_h$. Then, the average intra-cluster distance (AICD) of cluster C_h can be formulated as follows:

$$AICD(C_h) = \frac{1}{\#C_h} \sum_{e_i^{C_h} \in C_h} d(P_i^{C_h}, P_{C_h}), \quad (7)$$

where $\#C_h$ is the number of experts in C_h . It is noteworthy that the *AICD* serves as an indicator of the degree of subgroup cohesion. Specifically, a higher *AICD* value indicates lower subgroup cohesion, whereas a lower *AICD* value signifies higher subgroup cohesion.

To calculate the second element, let $P_{AI} = (p_{ij}^{AI})_{n \times n}$. Similarly, we can use Equation (3) to compute the distance $d(P_{AI}, P_{C_h})$ between the FPR P_{C_h} and P_{AI} . Given that the size, cohesion degree, and distance from the AI are factors that signify the cluster's importance, we synthesize these three dimensions as follows:

$$\varphi(C_h) = \frac{\#C_h}{\sum_{h=1}^N \#C_h} \cdot \frac{1/AICD_{C_h}}{\sum_{h=1}^N (1/AICD_{C_h})} \cdot \frac{1/d(P_{AI}, P_{C_h})}{\sum_{h=1}^N (1/d(P_{AI}, P_{C_h}))}. \quad (8)$$

It can be seen from Equation (8) that the proposed weight determination method shows significant differences from existing studies [5,19,21,22], which only considered human DMs. With the rapid development of AI and big data technologies, hybrid LSGDM involving both human and AI participants is becoming increasingly viable. This hybrid human–AI decision-making mode can leverage the complementary strengths of both humans and AI, mitigating their respective limitations. By integrating AI as an external referent rather than an infallible arbiter, our method seeks to enhance the robustness and informational diversity of the decision-making process. For this reason, we take into account the opinions of the AI in Equation (8). Finally, the normalized weight for each cluster can be defined as follows:

$$\omega(C_h) = \frac{\varphi(C_h)}{\sum_{h=1}^N \varphi(C_h)}. \quad (9)$$

3.3. A Novel Consensus Optimization Model

One can easily note that reaching consensus requires a certain degree of flexibility and willingness from each member of the group to modify his/her initial position. Moreover, it is worth noting that the information granule [41] is frequently employed to generalize and express a collective opinion at a more abstract level, finding broad application in group consensus [31,42]. In this paper, the subgroup serves as a fundamental decision unit and object of study after the experts are classified into multiple subgroups; the position of a subgroup can be represented by the collective FPR of all experts within it. We introduce some degree of flexibility into subgroups by using the following method to promote consensus reaching in the whole group.

Let $p_{ij}^{C_h}$ be an entry of the collective FPR of the cluster C_h ; consider the following information granule I formed around $p_{ij}^{C_h}$:

$$I = [p_{ij}^{C_h} - 0.5\alpha, p_{ij}^{C_h} + 0.5\alpha], \quad (10)$$

where $\alpha \in [0, 2 \min\{p_{ij}^{C_h}, 1 - p_{ij}^{C_h}\}]$ denotes the size of I . The range of α ensures that the granule I is located in the unit interval $[0, 1]$ and symmetric about the corresponding entry of the collective FPR P_{C_h} . In this way, the value of $p_{ij}^{C_h}$ can vary within a certain range, which depends on the size of granule I . Notably, as the size of I increases, the likelihood of achieving a substantial consensus rises, and there is a heightened chance of producing significantly inconsistent collective FPRs within each subgroup.

3.3.1. Objective Function

In this part, two objectives for improving consensus should be realized. One is to increase the consistency of the collective FPRs of subgroups. The other is to increase the consensus within the group by bringing all collective FPRs of subgroups close to each other.

First, let us focus on the consistency of the collective FPRs of subgroups $P_{C_h} = (p_{ij}^{C_h})_{n \times n}$. In order to quantify the inconsistency level of P_{C_h} , several consistency indices can be used. Here, we adopt Equation (2) and formulate the following function:

$$Q_1 = \frac{\sum_{h=1}^N CI(P_{C_h})}{N}. \quad (11)$$

The larger the value of Q_1 is, the higher the consistency level of the global group is. Second, in order to reach consensus among all subgroups, the distance between the collective FPRs of subgroups and the global one is considered. Different from previous studies, we introduce an AI DM into LSGDM, taking into account the opinions of both human experts and the AI DM. Specifically, inspired by Ref. [43], we aim to explore people's different attitudes towards AI, namely how assigning different relative weights to humans and AI affects the consensus reaching in LSGDM. Let η_{AI} represent the degree of trust humans have in the AI DM, which is also the relative weight assigned to the AI. This exploration will consider the following four scenarios:

- Humans prefer the opinions of the AI DM in LSGDM, meaning that the opinions of the AI have greater influence.
- Humans prefer an equal partnership between humans and AI in LSGDM, where the opinions of both humans and AI account for half.
- Humans prefer a partnership where they hold a majority of the voting power, rather than necessarily being the dictator.
- Humans prefer a relationship where they have absolute control, that is 100% human and 0% AI involvement.

Let $p_{ij}^{C_h}$ be an entry of each subgroup's collective matrix P_{C_h} , and let p_{ij}^C be an entry of the collective matrix of the global group P_C obtained by aggregating the collective matrices of all subgroups and the AI, which is expressed by the following formula:

$$P_C = \eta_{AI} \cdot P_{AI} + (1 - \eta_{AI}) \cdot P_H, \quad (12)$$

where P_H is the collective matrix of all human subgroups and is expressed by the following formula:

$$P_H = \sum_{h=1}^N \omega_{C_h} \cdot P_{C_h}. \quad (13)$$

Then, the second objective function is expressed using the formula as follows:

$$Q_2 = \frac{1}{n^2 \cdot N} \cdot \sum_{h=1}^N \sum_{i=1}^n \sum_{j=1}^n (1 - |p_{ij}^{C_h} - p_{ij}^C|), \quad (14)$$

where η_{AI} represents the degree of trust humans have in the AI member; we set $\eta_{AI} = 0.5$ in this paper. Undoubtedly, the bigger the value of Q_2 , the higher the level of group consensus. Ideally, the case with $Q_1 = 1$ corresponds to consistent collective matrices of all subgroups, and the maximum value of Q_2 is the optimal solution. This implies that the experts have achieved the utmost level of consensus, and the final decision is in perfect alignment. When considering the maximization of Q_1 and Q_2 , the objectives do not oppose each other. However, the maximum values of the two objectives may not be achieved simultaneously. This implies that there is a need to address a problem involving the optimization of multiple objectives. Hence, we use the linear combination of Q_1 and Q_2 to solve this multi-objective optimization problem, which takes the following form:

$$Q = \delta Q_1 + (1 - \delta) Q_2, \quad (15)$$

where $\delta \in [0, 1]$ is a parameter that establishes a tradeoff between the level of group consensus and group consistency. In the limit with $\delta = 0$, $Q = Q_2$, which implies that the focus is exclusively on the group consensus. When $\delta = 1$, $Q = Q_1$, implying that we are only concerned with the group consistency. Generally, for $\delta \neq 0$, the relative contributions of functions Q_1 and Q_2 are determined by the selection of different δ values.

In the end, it is worth noting that in the process of adjusting the collective matrices of subgroups, the adjusted matrices may be quite inconsistent. For this reason, the proposed method adds an essential step to examine whether all the subgroups meet the acceptable consistency threshold $\overline{CI} = 0.9$ when the objective function Q reaches the optimal value.

3.3.2. PSO Algorithm

It can be seen from the expressions of Q_1 , Q_2 and the consistency index in Equation (2) that the difficulty of the optimization problem (15) makes it difficult to solve by classical methods such as the differential evolution method. Hence, the PSO algorithm is applied to solve the nonlinear optimization problem (15). It should be noted that the PSO is a population-based stochastic optimization algorithm developed by Kennedy and Eberhart while studying the social behavior of bird flocks or fish schools [44]. Extensive research [45–48] has been conducted on the theoretical foundations and practical applications of the PSO. With respect to the optimization problem (15), the decision variables correspond to the matrix elements associated with each subgroup P_{C_h} . For a given number of alternatives and clusters, i.e., $n = 4$, $N = 4$, even if the number of DMs is relatively large, the number of decision variables of Equation (15) can reach 24 when the reciprocal property of the FPR is considered. In this case, the PSO algorithm is still applicable. Without loss of generality, the formulae of the PSO algorithm used in this paper are as follows [49]:

$$\mathbf{v}_{t+1} = \omega \times \mathbf{v}_t + \varphi_1 \mathbf{r}_1 \cdot (\mathbf{p}_t - \mathbf{x}_t) + \varphi_2 \mathbf{r}_2 \cdot (\mathbf{p}_g - \mathbf{x}_t),$$

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \mathbf{v}_{t+1},$$

where $\mathbf{x}_t$ denotes the current position of the particle, $\mathbf{v}_t$ denotes the current velocity of the particle, $\mathbf{p}_t$ represents the best position reported so far and $\mathbf{p}_g$ is the global best position for the particle. The learning factors φ_1 and φ_2 are set to 2. The remaining two parameters in the PSO, namely $\mathbf{r}_1$ and $\mathbf{r}_2$, consist of random numbers that are uniformly distributed in $[0, 1]^n$. The inertia weight w decreases linearly from 0.9 to 0.4 as the number of iterations increases. Furthermore, in the PSO algorithm, an important aspect is to find a suitable representation of the particle. Here, each particle is a vector whose elements are in the interval $[0, 1]$. Consider an entry $p_{ij}^{C_h}$ of a subgroup P_{C_h} and assume a given size α of the information granule I . For convenience, Equation (10) can be written as follows:

$$I = [a, b] = [p_{ij}^{C_h} - 0.5\alpha, p_{ij}^{C_h} + 0.5\alpha]. \quad (16)$$

Let us assume that the particle to be studied is x . Then, the change in $p_{ij}^{C_h}$ can be reflected by the linear relation of x according to the expression $z = a + (b - a)x$. For example, given $p_{ij}^{C_h} = 0.8, \alpha = 0.1$ ($\alpha \in [0, 0.4]$) and $x = 0.4$, based on Equation (16), we have $[a, b] = [0.75, 0.85]$ and $z = 0.79$. Therefore, the modified value of $p_{ij}^{C_h}$ is 0.79.

3.4. A Framework for Hybrid Human–AI LSGDM

In this section, the hybrid human–AI LSGDM framework is shown in Figure 1, and the detailed steps are presented in Algorithm 2.

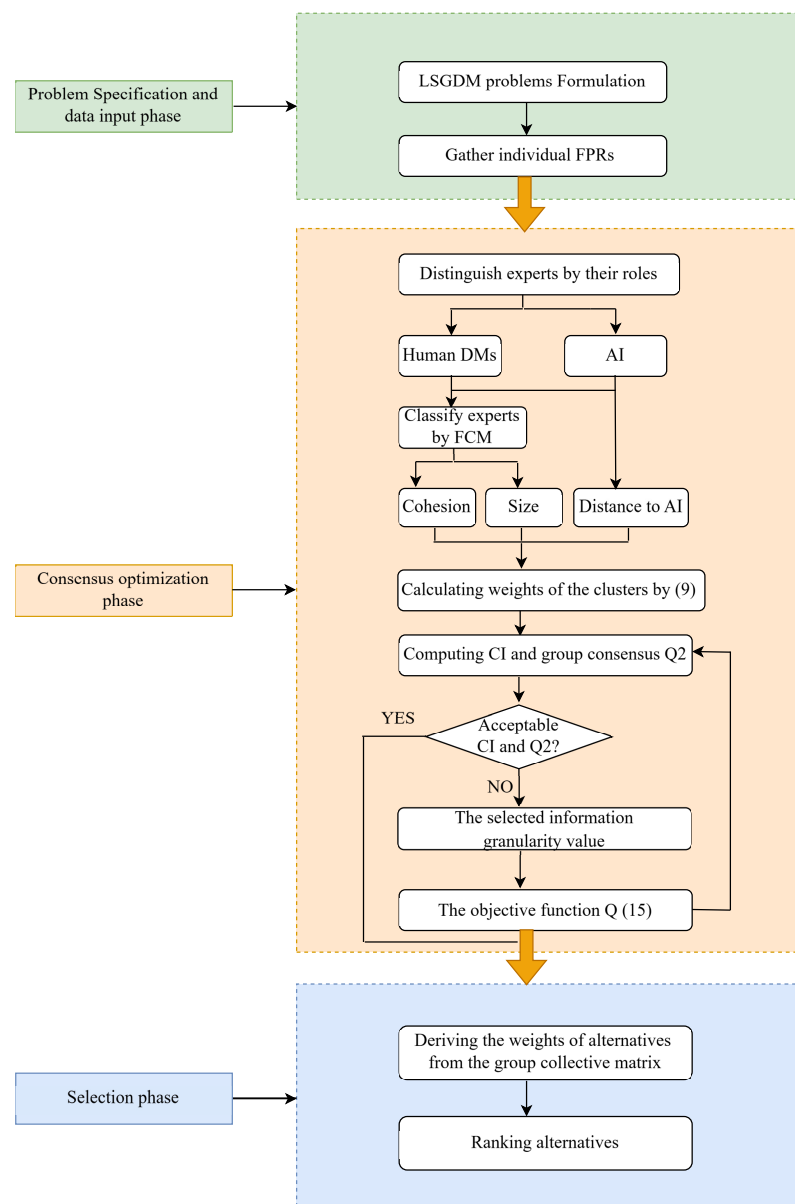


Figure 1. Framework for solving hybrid human–AI LSGDM problems with FPRs.

Algorithm 2 Steps of the proposed hybrid Human-AI LSGDM with FPRs.

Input: A set of alternatives $X = \{x_1, x_2, \dots, x_n\}$, human and AI FPRs $\{P^1, P^2, \dots, P^m, P^{AI}\}$, thresholds $\overline{CI}$, γ and the parameters δ , α , and η_{AI} .

Output: The ranking of alternatives.

Step 1: Perform a two-stage grouping mechanism. In the first stage, divide the DMs into human DMs and an AI DM based on their roles. In the second stage, partition the human DMs into several subgroups $C_h, h \in \{1, \dots, N\}$ according to Algorithm 1.

Step 2: Determine the weights of subgroups according to Equation (9), and display the initial structure of each subgroup, including its size and *AICD* value.

Step 3: Calculate the consistency level of each subgroup, compare it with the threshold $\overline{CI}$, and identify the subgroups with unacceptable consistency.

Step 4: Introduce information granularity into each subgroup and optimize the objective function in Equation (15) using the PSO algorithm, and obtain the optimized consistency level of each subgroup.

Step 5: Obtain the collective matrix of the group after the objective function Q converges, and acquire the structure of each subgroup, including its size, *AICD* value, and distance to the AI.

Step 6: Calculate the weights of the alternatives using a straightforward formula from [50], and thereby derive the ranking of alternatives $x_1, x_2, \dots, x_n$.

Step 7: End

4. Case Study

This section presents an emergency incident involving a large-scale group of DMs to verify the proposed model's effectiveness and feasibility, where the DMs' preference relations are adapted from Ref. [51]. The background of this event is that an earthquake of magnitude 7.0 occurred in Ya'an City, Sichuan Province of China on 20 April 2013. Due to the earthquake, traffic and communication in the disaster area were disrupted, and the emergency response was significantly hampered due to a lack of rescue personnel and medical resources. In response to this scenario, the rescue squad must select an optimal solution from the following four available rescue strategies to reduce damage to the lowest extent.

- (1) x_1 : Executing search operations to identify trapped persons and facilitating the evacuation of those with severe injuries from the disaster region to avoid the hazards of aftershocks.
- (2) x_2 : Every effort should be made by the rescue team to treat the injured persons and stop searching for trapped persons until the rescue facilities arrive.
- (3) x_3 : Rescue persons trapped in emergencies; provide on-site treatment to severely injured victims.
- (4) x_4 : Employ all available resources to rescue those entrapped and waiting for medical teams to provide treatment to the injured.

To deal with this problem, a rescue team of 20 human experts and an AI expert $E = \{e_1, e_2, \dots, e_{20}, e_{AI}\}$ is gathered to decide on the four alternatives based on their expertise and experience. Notably, the AI expert is instantiated by a large language model (LLM), e.g., GPT-4, which serves as a neutral DM with access to domain-specific knowledge about emergency management and disaster response. The AI's preference relation is elicited through a structured prompting procedure designed to mimic the cognitive process of a human expert. Specifically, the LLM is instructed to generate pairwise comparison matrices over the four aforementioned rescue alternatives $\{x_1, x_2, x_3, x_4\}$ using a $[0, 1]$ scale, where

the value r_{ij} indicates the degree to which alternative x_i is preferred to alternative x_j , with $r_{ij} + r_{ji} = 1$ ensuring additive reciprocity. The prompt employed is as follows:

“You are an experienced emergency response coordinator. A 7.0 magnitude earthquake has struck Ya’an City, Sichuan Province, China. The disaster has caused significant disruption to traffic and communication, severely impeding emergency response efforts due to a shortage of rescue personnel and medical resources. Four rescue alternatives are available (denoted as x_1, x_2, x_3 , and x_4). Please conduct a pairwise comparison of these alternatives using the $[0, 1]$ scale, where 0 signifies that alternative B is absolutely preferred to A, 0.5 signifies indifference, and 1 signifies that alternative A is absolutely preferred to B. Your judgments must satisfy additive reciprocity (i.e., if the preference of A over B is r , then the preference of B over A must be $1 - r$) and approximate consistency. Please present your response in a structured format, including the pairwise comparison matrix and a brief justification for each critical comparison.”

To mitigate the inherent randomness and enhance the reliability of the AI-generated preferences, the LLM is independently queried multiple times (or alternatively, multiple LLMs are employed), and the resulting pairwise comparison matrices are aggregated by averaging the corresponding entries. This procedure yields a refined matrix P_{AI} with values expressed to four decimal places, thereby preserving the additive reciprocity property while reducing individual response variance. The resulting matrix is reviewed to verify that it satisfies reciprocity and approximate consistency, and is structurally comparable to those provided by human experts. Assuming all experts express their opinions using additive RPRs, the 21 RPRs are provided in Appendix A for brevity.

In what follows, we adopt the proposed method to give the solution process of the LSGDM problem involving 21 experts.

Step 1: The FCM clustering algorithm is utilized to classify the 20 human experts into four distinct subgroups: $C_1 = \{e_1, e_{14}\}$, $C_2 = \{e_6, e_7, e_9, e_{10}\}$, $C_3 = \{e_2, e_3, e_4, e_8, e_{11}, e_{12}\}$, $C_4 = \{e_5, e_{13}, e_{15}, e_{16}, e_{17}, e_{18}, e_{19}, e_{20}\}$.

Step 2: By aggregating the preference relations of all experts within each subgroup through the arithmetic average operator, the collective FPRs of the four subgroups are as follows:

$$P_{C_1} = \begin{bmatrix} 0.5000 & 0.9000 & 0.8000 & 0.8000 \\ 0.1000 & 0.5000 & 0.7500 & 0.7500 \\ 0.2000 & 0.2500 & 0.5000 & 0.2500 \\ 0.2000 & 0.2500 & 0.7500 & 0.5000 \end{bmatrix}$$

$$P_{C_2} = \begin{bmatrix} 0.5000 & 0.4500 & 0.6000 & 0.7000 \\ 0.5500 & 0.5000 & 0.7750 & 0.8000 \\ 0.4000 & 0.2250 & 0.5000 & 0.8250 \\ 0.3000 & 0.2000 & 0.1750 & 0.5000 \end{bmatrix}$$

$$P_{C_3} = \begin{bmatrix} 0.5000 & 0.2677 & 0.6333 & 0.5667 \\ 0.7333 & 0.5000 & 0.4667 & 0.5667 \\ 0.3667 & 0.5333 & 0.5000 & 0.5667 \\ 0.4333 & 0.4333 & 0.4333 & 0.5000 \end{bmatrix}$$

$$P_{C_4} = \begin{bmatrix} 0.5000 & 0.5375 & 0.3500 & 0.2625 \\ 0.4625 & 0.5000 & 0.2750 & 0.3750 \\ 0.6500 & 0.7250 & 0.5000 & 0.5000 \\ 0.7375 & 0.6250 & 0.5000 & 0.5000 \end{bmatrix}$$

Then, Equation (9) is used to obtain the weight of each subgroup. The structure of the subgroups, including size, AICD value, distance from AI, and weight, is shown in Table 2. Next, the collective matrix of the whole group is computed as follows:

$$P_C = \begin{bmatrix} 0.5000 & 0.4592 & 0.5351 & 0.4967 \\ 0.5408 & 0.5000 & 0.4754 & 0.5529 \\ 0.4549 & 0.5246 & 0.5000 & 0.5598 \\ 0.5033 & 0.4471 & 0.4402 & 0.5000 \end{bmatrix}$$

Table 2. Structure of subgroups.

Subgroup	Size	AICD Value	Distance to AI	Weight
C_1	2	0.0791	0.0877	0.0795
C_2	4	0.1120	0.0606	0.1621
C_3	6	0.1430	0.0288	0.4018
C_4	8	0.1278	0.0484	0.3566

Step 3: Calculate the initial consistency level of each subgroup and the values of the two objective functions Q_1 , Q_2 . The results are as follows: $CI(P_{C_1}) = 0.8000$, $CI(P_{C_2}) = 0.8833$, $CI(P_{C_3}) = 0.8667$, $CI(P_{C_4}) = 0.9375$, $Q_1 = 0.8719$ and $Q_2 = 0.8686$. In practice, the initial consistency of experts' preference relations is not always high. Since subgroups C_1 , C_2 , C_3 fail to meet the acceptable consistency threshold, their collective FPRs are considered unacceptably inconsistent and thus require adjustment.

Step 4: We introduce an information granule α for each subgroup and, without loss of generality, set $\alpha = 0.15$. Due to time urgency, DMs must make a rapid and reasonable decision. The PSO algorithm is then applied to optimize the objective function Q ; the parameter $\delta = 0.5$ is chosen to indicate that individual consistency and group consensus are equally important. The relationship between the objective function values and the number of iterations is shown by the solid line in Figure 2. The improved consistency level of all subgroups and the values of functions Q_1 , Q_2 are: $CI(P_{C_1}) = 0.9500$, $CI(P_{C_2}) = 0.9750$, $CI(P_{C_3}) = 0.9417$, $CI(P_{C_4}) = 0.9833$, $Q_1 = 0.9542$ and $Q_2 = 0.8907$, respectively. Consequently, all subgroups have achieved an acceptable consistency level.

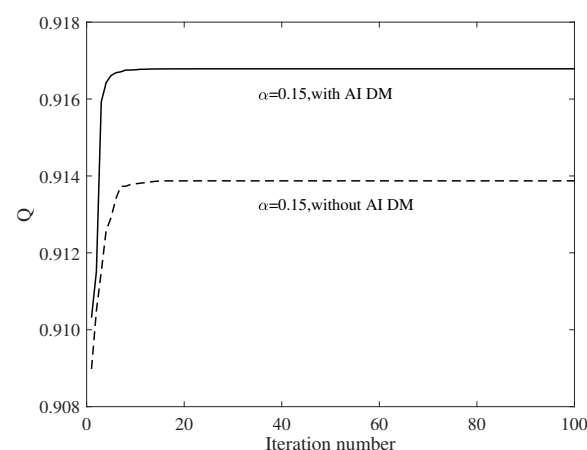


Figure 2. Values of the objective function Q versus the iteration number for $\alpha = 0.15$.

Step 5: After the objective function Q converges, the resulting collective matrix of the group is as follows:

$$P_C = \begin{bmatrix} 0.5000 & 0.4490 & 0.5081 & 0.4934 \\ 0.5510 & 0.5000 & 0.4931 & 0.5617 \\ 0.4919 & 0.5069 & 0.5000 & 0.5550 \\ 0.5066 & 0.4383 & 0.4450 & 0.5000 \end{bmatrix}$$

The structure of the subgroups after the optimal solution is reached is shown in Table 3.

Table 3. Structure of subgroups (after the optimal solution is reached).

Subgroup	Size	AICD Value	Distance to AI	Weight
C_1	2	0.1048	0.0877	0.0678
C_2	4	0.1336	0.0606	0.1539
C_3	6	0.1552	0.0288	0.4188
C_4	8	0.1434	0.0484	0.3596

Step 6: Then, a straightforward formula [50] is employed to calculate the weights of the alternatives: $(0.2438, 0.2632, 0.2567, 0.2362)$, from which their ranking is obtained, as detailed below: $x_2 \succ x_3 \succ x_1 \succ x_4$.

It should be pointed out that we also present the relationship between the objective function values and the number of iterations without AI involvement to illustrate the impact of the AI DM's participation on group consensus, as shown by the dashed line in Figure 2. The value of the objective function improves correspondingly with the introduction of an AI DM into LSGDM, and the group reaches a consensus more quickly. This implies that incorporating an AI DM into the decision-making process of a large group can, to a certain extent, increase the efficiency with which the group reaches a consensus.

Finally, we note that the current framework considers only one AI as an independent DM. Although it is conceptually feasible to extend the model to multiple AI DMs by aggregating their RPRs, multi-AI participation would raise new nontrivial challenges, including preference conflict resolution among different AI DMs and appropriate weight assignment, which deserve dedicated and systematic research. We leave the multi-AI extension for future investigation.

5. Discussions and Comparisons

In this section, we deliberate on the parameter setting of the proposed model and compare it with related methods.

5.1. Analyzing the Number of Clusters N

The clustering procedure plays a crucial part in LSGDM, enabling the reduction of the large-scale experts' dimensionality, thereby decreasing decision-making complexity and cost. Before running the FCM algorithm, it is necessary to set the initial number of clusters N . To evaluate the potential influence of cluster numbers on the final solution of the LSGDM problem, we apply our proposed method to different cluster scenarios, with the findings depicted in Table 4. According to Table 4, we can draw the following conclusions.

Table 4. Decision results under different cluster numbers (here $\delta = 0.5, \alpha = 0.15$).

<i>N</i>	Clustering Results	Initial <i>Q</i> Value	Initial NCI	Final <i>Q</i> Value	Final NCI	The Global Collective FPR	Ranking
2	$C_1 = \{e_5, e_{11}, e_{13}, e_{15}, e_{16}, e_{17}, e_{18}, e_{19}, e_{20}\},$ $C_2 = \{e_1, e_2, e_3, e_4, e_6, e_7, e_8, e_9, e_{10}, e_{11}, e_{12}\}$	0.9291	0	0.9685	0	$\begin{bmatrix} 0.5000 & 0.4955 & 0.4658 & 0.4844 \\ 0.5045 & 0.5000 & 0.4704 & 0.4890 \\ 0.5342 & 0.5296 & 0.5000 & 0.5186 \\ 0.5156 & 0.5110 & 0.4814 & 0.5000 \end{bmatrix}$	$x_2 \succ x_3 \succ x_1 \succ x_4$
3	$C_1 = \{e_1, e_{14}\},$ $C_2 = \{e_2, e_3, e_4, e_6, e_7, e_8, e_9, e_{10}, e_{12}\},$ $C_3 = \{e_5, e_{11}, e_{13}, e_{15}, e_{16}, e_{17}, e_{18}, e_{19}, e_{20}\}$	0.8708	1	0.9231	0	$\begin{bmatrix} 0.5000 & 0.4871 & 0.4898 & 0.4938 \\ 0.5129 & 0.5000 & 0.4763 & 0.5584 \\ 0.5102 & 0.5237 & 0.5000 & 0.5553 \\ 0.5062 & 0.4416 & 0.4447 & 0.5000 \end{bmatrix}$	$x_2 \succ x_3 \succ x_1 \succ x_4$
4	$C_1 = \{e_1, e_{14}\},$ $C_2 = \{e_6, e_7, e_9, e_{10}\},$ $C_3 = \{e_2, e_3, e_4, e_8, e_{11}, e_{12}\},$ $C_4 = \{e_5, e_{13}, e_{15}, e_{16}, e_{17}, e_{18}, e_{19}, e_{20}\}$	0.8702	3	0.9224	0	$\begin{bmatrix} 0.5000 & 0.4490 & 0.5081 & 0.4934 \\ 0.5510 & 0.5000 & 0.4931 & 0.5617 \\ 0.4919 & 0.5069 & 0.5000 & 0.5550 \\ 0.5066 & 0.4383 & 0.4450 & 0.5000 \end{bmatrix}$	$x_2 \succ x_3 \succ x_1 \succ x_4$
5	$C_1 = \{e_1, e_{14}\},$ $C_2 = \{e_2, e_3, e_4, e_7, e_8, e_{12}\},$ $C_3 = \{e_5, e_{11}, e_{17}, e_{18}, e_{20}\},$ $C_4 = \{e_{13}, e_{15}, e_{16}, e_{19}\},$ $C_5 = \{e_6, e_9, e_{10}\}$	0.8673	3	0.9295	1	$\begin{bmatrix} 0.5000 & 0.5209 & 0.5522 & 0.5035 \\ 0.4791 & 0.5000 & 0.5075 & 0.5070 \\ 0.4478 & 0.4925 & 0.5000 & 0.5262 \\ 0.4965 & 0.4930 & 0.4738 & 0.5000 \end{bmatrix}$	$x_2 \succ x_3 \succ x_1 \succ x_4$
6	$C_1 = \{e_{11}, e_{17}, e_{18}, e_{20}\},$ $C_2 = \{e_1, e_{14}\}, C_3 = \{e_6, e_9, e_{10}\},$ $C_4 = \{e_5, e_{13}, e_{15}, e_{16}, e_{19}\},$ $C_5 = \{e_4, e_7, e_8, e_{12}\},$ $C_6 = \{e_2, e_3\}$	0.8556	5	0.9234	2	$\begin{bmatrix} 0.5000 & 0.4656 & 0.5275 & 0.5161 \\ 0.5344 & 0.5000 & 0.4930 & 0.5582 \\ 0.4725 & 0.5070 & 0.5000 & 0.5412 \\ 0.4839 & 0.4418 & 0.4588 & 0.5000 \end{bmatrix}$	$x_2 \succ x_3 \succ x_1 \succ x_4$
7	$C_1 = \{e_{11}, e_{15}\}, C_2 = \{e_1, e_{14}\},$ $C_3 = \{e_6, e_9, e_{10}\},$ $C_4 = \{e_{13}, e_{15}, e_{16}, e_{19}\},$ $C_5 = \{e_4, e_7, e_8, e_{12}\}, C_6 = \{e_2, e_3\},$ $C_7 = \{e_{17}, e_{18}, e_{20}\}$	0.8600	6	0.9223	3	$\begin{bmatrix} 0.5000 & 0.4633 & 0.5208 & 0.5052 \\ 0.5367 & 0.5000 & 0.4961 & 0.5645 \\ 0.4792 & 0.5039 & 0.5000 & 0.5577 \\ 0.4948 & 0.4354 & 0.4423 & 0.5000 \end{bmatrix}$	$x_2 \succ x_3 \succ x_1 \succ x_4$

Note: NCI: the number of clusters whose consistency level does not reach the acceptable consistency threshold $\overline{CI}$.

- (1) As the number of clusters N increases, the initial value of the objective function Q decreases. Specifically, when there are two clusters, the initial value of Q is greater than 0.9. However, the $AICD$ is very high in this case. The relationship between the $AICD$ of the clustering and the number of clusters is depicted in Figure 3. As previously mentioned, the $AICD$ is an indicator of the degree of cohesion within the cluster. The larger the value of $AICD$, the less cohesive the clusters are. The clustering process exhibits a high $AICD$ when the number of clusters is 2, which can be attributed to an imprecise partition. The $AICD$ decreases sharply as the number of clusters increases from two to four, and the rate of decrease slows down for cluster numbers greater than four.
- (2) When the number of clusters $N = 2$, both clusters exhibit acceptable consistency. However, as the number of clusters increases from three to seven, the number of clusters with unacceptable consistency shows an upward trend. To address this, the proposed model incorporates a consistency threshold to ensure that all clusters meet the consistency requirement during the consensus process. The results indicate that for N ranging from two to four, all adjusted clusters achieve acceptable and improved consistency. Nevertheless, for N between five and seven, a few clusters fail to reach acceptable consistency, which may be attributed to the limited level of the introduced information granule α . Considering these factors, $N = 4$ is deemed a suitable choice. Furthermore, the final alternative ranking in Table 4 remains stable across different values of N . This demonstrates that the ultimate decision for the LSGDM problem is robust to variations in the number of clusters.

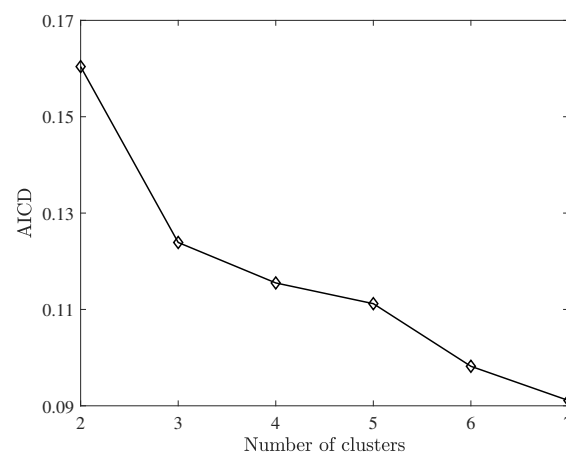


Figure 3. Variations in the $AICD$ value versus the number of clusters.

5.2. Analysis of Parameters α and δ

Once we have examined how the number of clusters N influences the final decision results, we then assess the impact of parameters α and δ . Without loss of generality, we define the number of clusters as $N = 4$ here. Firstly, the relationship between the consistency level of all subgroups and the level of information granule is drawn in Figure 4. It is seen from Figure 4 that the consistency level of all subgroups improves as the information granule level increases. The consistency improvement speed of subgroups is related to their initial consistency level. The consistency of subgroup P_{C_1} increases faster than that of subgroups P_{C_2} , P_{C_3} and P_{C_4} . When the level of information granule introduced, α , is approximately close to 0.15, all subgroups have an acceptable level of consistency, meaning that the optimal solution of Q is feasible and decisions with a high level of consensus and acceptance are reached among the DMs. In addition, we analyze the influence of the parameters α and δ on the stability of the final decision results. For simplicity, the parameters α and δ are represented in the form of a

two-tuple: (α, δ) . Tables 5 and 6 present the priority weight vectors of alternatives under the selected values of (α, δ) by using the simple formula in [50]. As observed in Tables 5 and 6, the ultimate ranking of the alternatives remains stable despite variations in the parameters (α, δ) . The result demonstrates that the final solution of the LSGDM problem is robust across varying values of parameters α and δ .

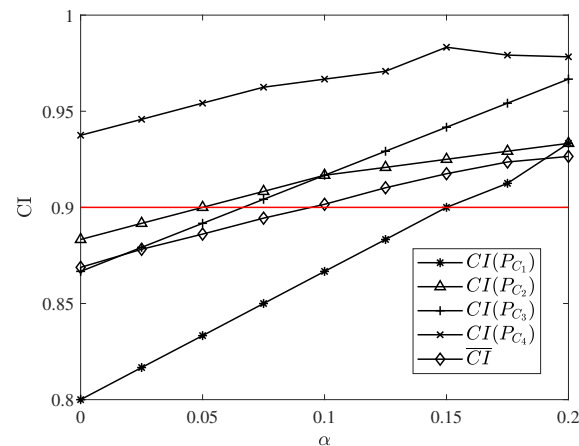


Figure 4. Variations in cluster consistency levels with respect to α .

Table 5. Priority weight vectors and alternative ranking for $\alpha = 0.15$ and different δ values.

δ Value	Priority Weight Vectors	Alternative Ranking
0.30	(0.2427, 0.2658, 0.2542, 0.2373)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.45	(0.2674, 0.2588, 0.2405, 0.2333)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.60	(0.2436, 0.2611, 0.2575, 0.2378)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.75	(0.2419, 0.2683, 0.2564, 0.2334)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.90	(0.2431, 0.2642, 0.2581, 0.2346)	$x_2 \succ x_3 \succ x_1 \succ x_4$

Table 6. Priority weight vectors and alternative ranking for $\delta = 0.5$ and different α values.

α Value	Priority Weight Vectors	Alternative Ranking
0.15	(0.2408, 0.2636, 0.2594, 0.2362)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.16	(0.2420, 0.2654, 0.2625, 0.2301)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.17	(0.2394, 0.2695, 0.2559, 0.2352)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.18	(0.2412, 0.2651, 0.2551, 0.2386)	$x_2 \succ x_3 \succ x_1 \succ x_4$
0.19	(0.2403, 0.2690, 0.2546, 0.2361)	$x_2 \succ x_3 \succ x_1 \succ x_4$

5.3. Analyzing the Parameter η_{AI}

As previously stated, with the ongoing advancement of AI and big data technology, LSGDM involving a mix of human and AI participation has become a reality. In particular, human DMs may face two extreme cases: either they fully trust and rely on AI outcomes, or they completely distrust the AI and rely solely on their own judgment. Beyond these extremes, some studies have identified a compromise mode in which human and AI opinions are assigned different relative weights [43]. Motivated by Ref. [43], we introduce the parameter η_{AI} to denote the extent to which humans trust the AI member; equivalently, η_{AI} represents the relative weight assigned to the AI. Specifically, $\eta_{AI} = 0$ indicates that humans completely distrust and reject the AI member. When $0 < \eta_{AI} < 0.5$, humans do not entirely reject the AI DM, but their opinions carry greater weight. If $\eta_{AI} = 0.5$, human and AI opinions are equally weighted. For $0.5 < \eta_{AI} \leq 1$, humans exhibit stronger trust toward the AI DM and therefore assign it a larger relative weight in LSGDM. Based on the above discussion, we examine how the parameter η_{AI} influences consensus formation

in LSGDM. We vary η_{AI} from 0 to 1 with a step size of 0.1, and evaluate its effects on the objective functions Q , Q_1 , and Q_2 . The results are presented in Figure 5.

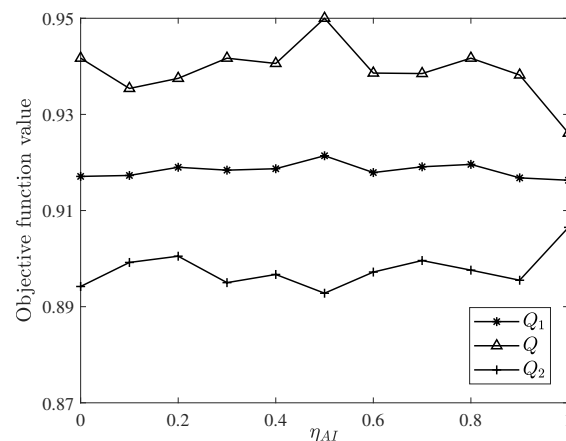


Figure 5. Variations in Q , Q_1 , Q_2 versus η_{AI} values.

It is seen from Figure 5 that when $\eta_{AI} = 0$ and $\eta_{AI} = 1$ the values of the objective function Q , Q_1 and Q_2 are relatively low. Conversely, in scenarios where both human and AI DMs are involved, the values of Q , Q_1 , Q_2 are relatively high. This implies that incorporating an AI DM into GDM can achieve higher values for the functions Q , Q_1 , Q_2 , regardless of the AI's relative weight compared to humans. Additionally, it is interesting to note that when humans and AI have equal weight ($\eta_{AI} = 0.5$), the value of the function Q reaches its maximum, indicating the highest level of consensus within the group. These findings suggest that the inclusion of AI DM in GDM can enhance the efficiency and level of consensus reached by the group.

5.4. Comparison with Related Methods

In this section, we mainly conduct comparisons from three perspectives, namely existing weight determination methods, LSGDM consensus models, and the human–AI LSGDM consensus model.

5.4.1. Comparison with Existing Weight Determination Methods

Many weight determination methods have been reported in LSGDM [5,19,21,22]. For example, Tang et al. [19] considered both subgroup size and cohesion to determine the weights of subgroups, where cohesion is measured by the silhouette coefficient. Li et al. [21] used the majority principle to measure the weights of subgroups; the more experts in a subgroup, the higher the weight of the subgroup. This method only considers the size of the subgroup. Li et al. [22] calculated the weight of a subgroup by combining its size and level of togetherness depicted by the deviation of a PDEHFLTS of a subgroup. More recently, Trillo et al. [5] determined subgroup weights based on four factors: subgroup size, experts' degree of aggressiveness, experts' degree of positivity, and subgroup consensus. Although the above literature greatly enriches the weight calculation methods for subgroups, to the best of our knowledge, research has seldom been conducted on the weights of subgroups under hybrid human–AI participation in LSGDM. Therefore, the weight determination method proposed in this paper incorporates a novel element, the distance from the subgroup to AI, thereby effectively filling this research gap.

5.4.2. Comparison with Existing LSGDM Consensus Models

To further substantiate the effectiveness and superiority of the proposed model, we compare it with two representative LSGDM consensus methods: the adaptive consensus

reaching process based on hybrid strategies proposed by Tang et al. [19] (referred to as Tang's method) and the dynamical consensus method incorporating an exit-delegation mechanism developed by Xu et al. [51] (referred to as Xu's method). The former represents a mainstream interactive consensus framework, whereas the latter is tailored for emergency large-group scenarios. The comparison is carried out on the same numerical example under the consensus threshold $\gamma = 0.8$ and the consistency threshold $CI = 0.9$. Table 7 summarizes the comparative results, detailing the number of iterations, the final average consistency (Q_1), the final consensus level (Q_2), the adjustment deviation, and the final alternative ranking.

Table 7. Comparison of different methods.

Method	Number of Iterations	Final Average Q_1	Final Consensus Level Q_2	Adjustment Deviation	Final Alternative Ranking
Tang's method [19]	2	0.9120	0.8540	0.8000	$x_2 \succ x_3 \succ x_1 \succ x_4$
Xu's method [51]	3	0.8312	0.7943	0.9088	$x_2 \succ x_3 \succ x_1 \succ x_4$
Proposed method	1	0.9542	0.8907	0.6500	$x_2 \succ x_3 \succ x_1 \succ x_4$

Based on the comparative results presented in Table 7, we can draw the following conclusions:

- (1) Superiority in efficiency and emergency responsiveness: As shown in Table 7, the proposed method reaches the optimal solution in a single iteration, whereas Tang's and Xu's methods require multiple rounds of interaction (two and three iterations, respectively). However, in practical emergency events, time is of utmost importance, and a rapid and productive decision should be reached. This highlights the advantage of using the PSO algorithm combined with information granules, which is particularly suitable for urgent emergency decision-making where time is critical.
- (2) Improvement of individual consistency: During the CRP, Xu's method focuses solely on global consensus, leading to a drop in the average consistency level below the acceptable threshold ($0.8312 < 0.9$). In contrast, our objective optimization model explicitly maximizes the consistency index, resulting in a high consistency of 0.9542. This proves that our model prevents the adjusted preferences from becoming logically contradictory.
- (3) Lower adjustment deviation: Thanks to the introduction of information granules, our model allows adjustments within a flexible boundary rather than forced directional modifications. Consequently, the adjustment deviation (0.6500) is significantly lower than that of the compared methods (0.8000 and 0.9088), indicating that the proposed model respects the original judgments of the experts to a greater extent and preserves the original preference information as much as possible.
- (4) Role of AI DM: Unlike the existing methods that only consider human experts, our model incorporates the AI DM. The final ranking remains consistent ($x_2 \succ x_3 \succ x_1 \succ x_4$), but the inclusion of the AI DM and the trust parameter η_{AI} accelerates the consensus process and enhances the efficiency of the decision-making, as previously discussed.

5.4.3. Comparison with Existing Human–AI LSGDM Consensus Model

Finally, as briefly mentioned in the introduction, Zhang et al. [14] also investigate human–AI coordination in LSGDM using heterogeneous feedback strategies. Although both this paper and their study address the integration of AI into large-scale group consensus, the underlying methodologies and targeted decision scenarios differ fundamentally, as summarized in Table 8.

Table 8. Comparison between Zhang et al. [14] and the proposed model.

Dimension	Zhang et al. [14]	Proposed Model
Consensus paradigm	Traditional iterative consensus reaching process based on a minimum cost consensus (MCC) model, requiring multiple rounds of interactive feedback wherein experts or AI modify their preferences toward a reference point.	Objective optimization problem maximizing both group consensus and individual consistency, solved globally via the PSO algorithm. Avoids tedious round-by-round negotiations, particularly advantageous for emergency decision-making under severe time constraints.
Preference adjustment	Adjustments constrained by unit costs inversely proportional to experts' attitudes toward AI; experts with AI aversion face higher modification costs, potentially forcing substantial compromise of original opinions.	Information granules provide flexibility for preference adjustment, allowing collective subgroup preferences to vary within an acceptable interval. Respects the inherent uncertainty and elasticity of human judgment without explicitly penalizing adjustment costs.
AI role handling	Three distinct scenarios (AI as decisive, equal, or auxiliary role), each with different feedback strategies; requires the decision context to be strictly categorized beforehand.	A trust parameter η_{AI} seamlessly embedded into the collective matrix calculation, smoothly navigating the continuum from $\eta_{AI} = 0$ to $\eta_{AI} = 1$, providing flexible control over AI's influence.
Consistency optimization	Primarily focuses on achieving the consensus threshold at minimum cost; does not explicitly guarantee the individual consistency of adjusted preferences.	Explicitly maximizes the consistency index alongside group consensus in the objective function, ensuring that adjusted subgroup preferences do not violate transitivity or logical coherence.

In summary, while Zhang et al. [14] provide profound insights into heterogeneous feedback behaviors in human–AI coordination, our proposed model offers a faster, more flexible approach that explicitly optimizes consistency. By leveraging information granules and a global optimization framework, our model is better suited for LSGDM scenarios that demand both rapid response and robust logical coherence, such as emergency management.

6. Conclusions

This paper addresses the challenge of achieving rapid and efficient consensus in LSGDM problems, particularly in complex and urgent scenarios such as emergency management. To this end, a novel hybrid human–AI consensus model is developed. The proposed model adopts a two-stage grouping mechanism: the large group of experts is first divided into human and AI experts according to their roles, after which the human experts are further clustered into subgroups using the FCM algorithm based on their RPRs. A novel objective function is formulated with the aim of improving consistency of the subgroups and reducing the deviations of the subgroup collective matrices from those of the overall group. The established optimization problem is solved using the PSO algorithm. An illustrative example and comparative analyses are provided to validate the proposed approach. The main contributions of this paper can be summarized as follows:

- A novel hybrid human–AI decision framework with a two-stage grouping mechanism is proposed: first, DMs are divided into human and AI based on their roles, and then human DMs are clustered into subgroups by FCM based on their RPRs.
- A novel subgroup weighting mechanism is proposed, which relies on three factors: the subgroup's cohesion degree, scale, and distance from the AI.
- A new objective function has been introduced, enabling swift and efficient decision-making through the application of the PSO algorithm for LSGDM problems in emergency management.

- Experimental results demonstrate the feasibility and effectiveness of the proposed model in solving LSGDM problems with FPRs. The findings further reveal that the participation of an AI DM can affect the CRP in LSGDM.

Despite these contributions, this study has several limitations. First, the treatment of the AI DM in this paper is somewhat simplified. The AI DM is assumed to be a reliable member who provides external, data-driven analytical perspectives. In practice, however, the AI may suffer from data bias, model deficiencies, or limited interpretability [52–54], potentially leading to suboptimal consensus outcomes. Second, non-cooperative behaviors among DMs are not considered, which could obstruct consensus in real-world applications [55].

To address these limitations, future research will pursue the following directions. First, we may relax the assumptions regarding the AI member in this consensus model. Real-world AI DMs can produce errors and biases, which may mislead preference revisions and distort the CRP for LSGDM. A promising research direction is to investigate how faulty AI inputs influence DMs' trust in AI and the preference adjustment dynamics in the CRP. Second, it is worthwhile to investigate methods for detecting and managing non-cooperative behaviors among DMs, so as to improve the robustness of the proposed model in complex LSGDM environments.

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Appendix A

The 21 RPRs from human and AI DMs are presented as follows:

$$\begin{aligned}
 P_1 &= \begin{bmatrix} 0.5 & 0.9 & 0.9 & 0.8 \\ 0.1 & 0.5 & 0.7 & 0.8 \\ 0.1 & 0.3 & 0.5 & 0.4 \\ 0.2 & 0.2 & 0.6 & 0.5 \end{bmatrix}, P_2 = \begin{bmatrix} 0.5 & 0.3 & 0.7 & 0.8 \\ 0.7 & 0.5 & 0.3 & 0.6 \\ 0.3 & 0.7 & 0.5 & 0.3 \\ 0.2 & 0.4 & 0.7 & 0.5 \end{bmatrix} \\
 P_3 &= \begin{bmatrix} 0.5 & 0.1 & 0.6 & 0.6 \\ 0.9 & 0.5 & 0.6 & 0.4 \\ 0.4 & 0.4 & 0.5 & 0.3 \\ 0.4 & 0.6 & 0.7 & 0.5 \end{bmatrix}, P_4 = \begin{bmatrix} 0.5 & 0.1 & 0.8 & 0.4 \\ 0.9 & 0.5 & 0.6 & 0.6 \\ 0.2 & 0.4 & 0.5 & 0.8 \\ 0.6 & 0.4 & 0.2 & 0.5 \end{bmatrix} \\
 P_5 &= \begin{bmatrix} 0.5 & 0.4 & 0.4 & 0.4 \\ 0.6 & 0.5 & 0.1 & 0.5 \\ 0.6 & 0.9 & 0.5 & 0.4 \\ 0.6 & 0.5 & 0.6 & 0.5 \end{bmatrix}, P_6 = \begin{bmatrix} 0.5 & 0.3 & 0.6 & 0.7 \\ 0.7 & 0.5 & 0.8 & 0.8 \\ 0.4 & 0.2 & 0.5 & 0.9 \\ 0.3 & 0.2 & 0.1 & 0.5 \end{bmatrix} \\
 P_7 &= \begin{bmatrix} 0.5 & 0.2 & 0.6 & 0.6 \\ 0.8 & 0.5 & 0.8 & 0.8 \\ 0.4 & 0.2 & 0.5 & 0.6 \\ 0.4 & 0.2 & 0.4 & 0.5 \end{bmatrix}, P_8 = \begin{bmatrix} 0.5 & 0.4 & 0.7 & 0.6 \\ 0.6 & 0.5 & 0.4 & 0.8 \\ 0.3 & 0.6 & 0.5 & 0.7 \\ 0.4 & 0.2 & 0.3 & 0.5 \end{bmatrix}
 \end{aligned}$$

$$\begin{aligned}
P_9 &= \begin{bmatrix} 0.5 & 0.6 & 0.6 & 0.7 \\ 0.4 & 0.5 & 0.9 & 0.9 \\ 0.4 & 0.1 & 0.5 & 0.9 \\ 0.3 & 0.1 & 0.1 & 0.5 \end{bmatrix}, P_{10} = \begin{bmatrix} 0.5 & 0.7 & 0.6 & 0.8 \\ 0.3 & 0.5 & 0.6 & 0.7 \\ 0.4 & 0.4 & 0.5 & 0.9 \\ 0.2 & 0.3 & 0.1 & 0.5 \end{bmatrix} \\
P_{11} &= \begin{bmatrix} 0.5 & 0.4 & 0.4 & 0.6 \\ 0.6 & 0.5 & 0.3 & 0.4 \\ 0.6 & 0.7 & 0.5 & 0.7 \\ 0.4 & 0.6 & 0.3 & 0.5 \end{bmatrix}, P_{12} = \begin{bmatrix} 0.5 & 0.3 & 0.6 & 0.4 \\ 0.7 & 0.5 & 0.6 & 0.6 \\ 0.4 & 0.4 & 0.5 & 0.6 \\ 0.6 & 0.4 & 0.4 & 0.5 \end{bmatrix} \\
P_{13} &= \begin{bmatrix} 0.5 & 0.6 & 0.2 & 0.3 \\ 0.4 & 0.5 & 0.4 & 0.3 \\ 0.8 & 0.6 & 0.5 & 0.4 \\ 0.7 & 0.7 & 0.6 & 0.5 \end{bmatrix}, P_{14} = \begin{bmatrix} 0.5 & 0.9 & 0.7 & 0.8 \\ 0.1 & 0.5 & 0.8 & 0.7 \\ 0.3 & 0.2 & 0.5 & 0.1 \\ 0.2 & 0.3 & 0.9 & 0.5 \end{bmatrix} \\
P_{15} &= \begin{bmatrix} 0.5 & 0.7 & 0.4 & 0.5 \\ 0.3 & 0.5 & 0.1 & 0.2 \\ 0.6 & 0.9 & 0.5 & 0.4 \\ 0.5 & 0.8 & 0.6 & 0.5 \end{bmatrix}, P_{16} = \begin{bmatrix} 0.5 & 0.4 & 0.4 & 0.2 \\ 0.6 & 0.5 & 0.1 & 0.2 \\ 0.6 & 0.9 & 0.5 & 0.4 \\ 0.8 & 0.8 & 0.6 & 0.5 \end{bmatrix} \\
P_{17} &= \begin{bmatrix} 0.5 & 0.4 & 0.4 & 0.1 \\ 0.6 & 0.5 & 0.5 & 0.4 \\ 0.6 & 0.5 & 0.5 & 0.7 \\ 0.9 & 0.6 & 0.3 & 0.5 \end{bmatrix}, P_{18} = \begin{bmatrix} 0.5 & 0.6 & 0.4 & 0.2 \\ 0.4 & 0.5 & 0.3 & 0.7 \\ 0.6 & 0.7 & 0.5 & 0.6 \\ 0.8 & 0.3 & 0.4 & 0.5 \end{bmatrix} \\
P_{19} &= \begin{bmatrix} 0.5 & 0.6 & 0.2 & 0.3 \\ 0.4 & 0.5 & 0.4 & 0.3 \\ 0.8 & 0.6 & 0.5 & 0.4 \\ 0.7 & 0.7 & 0.6 & 0.5 \end{bmatrix}, P_{20} = \begin{bmatrix} 0.5 & 0.6 & 0.4 & 0.1 \\ 0.4 & 0.5 & 0.3 & 0.4 \\ 0.6 & 0.7 & 0.5 & 0.7 \\ 0.9 & 0.6 & 0.3 & 0.5 \end{bmatrix}, \\
P_{AI} &= \begin{bmatrix} 0.5000 & 0.4750 & 0.5300 & 0.4950 \\ 0.5250 & 0.5000 & 0.4800 & 0.5550 \\ 0.4700 & 0.5200 & 0.5000 & 0.5600 \\ 0.5050 & 0.4450 & 0.4400 & 0.5000 \end{bmatrix}
\end{aligned}$$

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