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A Probabilistic Linguistic Large-Group Emergency Decision-Making Method Based on the Louvain Algorithm and Group Pressure Model

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Abstract: To tackle preference conflicts and uncertainty in large-group emergency decision-making (LGEDM), this study proposes a probabilistic linguistic LGEDM method integrating the Louvain algorithm and group pressure model. First, expert weights are determined based on a social trust network, and the Louvain algorithm is employed for expert clustering, reducing the complexity of large-scale decision information. Second, a group pressure model is introduced to dynamically adjust expert preferences, enhancing consensus and decision consistency. Third, probabilistic linguistic term sets (PLTSs) are utilized to represent fuzzy and uncertain information, while attribute weights are determined by incorporating both subjective and objective factors, ensuring scientific rigor in decision-making. Finally, an improved TODIM (an acronym in Portuguese for Interactive and Multicriteria Decision-Making) method is adopted to account for the loss aversion behavior of decision-makers (DMs), enabling a more accurate characterization of psychological decision-making traits. The experimental results demonstrate that the proposed method outperforms existing approaches in terms of decision efficiency, group consensus, and result robustness, offering effective support for emergency decision-making in crisis situations.

Keywords: large-group emergency decision-making (LGEDM); group pressure model; consensus model; Louvain algorithm; probabilistic linguistic term sets

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1. Introduction

In recent years, emergencies have occurred frequently on a global scale, drawing significant attention due to their widespread societal impacts and potential catastrophic consequences. Emergency decision-making (EDM) is characterized by time sensitivity, incomplete information, and high decision pressure stemming from potentially severe outcomes [1–3]. Although emergency plans are often in place, scientific and effective EDM remains critical for managing emergencies and mitigating disaster impacts. Therefore, EDM has garnered significant attention and emerged as a key research area globally. Due to the complexity and uncertainty of emergencies, the decision-making process often requires the participation of a large number of experts from various professional fields, leading to the formation of large-group emergency decision-making (LGEDM) problems. LGEDM has gradually gained recognition in the field of decision sciences [4–6]. Since emergencies typically involve public interests, LGEDM, aimed at supporting emergency management, often requires the collaboration of numerous decision-makers (DMs) from

diverse professional backgrounds. The key characteristics of LGEDM are as follows [2,7–9]: (1) the decision-making group typically comprises more than 20 experts from different departments and fields; (2) final decisions must be made quickly within a limited time frame; (3) significant opinion divergences often exist among DMs; and (4) the evaluation information provided by experts is often vague and incomplete.

Based on these characteristics, academic research on the LGEDM problem primarily focuses on three key aspects: (1) Selection of clustering methods—Clustering of DMs' preferences is a crucial foundation for vertical decision-making. Choosing appropriate clustering methods based on decision needs or preference expression forms is essential for grouping and dimensionality reduction in EDM. (2) Design of consensus models—Due to the complexity of decision problems and the differences in cognitive levels and knowledge structures among DMs, consensus models are required to coordinate divergences among experts and achieve a group consensus. Effective consensus models can dynamically adjust experts' consensus levels, thereby improving decision efficiency and the satisfaction of decision outcomes. Hence, constructing consensus models is vital. (3) Selection and evaluation of alternative solutions—In EDM, the selection of alternative solutions is crucial. DMs must quickly filter and assess the options based on expert evaluations, particularly in scenarios where the information is fuzzy or incomplete, ensuring that the optimal solution is chosen.

To reduce the complexity of group decision-making and improve decision efficiency, scholars have proposed various clustering methods to group and reduce the dimensionality of DMs. Currently, these clustering methods can be broadly categorized into two types. The first category involves clustering methods based on the independence assumption, which assumes that DMs are independent of each other, without considering internal relationships such as social connections or interest associations. These methods typically use distances or similarities between decision matrices as the basis for clustering. For instance, Jiang et al. [10] proposed a hybrid correlation coefficient based on probabilistic hesitant fuzzy sets (PHFSs), which reduces the complexity of LGEDM through hierarchical clustering. Ma et al. [11] developed a similarity measurement for DMs based on multi-stage hesitant fuzzy linguistic terms, incorporating both hesitation degrees and expected distances, and constructed a corresponding clustering model. Xu et al. [12] introduced a preference-based risk measurement method and designed an expert clustering algorithm that groups experts into subsets with similar decision risk levels, thereby effectively controlling the overall decision risks. The second category leverages social network relationships to address large-group decision-making problems. These methods consider the social connections among DMs to reduce the decision complexity and align with practical requirements. For example, Liu et al. [13] proposed a dual-trust social network based on familiarity and similarity to cluster decision-making groups. Wu et al. [14] designed a consensus adjustment model incorporating trust relationships to address group decision-making problems with incomplete linguistic information. Xu et al. [15], inspired by the modularity concept in social networks, applied the Louvain algorithm to LGEDM to cluster experts based on their interconnections. In practical decision-making processes, individual decisions are often influenced by the opinions of other DMs and the group as a whole. With the rapid development of internet technologies and social media, the social connections among DMs have become increasingly complex. In this context, constructing clustering models based on trust relationships emerges as a crucial approach to address large-group decision-making problems, offering both significant theoretical value and practical relevance. Furthermore, this study proposes viewing clustering as a modular process within small groups, where consensus convergence is achieved locally before enhancing the overall group consensus. This approach facilitates the exploration of more optimal decision solutions.

The complexity of group decision-making and the diversity among DMs often result in varying behavioral characteristics during the consensus adjustment process. These behaviors encompass both psychological traits and practical actions, significantly influencing group consistency and decision quality. For instance, Yan et al. [16] designed a two-stage adaptive consensus model that considers experts' preferences. This model employs a dynamic adjustment mechanism to effectively reduce adjustment bias and time costs, while adaptively revising expert opinions based on the consensus context. Xu et al. [17] proposed a feedback recommendation strategy under time pressure, developing a novel subgroup identification method to enhance group decision-making efficiency. Wang et al. [18] introduced a personalized consensus model with acceptance probability, which improves consensus satisfaction by modeling individual evaluators' preferences. However, most existing studies have primarily focused on leveraging diverse decision behaviors to enhance group consensus levels. Less attention has been given to how these decision behaviors contribute to improving decision quality under varying consensus levels. Furthermore, the impact of group pressure on group decision-making has been underexplored. According to social influence theory, individuals' behaviors and attitudes are susceptible to the influence of prevailing group opinions, leading to phenomena such as conformity, compliance, obedience, and group polarization [19]. In group decision-making, group pressure plays a significant role in shaping group preferences and decision outcomes. Therefore, effectively leveraging group intelligence to improve the scientific validity and accuracy of decisions is of critical importance. The core concept of group intelligence is that group decisions, in most cases, exhibit greater intelligence compared to individual decisions [20]. This analysis highlights that while consensus models grounded in decision behaviors have seen significant advancements, there remains a pressing need to address how group intelligence can be fully utilized to enhance the decision quality in large-group decision-making scenarios. Consequently, investigating the influence of group pressure on group intelligence in the context of LGEDM not only holds substantial theoretical value but also offers meaningful practical implications.

In the study of LGEDM, accurately describing decision-making problems and effectively expressing the individual preferences of DMs are key areas of scholarly focus. Due to the complexity of decision problems and the cognitive biases of individuals, DMs often face challenges in precisely articulating their preference information. To address this issue, Zadeh [21] introduced the theory of fuzzy sets (FS), which provides a theoretical foundation for handling problems characterized by fuzziness and uncertainty. Later, Atanassov [22] extended this framework by introducing the concept of intuitionistic fuzzy sets (IFSs), which consider both membership and non-membership degrees. He further developed the interval-valued intuitionistic fuzzy set (IVIFS) theory [23]. Building upon these advancements, Torra [24] proposed hesitant fuzzy sets (HFSs), enabling a more accurate representation of uncertainty in the expression of evaluative information by DMs. To better reflect preferences under uncertain conditions, Pang et al. [25] defined probabilistic linguistic term sets (PLTSs). PLTSs offer significant advantages in expressing information within EDM contexts. Their flexibility allows them to more effectively meet the demands of practical decision-making and better reflect the complexities of real-world decision scenarios [26–31]. Therefore, this study focuses on group decision-making problems where DM preferences are expressed using PLTSs, aiming to provide more accurate methods for expressing and processing information in complex EDM situations.

Although existing research has made progress in these areas, current EDM methods still face several limitations. First, traditional clustering methods are mostly based on the assumption of independence, which fails to fully account for the social connections between DMs and the dynamic influences within the group. Second, while existing con-

sensus models address some differences in opinions, most methods do not consider the dynamic changes in experts' preferences or the effects of group pressure. This oversight affects decision consistency and coordination. Lastly, many decision evaluation methods overlook the psychological behaviors of DMs, particularly in emergency situations. Specifically, the impact of loss aversion on final decisions has not been sufficiently addressed. To overcome these limitations, this paper proposes a probabilistic linguistic LGEDM method that integrates the Louvain algorithm and a group pressure model. The proposed method aims to fill these research gaps in the following ways: (1) The expert clustering method, based on social trust networks and the Louvain algorithm, reduces decision complexity and enhances coordination among experts. (2) A group pressure model is introduced to dynamically adjust experts' preferences, improving decision consistency and group consensus. (3) By combining PLTSs with an improved TODIM method, the model incorporates decision-makers' loss aversion psychological traits, thus improving the scientific rigor and robustness of the decisions.

Building upon the above analysis, this study proposes a probabilistic linguistic LGEDM method that integrates group pressure and Louvain community clustering to explore optimal decision-making solutions within the framework of group intelligence. First, a trust relationship matrix among large-group DMs is established, and the Louvain algorithm is employed to cluster DMs, determining both expert and group weights. Second, individual-to-group preference relationships are modeled using opinion similarity, and an expert consensus model based on the group pressure model is constructed. Third, a comprehensive attribute weight determination model is developed, incorporating both subjective and objective factors, to reflect the stability and variability of attributes. Finally, in the context of emergencies, an improved TODIM method is adopted to rank alternative emergency solutions, accounting for the loss aversion behavior of DMs. The effectiveness and feasibility of the proposed method are verified through a case study.

The primary contributions of this study include the following:

(1) Proposing an expert clustering mechanism based on the Louvain algorithm. For LGEDM scenarios, the Louvain algorithm is utilized to cluster and reduce the dimensionality of experts. This approach effectively reduces the complexity of information processing while fully considering the social trust relationships among experts, thereby enhancing the operability and accuracy of group decision-making.

(2) Constructing an expert consensus model integrating group pressure. Group pressure is introduced as a key factor, and a mathematical model is developed to capture and adjust the dynamic deviations of experts' preferences from the group consensus. This model enhances the consistency and coordination of the decision-making process, improving the scientific rigor and efficiency of large-group decision-making in response to emergencies.

(3) Developing a comprehensive attribute weight determination model and extending the application of PLTSs in EDM. A combined subjective and objective attribute weight determination model is proposed, achieving a balanced and comprehensive approach to attribute weighting. Simultaneously, PLTSs are applied to EDM scenarios, enabling experts to express their preferences more flexibly and accurately under the complex and uncertain conditions of emergencies.

(4) Improving the TODIM method to incorporate the psychological behavioral characteristics of DMs. In the evaluation and selection of alternatives, the improved TODIM method incorporates DMs' loss aversion behavior, providing a more realistic representation of EDM processes. This enhancement significantly improves the rationality and applicability of the decision-making outcomes.

The structure of the remaining sections of this paper is as follows: Section 2 provides a review of the fundamental concepts of PLTSs, the Louvain algorithm, and the group pressure model, establishing the theoretical foundation for the subsequent research. Section 3 presents a probabilistic linguistic LGEDM method that integrates the Louvain algorithm and the group pressure model, building upon the aforementioned concepts, and offers a detailed explanation of the design and implementation of its key components. Section 4 introduces a case study to analyze and apply the proposed method, demonstrating its effectiveness and feasibility in practical scenarios. Finally, Section 5 summarizes the study and provides a brief outlook on future research directions.

2. Methodology

2.1. Probabilistic Linguistic Term Sets

Definition 1 ([25]). *Let* $S = \{s_\varsigma | \varsigma = 0, 1, \cdots, \tau\}$ *be a linguistic term set. A probabilistic linguistic term set (PLTS) associated with S is defined as*

$$L(p) = \left\{ L^k\left(p^k\right) \middle| L^k \in S, r^k \in \varsigma, p^k \geq 0, k = 1, 2, \cdots, \#L(p), \sum_{k=1}^{\#L(p)} p^k \leq 1 \right\} \tag{1}$$

where p^k *represents the probability associated with linguistic term* L^k, r^k *is the subscript of linguistic terms* L^k, *and* $\#L(p)$ *denotes the total number of linguistic terms included in the PLTS.*

To compare two different PLTSs, a score function and a deviation function are defined. These measures are employed to facilitate their comparison.

Definition 2 ([25]). *Let* $L(p) = \left\{ L^k\left(p^k\right) | k = 1, 2, \cdots, \#L(p) \right\}$ *represent a PLTSs, where* r^k *is the subscript of linguistic terms* L^k. *The score function of the PLTS is defined as*

$$S(L(p)) = \textstyle\sum_{k=1}^{\#L(p)} r^k p^k / \sum_{k=1}^{\#L(p)} p^k \tag{2}$$

Additionally, the deviation function of the PLTS is defined as

$$\sigma(L(p)) = \left(\sum_{k=1}^{\#L(p)} \left(p^k \left(r^k - \widetilde{\alpha} \right) \right)^2 \right)^{1/2} / \sum_{k=1}^{\#L(p)} p^k \tag{3}$$

Based on the score function and deviation function, two PLTSs can be compared using the following rules:

(1) If $S(L_1(p)) > S(L_2(p))$, then $L_1(p) > L_1(p)$;
(2) If $S(L_1(p)) < S(L_2(p))$, then $L_1(p) < L_1(p)$;
(3) If $S(L_1(p)) = S(L_2(p))$, then
1) If $\sigma(L_1(p)) > \sigma(L_2(p))$, then $L_1(p) < L_1(p)$;
2) If $\sigma(L_1(p)) < \sigma(L_2(p))$, then $L_1(p) > L_1(p)$;
3) If $\sigma(L_1(p)) = \sigma(L_2(p))$, then $L_1(p) \sim L_1(p)$.

Definition 3 ([32]). *Let* $L(p) = \left\{ L^k\left(p^k\right) | k = 1, 2, \cdots, \#L(p) \right\}$ *represent a PLTSs, where* r^k *is the subscript of linguistic terms* L^k. *The expectation of the PLTS is defined as*

$$E(L(p)) = \sum_{k=1}^{\#L(p)} \left(\frac{r^k}{\tau} \cdot p^k \right) \tag{4}$$

Definition 4 ([33]). *Let* $\gamma = (\gamma_1, \gamma_2, \cdots, \gamma_\kappa)$ *denote the weight of expert* $E = \{e_1, e_2, \cdots, e_\kappa\}$, *and let* $L_{(t)}(p) = \left\{ L^k\left(p^k_{(t)}\right) | k = 1, 2, \cdots, \#L(p) \right\}$ *represent the probabilistic linguistic preference information provided by expert* e_t *over the linguistic term set* $S = \{s_\varsigma | \varsigma = 0, 1, \cdots, \tau\}$. *The aggregated preference information from* κ *experts can be obtained using the following aggregation operator:*

$$L(p) = \left\{ L^k\left(p^k\right) \middle| L^k \in S, p^k = \sum_{t=1}^{\kappa} p^k_{(t)} \gamma_t, k = 1, 2, \cdots, \#L(p) \right\} \tag{5}$$

2.2. Louvain Algorithm

In the context of social networks, the presence of large-scale groups and multi-source heterogeneous information demands the development of efficient clustering algorithms to reduce dimensionality in large-group decision-making problems. This is essential for improving decision-making efficiency. The goal of expert clustering is to group experts with strong associative relationships into the same subgroup, thereby simplifying information processing and enhancing decision-making efficiency. Several clustering methods, such as fuzzy clustering [34] and the K-means algorithm [35], have been proposed. However, traditional clustering methods may assign experts to multiple subgroups simultaneously, leading to overlapping groupings that lack clear and convincing results for large-group decision-making. To overcome these limitations, Blondel et al. [36] proposed the Louvain algorithm, which is characterized by its speed, efficiency, and accuracy. Building upon these advantages, this study adopts the Louvain algorithm to perform expert clustering, considering the social relationships among experts.

Definition 5 ([36]). *The Louvain algorithm uses modularity to evaluate the quality of community divisions. Modularity reflects the density of relationships within communities and is defined as*

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \cdot \delta(c_i, c_j) \tag{6}$$

where m *represents the total weight of all edges in the network,* A *denotes the adjacency matrix,* A_{ij} *is the weight of the edge between node* i *and node* j, k_i *represents the sum of weights of all edges originating from node* i, *and* k_j *represents the sum of weights of all edges directed to node* j. *The term* $\delta(c_i, c_j)$ *equals 1 if nodes* i *and* j *belong to the same community and 0 if they do not.*

Definition 6 ([36]). *To evaluate the effectiveness of the algorithm's iterations, the modularity increment* ΔQ *is introduced as a numerical indicator, defined as follows:*

$$\Delta Q = \left[\frac{\Sigma_{in} + k_{i,in}}{2m} - \left(\frac{\Sigma_{tot} + k_i}{2m} \right)^2 \right] - \left[\frac{\Sigma_{in}}{2m} - \left(\frac{\Sigma_{tot}}{2m} \right)^2 - \left(\frac{k_i}{2m} \right)^2 \right] \tag{7}$$

where Σ_{in} *represents the total weight of edges within community* c, Σ_{tot} *denotes the total weight of edges connected to the nodes in community* c, k_i *is the total weight of edges connected to node* i, *and* $k_{i,in}$ *represents the total weight of edges connecting node* i *to the nodes in community* c.

By employing the Louvain algorithm to cluster the social network relationships of experts, the complexity of LGEDM is reduced. The algorithm maximizes modularity to identify communities within the expert network, thereby ensuring efficient group formation. A detailed explanation of the Louvain algorithm can be found in Appendix A.

2.3. Group Pressure Model

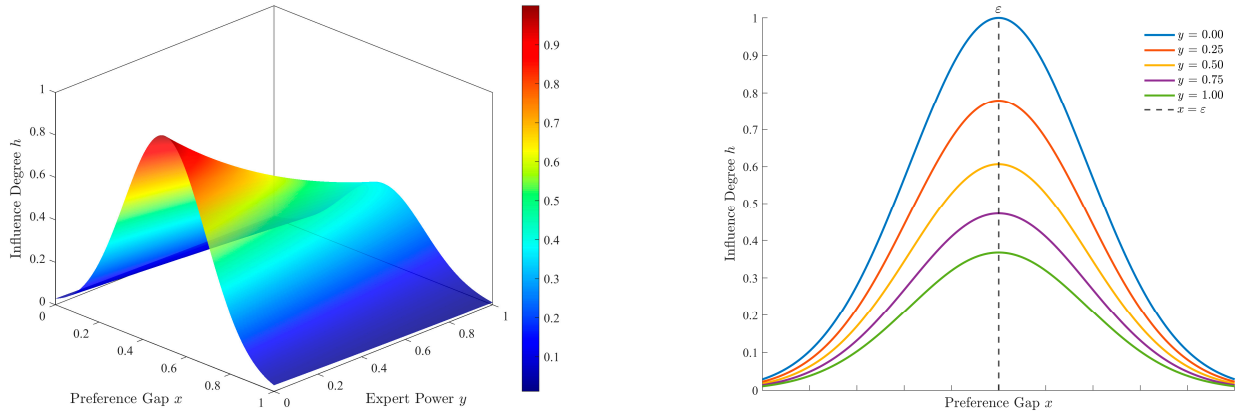
Research has shown that in uncertain environments, group members influence one another through interaction and communication during the decision-making process. This mutual influence can lead to similar or identical decisions, which may compromise the rationality of the decision-making process. Group pressure plays a key role in driving such conformity behaviors. It manifests in the following way: when a group establishes an expected value for a decision problem, individual decisions that closely align with this expectation are typically recognized and supported by the group. Conversely, decisions that deviate from the expectation may face rejection or opposition from other group members. According to the psychological theory of group polarization [37], when an expert's decision significantly deviates from the group consensus, conflicting decisions may become further reinforced, leading the expert to become increasingly convinced of his or her own judgment. In such cases, the effect of group pressure diminishes. Specifically, when individual decisions align closely with the group consensus, perceived group pressure is minimal and has little influence. As the decision gap widens, group pressure intensifies. However, once the gap exceeds a certain threshold, the influence of group pressure starts to decline. Additionally, an expert's status and influence within the group also shape his or her perception of group pressure, with highly influential experts showing greater resistance to its effects.

Definition 7. *Based on the above concepts, a Gaussian function is adopted as the mathematical foundation for the group pressure utility function, and is expressed as follows:*

$$h = e^{-(x-\varepsilon)^2/2\sigma^2} \cdot e^{-ky} \tag{8}$$

where h represents the degree of group pressure experienced by an expert, x denotes the preference gap between the individual and the group, y is the expert's power within the group, ε is the pressure inflection point that determines the maximum impact of group pressure (achieved when $x = \varepsilon$), σ is the sensitivity parameter reflecting the response to preference differences (calculated based on the standard deviation of experts' evaluations), and k is the power parameter determining the rate at which expert power mitigates group pressure.

To validate the characteristics of the group pressure model, analytical graphs were generated, as shown in Figure 1.



(**a**) (**b**)

Figure 1. Analytical graphs of the group pressure model. (**a**) The impacts of the preference gap and expert power on group pressure. (**b**) Group pressure utility under varying levels of expert power.

From Equation (8) and Figure 1, the characteristics of the group pressure model can be clearly understood. Using the pressure inflection point $x = \varepsilon$ as a boundary, the group pressure utility can be divided into two phases. When $x < \varepsilon$, as the preference gap gradually increases, the group pressure utility also increases. When $x > \varepsilon$, the preference gap between the expert and the group consensus becomes substantial, leading the expert to reinforce confidence in his or her own decision while resisting the group consensus. In this phase, the group pressure utility gradually diminishes. Overall, as expert power y increases, the group pressure utility h exhibits an exponential decline, reflecting the greater resistance of highly influential experts to group pressure during the decision-making process.

The proposed group pressure model has the following advantages:

(1) Accuracy—The model effectively captures the dynamic changes in group pressure as a function of the preference gap between individual and group consensus and expert power.
(2) Simplicity and flexibility—The model's concise structure and flexible parameters allow it to adapt to diverse requirements for modeling conformity behavior and the resilience of experts in group decision-making.
(3) High adjustability—By introducing the parameters ε, σ, and k, the model enables precise control over the group pressure utility, ensuring strong adaptability and extensibility across various research scenarios and application needs.

3. The Proposed Method

3.1. Problem Description

In the context of a LGEDM problem during an emergency, let the emergency response team composed of κ experts be denoted as $E = \{e_1, e_2, \cdots, e_\kappa\}$. Each expert has a corresponding weight $\gamma = (\gamma_1, \gamma_2, \cdots, \gamma_\kappa)$, where $\sum_{t=1}^{\kappa} \gamma_t = 1$ and $0 \leq \gamma_t \leq 1 (t = 1, 2, \cdots, \kappa)$. The decision-making problem involves a set of m alternative solutions $A = \{a_1, a_2, \cdots, a_m\}$ and a set of n attributes $C = \{c_1, c_2, \cdots, c_n\}$. The weight of each attribute is denoted as $w = (w_1, w_2, \cdots, w_n)$, where $\sum_{j=1}^{n} w_j = 1$ and $0 \leq w \leq 1 (j = 1, 2, \cdots, n)$. The evaluation results of the experts regarding the alternatives are represented by an evaluation matrix $R_t = [L_{ij(t)}(p)]_{m \times n}$, where $L_{ij(t)}(p)$ denotes the preference evaluation value of expert e_t for alternative a_i with respect to attribute c_j. The trust relationship among the emergency experts is expressed through a trust relationship matrix $T = [t_{tl}]_{\kappa \times \kappa}$, where t_{tl} represents the trust relationship between experts e_t and e_l.

In this process, experts evaluate alternatives using PLTSs, which effectively capture the vagueness and uncertainty inherent in expert assessments. To reduce the complexity of information processing and improve decision-making efficiency, expert clustering methods are employed. These methods group experts with strong associative relationships into several subgroups. Specifically, the expert set $E = \{e_1, e_2, \cdots, e_\kappa\}$ is clustered into g subgroups, denoted as $U = \{U_1, U_2, \ldots, U_g\}$. For each subgroup U_t, n_t represents the number of experts in the subgroup, and ρ_t represents the weight of the subgroup, where $U_t \subseteq E$. When constructing the consensus model, this study treats clustering as a modular process within small groups. The Louvain algorithm is used to cluster the expert group, and the preferences of experts are dynamically adjusted based on the group pressure model. After achieving consensus convergence within small groups, the overall group consensus is further enhanced. This approach integrates social relationships among experts with a preference adjustment mechanism, facilitating the exploration of more optimal decision-making solutions in complex scenarios. Using the comprehensive group preference matrix generated through the expert consensus process, this study adopts an improved TODIM method to rank alternative emergency solutions. This effectively captures the loss aversion psychology of DMs in emergency contexts.

Based on the above analysis, this study proposes a probabilistic linguistic LGEDM method that integrates the Louvain algorithm and group pressure model to explore optimal decision solutions under the framework of group intelligence. The combination of the Louvain algorithm and the group pressure model enhances large-group decision-making by improving both computational efficiency and decision consistency. The Louvain algorithm clusters experts effectively, reducing complexity, while the group pressure model dynamically adjusts expert preferences, ensuring a better consensus. This synergy makes the method particularly effective in complex and dynamic emergency decision-making scenarios. To intuitively illustrate the specific steps of this method, a process flowchart has been constructed (see Figure 2).

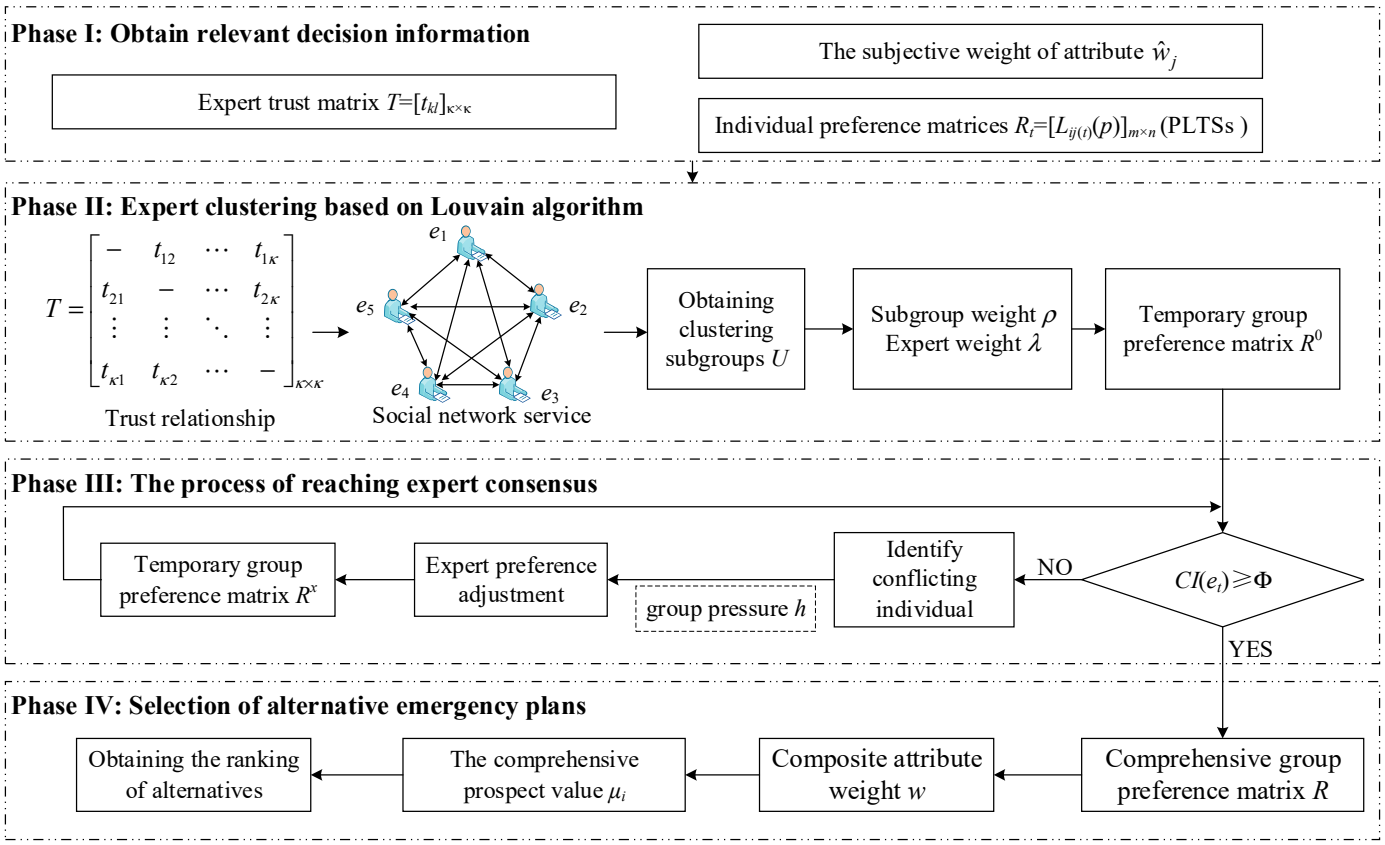


Figure 2. Process of the proposed probabilistic linguistic LGEDM.

3.2. Large-Group Clustering Based on the Louvain Algorithm

3.2.1. Determination of Expert Power and Their Weights

In emergency response teams, complex social trust networks often exist among members, with significant variations in the trust relationships between experts. To ensure fairness in weight allocation and the reliability of decision outcomes, it is essential to comprehensively account for these trust relationships within the expert group. For this purpose, the adjacency matrix of the expert trust network is constructed as follows:

$$T=\begin{bmatrix} - & t_{12} & \cdots & t_{1\kappa} \\ t_{21} & - & \cdots & t_{2\kappa} \\ \vdots & \vdots & \ddots & \vdots \\ t_{\kappa 1} & t_{\kappa 2} & \cdots & - \end{bmatrix}_{\kappa\times\kappa} \tag{9}$$

where t_{tl} represents the trust relationship between expert e_t and expert e_l, and $t_{tl} \in \{0, 1\}$. When $t_{tl} = 0$, it indicates that expert e_t has no direct trust relationship with e_l, whereas $t_{tl} = 1$ signifies that expert e_t trusts e_l.

In general, the more trust an expert receives from other members of the group, the greater his or her power. The position of expert e_t in the group can be calculated as follows:

$$I(e_t) = \sum_{l=1}^{\kappa} t_{lt} \tag{10}$$

where $I(e_t)$ denotes the total trust received by expert e_t from other experts. Based on this, the power of expert e_t within the group can be quantified as

$$\eta_t = \frac{I(e_t) - \min\limits_{l=1,2,\cdots,\kappa} \{I(e_l)\}}{\max\limits_{l=1,2,\cdots,\kappa} \{I(e_l)\} - \min\limits_{l=1,2,\cdots,\kappa} \{I(e_l)\}} \tag{11}$$

The determination of expert weights is a critical component in emergency decision-making processes. A well-balanced distribution of expert weights ensures the effective utilization of the evaluation information provided by the experts. In this study, experts' weights are determined based on their influence within the group. The specific calculation method is as follows:

$$\lambda_t = \frac{\sum_{l=1}^{\kappa} t_{lt}}{\sum_{t=1}^{\kappa} \sum_{l=1}^{\kappa} t_{lt}} \tag{12}$$

where t_{lt} represents the trust relationship between expert e_l and expert e_t. The higher the trust level of expert e_l toward expert e_t, the greater the influence of expert e_t within the group. Consequently, the weight assigned to expert e_t should be correspondingly higher.

3.2.2. Temporary Comprehensive Group Preference Matrix Under PLTSs

The basic steps of the Louvain algorithm are as follows:

(1) Initialization—Treat each node as an independent community, with the initial number of communities equal to the total number of nodes.
(2) Local optimization—For each node i, attempt to assign it to the community of each neighboring node, calculating the modularity increment ΔQ. If $\Delta Q > 0$, assign node i to the community with the highest modularity increment.
(3) Iterative optimization—Repeat Step 2 until the community assignments of all nodes remain unchanged, achieving local stability.
(4) Community aggregation—Aggregate nodes within the same community into a new node. The total weight of intra-community edges is represented as the weight of the new node, while the weights of inter-community edges are aggregated as the weights between new nodes. Repeat Steps 1–4 until the modularity no longer changes, achieving global stability.

Using the hierarchical clustering and dimensionality reduction results of the Louvain algorithm applied to the social trust network, the weights of subgroups and their internal members can be determined. The weight of a subgroup is closely related to both the number of DMs in the subgroup and their level of trustworthiness. A subgroup containing more DMs with higher credibility is considered to have more authoritative preferences. The weight of subgroup U_t can be calculated as follows:

$$\rho_t = \frac{n_t^2}{\sum_{i=1}^{g} n_i^2} \tag{13}$$

where n_t represents the number of experts in the subgroup.

Based on the trust network among experts, the weights of the expert set $E = \{e_1, e_2, \cdots, e_\kappa\}$ can be determined as $\gamma = (\gamma_1, \gamma_2, \cdots, \gamma_\kappa)$. Using Equation (5), the individual preference matrices of κ experts, denoted as $R_t = [L_{ij(t)}(p)]_{m\times n}$, $(t = 1, 2, \cdots, \kappa)$, are aggregated to obtain the temporary comprehensive group preference matrix $R^0 = [L_{ij}(p)]_{m\times n}$. The computation of $L_{ij}(p)$ is as follows:

$$L_{ij}(p) = \left\{ L^k\left(p_{ij}^k\right) \middle| L^k \in S, p_{ij}^k = \sum_{t=1}^{\kappa} p_{ij(t)}^k \gamma_t, k = 1, 2, \cdots, \#L(p) \right\} \tag{14}$$

3.3. Group Pressure-Based Expert Consensus Model

3.3.1. Measurement of the Consensus Level

To measure individual consensus levels, the similarity between the opinions of experts and the group is utilized [38]. Let $R_t = [L_{ij(t)}(p)]_{m\times n}$ represent the preference matrix of expert e_t, and $R = [L_{ij}(p)]_{m\times n}$ represent the comprehensive group preference matrix. The preference distance between expert e_t and the group for alternative a_i on attribute c_j is defined as

$$d\left(L_{ij(t)}(p), L_{ij}(p)\right) = \left(E\left(L_{ij(t)}(p)\right) - E\left(L_{ij}(p)\right)\right)^2 \tag{15}$$

where $E(L(p))$ is the expected value of $L(p)$ calculated using Equation (4).

The overall preference gap between expert e_t and the group can be quantified as

$$d(e_t, E) = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} d\left(L_{ij(t)}(p), L_{ij}(p)\right)} \tag{16}$$

Using the calculated preference gap, the consensus level of expert e_t with the group can be determined as

$$\varphi(e_t) = 1 - d(e_t, E) \tag{17}$$

Furthermore, the consensus level of a subgroup U_t is calculated as the average consensus level of the experts within the subgroup. The overall group consensus level is the weighted average of the consensus levels of all subgroups. A higher value of $\varphi(E)(0 \le \varphi(E) \le 1)$ indicates a higher group consensus level. When the group consensus level reaches a predefined threshold Φ, the comprehensive group preference matrix satisfies the consensus degree criterion. Otherwise, adjustments to the preferences of certain experts are required to achieve consensus convergence.

3.3.2. Expert Consensus Process

This study introduces a group pressure mechanism as a preference adjustment coefficient to dynamically guide experts in modifying their preferences during the decision-making process, thereby reducing the risks associated with decision errors. For emergency scenarios, the preference adjustment coefficient is constructed based on the group pressure model as follows:

$$h(e_t) = \exp\left(-\frac{(d(e_t, E) - \varepsilon)^2}{2\sigma^2} - k\eta_t\right) \tag{18}$$

where $d(e_t, E)$ represents the preference gap between expert e_t and the group, and η_t denotes the power of expert e_t within the group. The parameter ε is the pressure inflection point, determining the maximum impact of group pressure. At $x = \varepsilon$, the impact of group pressure reaches its peak. In this study, ε is determined based on the consensus threshold Φ, such that $\varepsilon = 1 - \Phi$. The parameter σ is a control parameter reflecting the group's sensitivity to preference gaps and is calculated based on the standard deviation of expert

evaluations. Finally, k is the expert power parameter, which determines the rate at which an expert's power mitigates the effect of group pressure.

The core principle of group intelligence lies in enhancing decision accuracy by aggregating individual opinions into a cohesive whole. In this study, the group pressure value is used as a dynamic preference adjustment coefficient and is combined with the comprehensive group preference matrix to modify individual expert preferences. By clustering DMs using the Louvain algorithm, a total of g subgroups, $U = \{U_1, U_2, \ldots, U_g\}$, are formed. The process of adjusting expert preferences involves the following two steps: (1) calculate subgroup consensus levels by computing the consensus level of each subgroup $\varphi(U_t)$ and identifying subgroups $\varphi_{\min}(U_t)$ with low consensus levels; and (2) adjust individual preferences by locating individual experts e_t whose preferences require adjustment within the identified subgroups, and modifying their preferences according to the formula

$$R_t^{x+1} = (1 - h(e_t))R_t^x + h(e_t)R^x, x = 0, 1, \cdots, X \tag{19}$$

where R_t^{x+1} denotes the preference matrix of expert e_t after the $x + 1 - th$ adjustment, R^x is the comprehensive group preference matrix, x is the current adjustment iteration, and X is the maximum number of adjustment iterations.

The consensus level $\varphi(E)(0 \leq \varphi(E) \leq 1)$ measures the extent of alignment among group preferences. When $\varphi(E) \geq \Phi$, the comprehensive group preference matrix meets the consensus requirements. Otherwise, adjustments to certain experts' preferences are necessary to achieve consensus convergence. The specific steps of the adjustment process are as follows:

Step 1—If $\varphi(E) \geq \Phi$, proceed to Step 6. Otherwise, move to the next step.
Step 2—Calculate the preference adjustment coefficient $h(e_t)$ using Equation (18).
Step 3—Adjust the preferences of the identified experts using Equation (19).
Step 4—Update the comprehensive group preference matrix R^x.
Step 5—Recalculate the group consensus level $\varphi(E)$ and return to Step 1.
Step 6—Output the final comprehensive group preference matrix R^x.

3.4. Determination of Comprehensive Attribute Weights

In the context of EDM for unexpected events, the attributes of decision-making are often initially unknown, and the proper allocation of attribute weights is crucial in determining the final decision outcome. Attribute weights are generally categorized into two types: subjective weights and objective weights. Subjective weights are assigned based on the DMs' personal knowledge and experiences, while objective weights are derived using appropriate mathematical models. Using the normalized group decision matrix $R = [L_{ij}(p)]_{m \times n}$, let the objective weight of attribute be denoted as $w^o = (w_1^o, w_2^o, \cdots, w_n^o)$. Objective weights are determined by evaluating the deviation of each alternative's assessment from both the positive ideal solution and the negative ideal solution. Specifically, an alternative's evaluation is considered better if it is closer to the positive ideal solution and farther from the negative ideal solution.

The following objective weight model is constructed based on the deviation between alternative a_i and the positive/negative ideal solutions:

$$\begin{aligned} &\min \sum_{i=1}^{m} \sum_{j=1}^{n} \left(w_j^o\right)^2 \left(\frac{d\left(L_{ij}(p), L_j^+(p)\right)}{d\left(L_{ij}(p), L_j^+(p)\right) + d\left(L_{ij}(p), L_j^-(p)\right)} \right)^2 \\ &s.t. \begin{cases} \sum_{j=1}^{n} w_j^o = 1; \\ w_j \geq 0, j = 1, 2, \cdots, n. \end{cases} \end{aligned} \tag{20}$$

where $L_j^+(p) = \max_i\{L_{ij}(p)\}$ and $L_j^-(p) = \min_i\{L_{ij}(p)\}$ represent the positive and negative ideal values of attribute c_j, respectively.

To optimize the solution, the Lagrange function is constructed as follows:

$$L(w,\varsigma) = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(w_j^o\right)^2\left(\frac{d\left(L_{ij}(p),L_j^+(p)\right)}{d\left(L_{ij}(p),L_{ij}^+(p)\right)+d\left(L_{ij}(p),L_j^-(p)\right)}\right)^2 + 2\varsigma\left(\sum_{j=1}^{m}w_j^o - 1\right) \quad (21)$$

$$\begin{cases} \frac{\partial L(w,\varsigma)}{\partial w_j^o} = 0, \\ \frac{\partial L(w,\lambda)}{\partial \lambda} = 0 \end{cases} \quad (22)$$

Solving these equations yields the following objective weight of attribute w_j^o:

$$w_j^o = \frac{\left(\sum\limits_{i=1}^{m}\left(\frac{d\left(L_{ij}(p),L_j^+(p)\right)}{d\left(L_{ij}(p),L_j^+(p)\right)+d\left(L_{ij}(p),L_j^-(p)\right)}\right)^2\right)^{-1}}{\sum\limits_{j=1}^{n}\left(\sum\limits_{i=1}^{m}\left(\frac{d\left(L_{ij}(p),L_j^+(p)\right)}{d\left(L_{ij}(p),L_j^+(p)\right)+d\left(L_{ij}(p),L_j^-(p)\right)}\right)^2\right)^{-1}} \quad (23)$$

In addition to objective weights, attributes also include subjective weights. Let the subjective weight assigned by expert e_t to attribute c_j be w_{tj}^s, $j = 1, 2, \cdots, n$. These subjective weights reflect the expert's domain knowledge and experience. The subjective weight of an attribute can be expressed as

$$w_j^s = \frac{1}{\kappa}\sum_{t=1}^{\kappa} w_{tj}^s \quad (24)$$

Finally, the comprehensive weight of attribute c_j is calculated as

$$w_j = \alpha w_j^o + (1-\alpha)w_j^s \quad (25)$$

where α determines the relative contributions of subjective and objective weights. A higher value of α indicates a greater influence of subjective weights on the comprehensive weight. In this study, α is set to 0.5 [39], ensuring that objective weights adjust and refine the subjective weights provided by experts.

3.5. Alternative Selection

In LGEDM scenarios, challenges such as information ambiguity, unknown weights, and individual preference differences are common. Translating these practical issues into theoretical problems and proposing optimal alternatives is crucial. To address these challenges, this study developed a DM clustering model based on the Louvain algorithm and designed an expert consensus model that incorporates group pressure. This model generates a comprehensive group preference matrix $R = [L_{ij}(p)]_{m\times n}$, significantly enhancing decision quality. Based on this matrix and by integrating both subjective and objective attribute weights, the comprehensive attribute weights $w = (w_1, w_2, \cdots, w_n)$ are determined.

Considering the loss aversion psychology of DMs in emergency scenarios, an improved TODIM method is proposed to rank alternative emergency options. TODIM, grounded in prospect theory, involves pairwise comparisons among alternatives. It calculates the relative dominance of each alternative over others using a defined dominance function and ranks the alternatives based on their overall prospect values. The improved

TODIM method also incorporates the preference distance to measure the differences between alternatives. The detailed calculation steps are as follows:

Step 1—Calculate the relative weight of attributes w_j^* using

$$w_j^* = \frac{w_j}{w_r}, w_r = \max\{w_1, w_2, \cdots, w_n\} \tag{26}$$

Step 2—Calculate the dominance degree of alternative a_i over alternative a_k with respect to attribute c_j using

$$\psi_j(a_i, a_k) = \begin{cases} \sqrt{\phi_j^* d\Big(L_{ij}(p), L_{kj}(p)\Big)}, L_{ij}(p) > L_{kj}(p) \\ 0, L_{ij}(p) = L_{kj}(p) \\ -\frac{1}{\theta}\sqrt{d\Big(L_{ij}(p), L_{kj}(p)\Big)/\phi_j^*}, L_{ij}(p) < L_{kj}(p) \end{cases} \tag{27}$$

Step 3—Compute the overall dominance degree of alternative a_i over alternative a_k using

$$\Psi(a_i, a_k) = \sum_{j=1}^{n} \psi_j(a_i, a_k) \tag{28}$$

Step 4—Calculate the comprehensive prospect value μ_i of each alternative a_i using

$$\mu_i = \frac{\sum\limits_{k=1}^{m} \Psi(a_i, a_k) - \min\limits_i \left\{ \sum\limits_{k=1}^{m} \Psi(a_i, a_k) \right\}}{\max\limits_i \left\{ \sum\limits_{k=1}^{m} \Psi(a_i, a_k) \right\} - \min\limits_i \left\{ \sum\limits_{k=1}^{m} \Psi(a_i, a_k) \right\}} \tag{29}$$

Step 5—Rank the alternatives based on their comprehensive prospect values μ_i. Alternatives with higher μ_i values are given higher priority.

3.6. Steps of the Proposed Method

For LGEDM, the proposed method uses the Louvain algorithm to cluster DMs, dividing the large group into multiple subgroups. Based on this clustering, a consensus adjustment model is developed, incorporating the influence of group pressure to improve the decision quality. Additionally, an improved TODIM method is employed to rank and select the optimal alternative. The specific steps are as follows:

Step 1—Experts evaluate alternative emergency solutions using PLTSs. A linguistic term set with granularity $\tau + 1$ is selected, and experts provide evaluation values for each alternative based on different decision attributes, resulting in a probabilistic linguistic preference matrix $R_t = [L_{ij(t)}(p)]_{m \times n}, t = 1, 2, \cdots, \kappa$ for each expert e_t.

Step 2—Based on the expert trust matrix, the Louvain algorithm is applied to cluster experts into subgroups. Individual preference matrices from experts are aggregated using their weights, resulting in a temporary comprehensive group preference matrix.

Step 3—Individual consensus levels $\varphi(e_t)$ are measured based on the similarity of expert opinions to the group. Subgroup consensus levels $\varphi(U_t)$ and the overall group consensus level $\varphi(E)$ are subsequently calculated.

Step 4—Group pressure values are introduced as preference adjustment coefficients. These coefficients are combined with the comprehensive group preference matrix to iteratively adjust individual experts' preferences, gradually achieving a consensus among experts and forming an updated comprehensive group preference matrix.

Step 5—Comprehensive attribute weights are determined by integrating subjective and objective attribute weights using a weight determination model.

Step 6—Using the updated comprehensive group preference matrix $R = [L_{ij}(p)]_{m\times n}$ and the comprehensive attribute weights $w = (w_1, w_2, \cdots, w_n)$, the improved TODIM method is employed to rank the alternatives. The alternative with the highest comprehensive prospect value is selected as the optimal solution.

4. Case Study and Method Comparison

4.1. Case Study

The COVID-19 pandemic has significantly disrupted global population health, causing severe and widespread impacts on health, the economy, families, and society since 2020. These devastating consequences are anticipated to persist and evolve in the coming years. According to the World Health Statistics 2024: Monitoring Health for the SDGs, Sustainable Development Goals, COVID-19 was among the top three leading causes of death worldwide in 2020 and 2021, accounting for 4.1 million and 8.8 million deaths, respectively. In the region of the Americas, it was the leading cause of death in both years, and it ranked among the top five causes of death in all regions except for the African and Western Pacific regions [40]. Responding to public health emergencies entails multifaceted decision-making, with the effective disposal of medical waste being a critical component in managing pandemics. During the COVID-19 outbreak, the volume of medical waste (such as protective equipment, diagnostic kits, and medical supplies) surged dramatically due to the intensity of healthcare activities. Improper management of this waste could lead to secondary transmission risks, further exacerbating public health and safety concerns. As such, determining the appropriate disposal methods for medical waste became a pivotal issue in emergency management.

In the winter of 2021, a major urban center experienced a large-scale outbreak of infectious disease caused by an external input, which led to a rapid increase in new cases. Despite stringent lockdown measures, medical facilities and quarantine centers generated substantial quantities of contaminated medical waste daily. While emergency actions, such as improving waste disposal technologies for high-risk and industrial waste and deploying mobile medical waste processing units from neighboring provinces, were implemented, the amount of waste generated exceeded initial projections, rendering it impossible to achieve the "daily disposal" goal. Against this backdrop, local governments urgently needed to establish efficient and feasible medical waste disposal facilities to ensure timely and safe disposal, mitigating the risks of secondary contamination and cross-infection. Assuming that medical waste management personnel followed standardized operating protocols, thus minimizing the infection risk, a group of experts from multiple fields was convened to provide decision-making support based on emergency management principles. Three medical waste disposal alternatives were initially identified: chemical disinfection equipment a_1, incinerators a_2, and high-temperature steam devices a_3.

To ensure the robustness and scientific integrity of the decision-making process, a panel of 20 experts from diverse fields—such as environmental engineering, public health, and materials science—was assembled. The group utilized collective intelligence to assist in selecting the optimal emergency solution. Expert preferences were articulated using PLTSs, and following comprehensive discussions, three core evaluation criteria were established: timeliness c_1, technological maturity c_2, and environmental pollution c_3. During the large-group decision-making process, the experts assessed each alternative using a linguistic term set with granularity of five, $S = \{s_0, s_1, s_2, s_3, s_4\}$, where s_0 was very poor, s_1 was poor, s_2 was average, s_3 was good, and s_4 was excellent.

This study employs the proposed probabilistic linguistic LGEDM method, integrating the Louvain algorithm and a group pressure model. It effectively incorporates expert opinions, social trust networks, and group dynamics to identify the optimal medical waste

disposal solution, offering crucial support for decision-making in emergency situations. The decision process is outlined below.

Step 1: Construct the trust matrix $T = [t_{tl}]_{\kappa\times\kappa}$ for the emergency decision-making experts and the initial preference matrix $R_t = [L_{ij(t)}(p)]_{m\times n}, \kappa = 1, 2, \cdots, 20$ for the experts. In this study, the consensus threshold $\Phi = 0.88$, the pressure inflection point $\varepsilon = 0.12$, the maximum number of consensus adjustments $X = 10$, and the expert power parameter $k = 1$. Using the trust matrix $T = [t_{tl}]_{\kappa\times\kappa}$, the social network structure of the 20 emergency experts was visualized, as shown in Figure 3. The initial preference information for a subset of experts is provided below. The complete evaluation dataset for all experts is available at https://github.com/Joy-618/dataset (accessed on 13 February 2025).

$$T = \begin{bmatrix}
0&0&0&1&0&0&0&0&0&1&0&0&0&1&1&0&0&0&1&0\\
0&0&0&0&1&0&0&0&1&0&1&1&1&0&0&1&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&1&1&0&0&0&0&1&1&0&0&1&0&0&1&0&0&0&0&0\\
0&0&0&0&0&0&1&0&0&0&1&0&0&0&1&1&1&1&0&0\\
0&0&1&0&0&0&0&1&1&0&1&1&1&1&0&0&0&0&1&0\\
0&0&0&0&0&0&0&0&0&0&1&1&0&1&0&0&0&0&1&0\\
0&1&0&1&1&0&0&0&0&1&0&1&0&0&1&0&0&0&0&0\\
1&0&0&0&0&1&0&1&0&0&0&0&0&0&0&0&1&0&0&0\\
0&0&1&0&0&0&1&0&0&0&0&0&0&0&0&1&0&1&0&0\\
0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&1\\
1&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&1&0&0&0\\
0&0&0&0&0&1&0&0&0&0&0&0&0&1&0&0&0&0&1&0\\
0&0&0&1&1&1&0&1&0&0&0&0&0&0&0&1&0&1&1&0\\
0&0&1&1&0&1&0&1&1&0&0&1&1&0&0&0&1&0&0&0\\
0&0&0&0&0&0&1&1&0&0&0&0&1&1&0&0&0&1&0&1\\
0&0&0&0&0&0&0&0&1&1&0&0&0&0&0&0&0&0&0&0\\
1&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0\\
0&1&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0\\
1&0&0&0&0&0&0&0&0&0&0&0&1&1&0&0&0&0&1&0
\end{bmatrix}$$

$$R_1 = \begin{bmatrix}
\{s_0(0.15), s_2(0.35), s_3(0.50)\} & \{s_1(0.30), s_3(0.70)\} & \{s_1(0.50), s_3(0.50)\}\\
\{s_1(0.30), s_3(0.50), s_4(0.20)\} & \{s_0(0.10), s_2(0.40), s_4(0.50)\} & \{s_1(1.00)\}\\
\{s_0(1.00)\} & \{s_0(0.25), s_3(0.30), s_4(0.45)\} & \{s_1(0.30), s_4(0.70)\}
\end{bmatrix}$$

$$R_2 = \begin{bmatrix}
\{s_2(1.00)\} & \{s_1(0.35), s_3(0.65)\} & \{s_0(0.50),\ s_2(0.50)\}\\
\{s_1(0.22),\ s_3(0.30),\ s_4(0.48)\} & \{s_0(0.20), s_1(0.20),\ s_2(0.60)\} & \{s_1(1.00)\}\\
\{s_3(1.00)\} & \{s_0(0.25), s_3(0.35),\ s_4(0.40)\} & \{s_0(0.1),\ s_1(0.70),\ s_2(0.20)\}
\end{bmatrix}$$

$$R_3 = \begin{bmatrix}
\{s_2(0.20),\ s_3(0.80)\} & \{s_1(0.42),\ s_3(0.58)\} & \{s_0(0.30),\ s_3(0.70)\}\\
\{s_0(0.50),\ s_3(0.50)\} & \{s_0(0.10),\ s_2(0.40),\ s_4(0.50)\} & \{s_2(0.50),\ s_3(0.50)\}\\
\{s_2(0.25),\ s_3(0.50),\ s_4(0.25)\} & \{s_0(0.20),\ s_3(0.30),\ s_4(0.50)\} & \{s_2(0.60),\ s_4(0.40)\}
\end{bmatrix}$$

$$\cdots\cdots$$

$$R_{18} = \begin{bmatrix}
\{s_0(0.30),\ s_3(0.70)\} & \{s_1(0.20),\ s_3(0.80)\} & \{s_0(0.20), s_2(0.80)\}\\
\{s_1(0.10),\ s_3(0.40),\ s_4(0.50)\} & \{s_0(0.15) s_2(0.25),\ s_4(0.60)\} & \{s_4(1.00)\}\\
\{s_2(0.25),\ s_3(0.45),\ s_4(0.30)\} & \{s_0(0.20) s_3(0.35),\ s_4(0.45)\} & \{s_2(0.60), s_4(0.40)\}
\end{bmatrix}$$

$$R_{19} = \begin{bmatrix}
\{s_0(0.20),\ s_2(0.30),\ s_3(0.50)\} & \{s_1(0.35),\ s_3(0.65)\} & \{s_3(1.00)\}\\
\{s_1(0.20),\ s_3(0.50),\ s_4(0.30)\} & \{s_0(0.10),\ s_2(0.40),\ s_4(0.50)\} & \{s_1(1.00)\}\\
\{s_2(0.25),\ s_3(0.50),\ s_4(0.25)\} & \{s_0(0.25),\ s_3(0.35),\ s_4(0.40)\} & \{s_2(0.25),\ s_3(0.50),\ s_4(0.25)\}
\end{bmatrix}$$

$$R_{20} = \begin{bmatrix} \{s_0(0.15),\ s_2(0.30),\ s_3(0.55)\} & \{s_1(0.40),\ s_3(0.60)\} & \{s_2(0.20),\ s_3(0.80)\} \\ \{s_1(0.80),\ s_3(0.20)\} & \{s_0(0.10),\ s_2(0.40),\ s_4(0.50)\} & \{s_1(1.00)\} \\ \{s_2(0.20),\ s_3(0.80)\} & \{s_0(0.25),\ s_3(0.35),\ s_4(0.40)\} & \{s_1(0.40),\ s_4(0.60)\} \end{bmatrix}$$

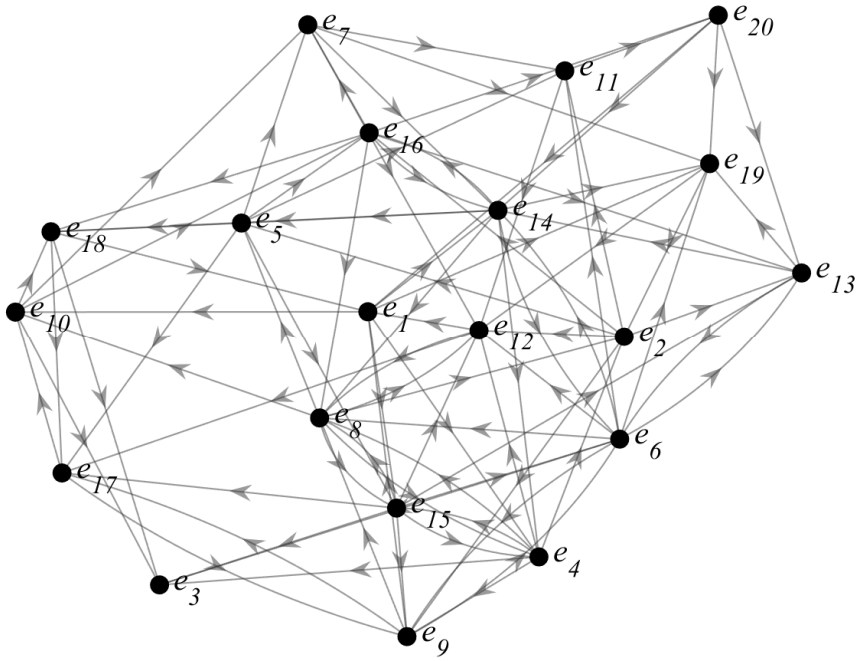


Figure 3. Social network structure of the 20 emergency experts.

Step 2: Based on the expert trust matrix, the Louvain algorithm was employed to cluster the decision-making experts into three subgroups, $U_1 = \{e_3, e_{10}, e_{17}, e_{18}\}$, $U_2 = \{e_1, e_4, e_6, e_8, e_9, e_{12}, e_{15}\}$, and $U_3 = \{e_2, e_5, e_7, e_{11}, e_{13}, e_{14}, e_{16}, e_{19}, e_{20}\}$, as shown in Figure 4. The weights of the subgroups were calculated based on the number of experts in each group, resulting in $\rho_1 = 0.11$, $\rho_2 = 0.34$, and $\rho_3 = 0.55$ The distribution of expert weights within each subgroup is detailed in Tables 1–3.

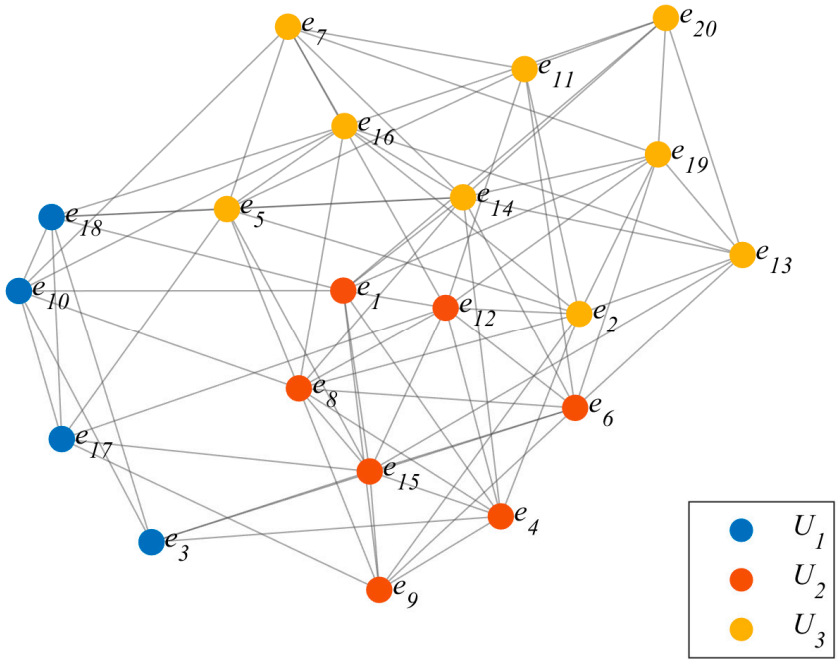


Figure 4. Expert clustering results based on the Louvain algorithm.

Table 1. Expert weights in subgroup U_1.

e_3	e_{10}	e_{17}	e_{18}
0.045	0.034	0.056	0.045

Table 2. Expert weights in subgroup U_2.

e_1	e_4	e_6	e_8	e_9	e_{12}	e_{15}
0.034	0.045	0.034	0.079	0.056	0.034	0.045

Table 3. Expert weights in subgroup U_3.

e_2	e_5	e_7	e_{11}	e_{13}	e_{14}	e_{16}	e_{19}	e_{20}
0.090	0.056	0.067	0.045	0.045	0.056	0.045	0.067	0.022

Using the initial preference information of the experts and the group pressure control parameter $\sigma = 0.187$, individual expert preferences were aggregated using weights and Equation (14) to form the initial comprehensive group preference matrix R^0.

$$R^0 = \begin{bmatrix} \{s_0(0.13),\ s_1(0.07),\ s_2(0.33),\ s_3(0.47)\} & \{s_1(0.36),\ s_2(0.05),\ s_3(0.57),\ s_4(0.02)\} & \{s_0(0.21),\ s_1(0.16),\ s_2(0.28),\ s_3(0.29),\ s_4(0.07)\} \\ \{s_0(0.04),\ s_1(0.19),\ s_2(0.09),\ s_3(0.44),\ s_4(0.25)\} & \{s_0(0.11),\ s_1(0.07),\ s_2(0.42),\ s_4(0.40)\} & \{s_1(0.63),\ s_2(0.11),\ s_3(0.14),\ s_4(0.13)\} \\ \{s_0(0.03),\ s_1(0.18),\ s_2(0.18),\ s_3(0.48),\ s_4(0.13)\} & \{s_0(0.24),\ s_2(0.01),\ s_3(0.34),\ s_4(0.41)\} & \{s_0(0.02),\ s_1(0.27),\ s_2(0.26),\ s_3(0.26),\ s_4(0.20)\} \end{bmatrix}$$

Step 3: The individual consensus level $\varphi(e_t)$ for each expert was computed based on the similarity of their opinions to the group preferences. Subgroup consensus levels $\varphi(U_1) = 0.844$, $\varphi(U_2) = 0.816$, and $\varphi(U_3) = 0.839$ were derived. By taking a weighted average of the subgroup consensus levels, the overall group consensus level $\varphi(E) = 0.832$ was calculated. Since $\varphi(E) < \Phi$, experts' preferences required adjustment.

Step 4: Group pressure values were applied as adjustment coefficients to align individual preferences with the comprehensive group preferences. Adjustments were iteratively performed until a consensus was achieved. The consensus-reaching process is illustrated in Figure 5.

Following the adjustment process, the final comprehensive group preference matrix RRR was obtained.

$$R = \begin{bmatrix} \{s_0(0.23),\ s_1(0.06),\ s_2(0.32), s_3(0.40)\} & \{s_0(0.01),\ s_1(0.35),\ s_2(0.06),\ s_3(0.55), s_4(0.03)\} & \{s_0(0.14),\ s_1(0.14),\ s_2(0.21),\ s_3(0.46), s_4(0.05)\} \\ \{s_0(0.03),\ s_1(0.17),\ s_2(0.09),\ s_3(0.43), s_4(0.27)\} & \{s_0(0.09),\ s_1(0.09),\ s_2(0.48), s_4(0.33)\} & \{s_1(0.46),\ s_2(0.07),\ s_3(0.18), s_4(0.29)\} \\ \{s_1(0.09),\ s_2(0.23),\ s_3(0.51), s_4(0.17)\} & \{s_0(0.25), s_3(0.35), s_4(0.40)\} & \{s_0(0.02),\ s_1(0.21),\ s_2(0.43),\ s_3(0.21), s_4(0.14)\} \end{bmatrix}$$

Step 5: Using the final comprehensive group preference matrix and the proposed attribute weight determination method, the objective attribute weights were calculated as $w_1^o = 0.300$, $w_2^o = 0.365$, and $w_3^o = 0.335$. Assuming that the subjective weights provided by the experts were $w_1^s = 0.4$, $w_2^s = 0.3$, and $w_3^s = 0.3$, the comprehensive attribute weights were computed as $w_1 = 0.349$, $w_2 = 0.333$, and $w_3 = 0.318$.

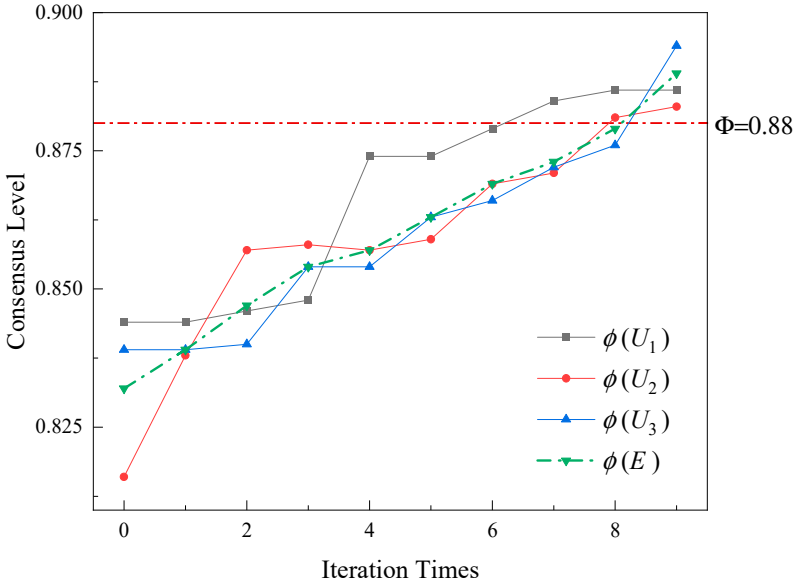


Figure 5. Consensus-reaching process among experts.

Step 6: The improved TODIM method was applied to rank the alternative emergency solutions. Relative attribute weights were calculated using Equation (26), with the parameter $\theta = 2.25$. Using Equations (27) and (28), the overall dominance degree matrix was computed.

$$\Psi(a_i, a_k) = \begin{bmatrix} 0.000 & -0.218 & -0.216 \\ 0.169 & 0.000 & -0.045 \\ 0.201 & 0.029 & 0.000 \end{bmatrix}$$

Finally, Equation (29) was used to determine the comprehensive prospect values of the alternatives: $\mu_1 = 0.000$, $\mu_2 = 0.840$, and $\mu_3 = 1.000$. The ranking of alternatives was $a_3 \succ a_2 \succ a_1$, with a_3 (high-temperature steam devices) identified as the optimal solution.

4.2. Sensitivity Analysis

The proposed probabilistic linguistic LGEDM method incorporates several key controllable parameters. To assess the potential impacts of these parameters on decision outcomes and validate the stability and reliability of the method, a sensitivity analysis was conducted. The analysis specifically examined whether variations in the loss aversion coefficient θ and the attribute weight adjustment coefficient α would affect the ranking of alternative emergency solutions.

First, the attribute weight adjustment coefficient α was fixed at $\alpha = 0.5$, and the range of the loss aversion coefficient θ was set to $[1, 5]$. The ranking of alternatives was analyzed as θ varied. Next, the loss aversion coefficient θ was fixed at $\theta = 2.25$, and the range of the attribute weight adjustment coefficient α was set to $[0.1, 0.9]$. The ranking of alternatives was analyzed as α varied. The results of alternative rankings for different parameter values are shown in Figure 6. As observed in Figure 6, the ranking of alternatives remains consistent regardless of variations in θ and α, fully validating the stability and reliability of the proposed method. Furthermore, as the loss aversion coefficient θ increases, the differentiation among alternatives gradually diminishes. This trend indicates that the method effectively captures DMs' inclination toward loss aversion, reflecting their psychological tendencies during EDM.

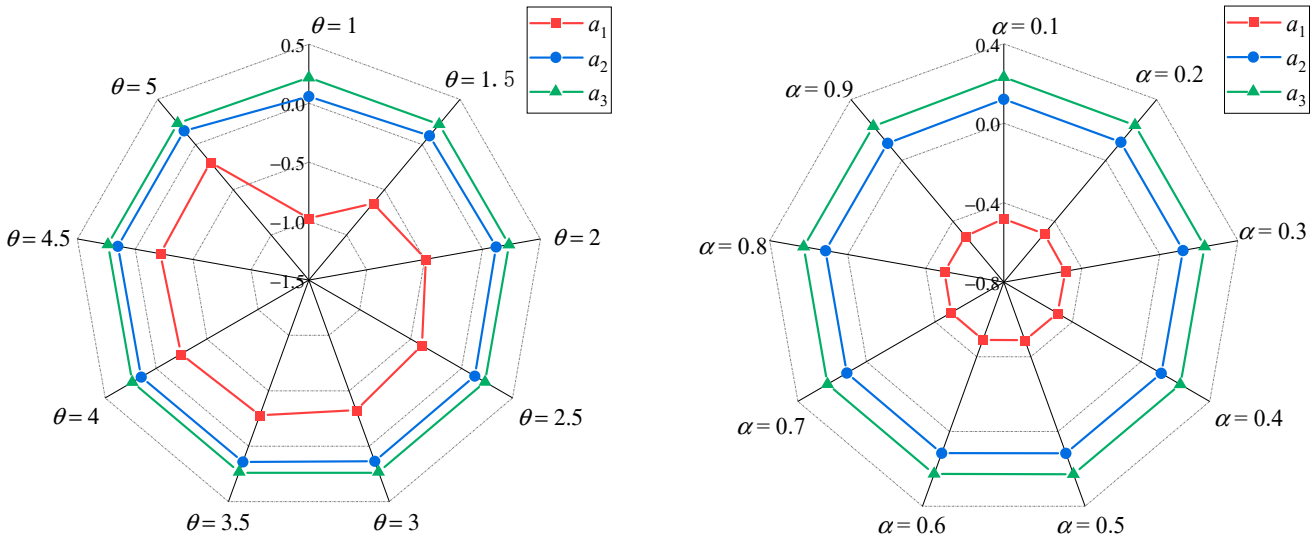


Figure 6. Ranking of alternatives for various values of θ and α. (**a**) Ranking of alternatives for various values of θ. (**b**) Ranking of alternatives for various values of α.

4.3. Comparative Analysis

This study proposes a novel probabilistic linguistic LGEDM method that integrates a modular group pressure model with the Louvain algorithm. Compared to existing methods, this approach fully incorporates the preference information of large-scale DMs by leveraging social trust relationships, expert clustering, preference adjustment, and behavioral modeling. These components collectively enhance the scientific reliability and robustness of EDM processes. To further validate the advantages of the proposed method, Table 4 presents a detailed comparison with existing methods across key dimensions, including large-group environments, social trust relationships, expert clustering, preference adjustment, and behavioral considerations.

Table 4. Comparison of different EDM methods.

Methods	Large Group Environment	Social Trust Relationships	Expert Clustering	Preference Adjustment	Behavior of DMs
Liu et al. [26]	×	√	×	√	×
Li and Wei [28]	×	×	×	×	×
Li et al. [41]	×	×	×	×	√
Tang et al. [42]	√	×	√	√	×
Ding et al. [39]	×	×	×	×	√
Wu et al. [43]	×	√	×	√	×
Li et al. [44]	√	×	√	√	×
Proposed method	√	√	√	√	√

As shown in Table 4, the proposed method demonstrates significant advantages across several critical aspects. First, most existing methods, such as those in [26,28,39,41,43], fail to effectively address the complexities of preference integration in large-group environments. In contrast, the proposed method employs the Louvain algorithm to cluster DMs and integrates a group pressure model to enhance decision consistency, making it more suitable for complex large-scale decision-making scenarios. Second, while some methods, such as those in [26,43], consider social trust relationships, they lack a comprehensive approach to expert clustering and dynamic preference adjustment. This limitation hinders their

ability to resolve preference conflicts in large-scale group decision-making. The proposed method overcomes this by dynamically adjusting preferences through the integration of social trust relationships and expert clustering, significantly improving group decision-making coordination and consistency. Finally, although studies such as [39,41] explore the behavioral modeling of DMs, they inadequately address the roles of preference adjustment and group pressure. As a result, these methods are less suited for the real-time and adaptive requirements of EDM. By introducing a group pressure-based expert consensus model and incorporating an improved TODIM method, the proposed method effectively captures loss aversion psychology in decision-making, enabling a more realistic simulation of behavioral characteristics in emergency scenarios.

To further evaluate the effectiveness and applicability of the proposed method, a comparative analysis was conducted using the methods in [25,26,45]. Table 5 presents the alternative solution rankings obtained with these methods.

Table 5. Comparison of solution rankings using different methods.

Methods	Solution Ranking
Pang et al. [25]	$a_3 \succ a_2 \succ a_1$
Liu et al. [26]	$a_3 \succ a_2 \succ a_1$
Xu et al. [45]	$a_3 \succ a_2 \succ a_1$
Proposed method	$a_3 \succ a_2 \succ a_1$

As shown in Table 5, the solution rankings derived from the methods in [25,26,45] are largely consistent with those of the proposed method, providing partial validation of its rationality and effectiveness. However, a closer analysis reveals significant differences in the theoretical foundations and applicability of these methods. The method proposed by Pang et al. [25], based on PLTSs, is theoretically simple but fails to account for the impact of individual behavior on decision outcomes. This limits its ability to effectively address preference conflicts in group decision-making. Liu et al. [26] introduces a novel distance measure, offering a more scientific approach to quantifying differences between alternatives. However, it lacks a sufficient capacity to adjust for conflicting information in large-group contexts. Xu et al. [45] develops a conflict resolution model that effectively mitigates preference conflicts but struggles with processing fuzzy information and addressing uncertainties in emergency scenarios.

Based on the above analysis, the proposed method, which integrates the Louvain algorithm and a group pressure-based expert consensus model, demonstrates the following significant advantages:

(1) Integration of large-scale group preferences—The Louvain algorithm efficiently clusters large-scale DMs, reducing preference differences and enhancing decision consistency through the group pressure model. This approach effectively addresses the complex preference integration challenges in EDM.
(2) Scientific weight determination—By combining subjective and objective weights, the method captures both the experiential and preferential characteristics of DMs while reflecting the objective properties of the data. This ensures a more scientifically rigorous and balanced distribution of weights.
(3) Behavioral modeling—The improved TODIM method incorporates DMs' loss aversion psychology, enabling realistic simulations of behavioral preferences and risk-averse tendencies. This significantly enhances the rationality and applicability of the method in EDM contexts.

5. Conclusions

This study addresses the LGEDM problem in the context of sudden incidents, considering multiple factors, such as social trust networks, expert clustering, group pressure, and decision-making psychology. We propose a probabilistic linguistic large-group emergency decision-making method based on the Louvain algorithm and the group pressure model. The main contributions of this research are as follows:

First, we extract the relationships between experts using the social trust network and apply the Louvain algorithm to efficiently cluster experts. This approach significantly reduces the computational complexity of large-group decision-making problems while enhancing the operability and accuracy of group decision-making. Second, during the decision preference integration phase, we introduce a group pressure model to dynamically adjust expert preferences. We also establish an expert consensus mechanism to improve the consistency and coordination of the decision-making process. Next, in the solution selection phase, we enhance the TODIM method by combining PLTSs, taking into account DMs' loss aversion psychology. This better captures the psychological decision-making characteristics in emergency situations. Finally, through comparative and sensitivity analyses, we demonstrate the significant advantages of our proposed method in terms of decision-making efficiency, group consistency, and result robustness, particularly in handling large-scale expert preference conflicts and uncertainty.

This study provides a novel modeling approach for LGEDM at the theoretical level and shows considerable practical value. In particular, the proposed method can more accurately reflect DMs' psychological changes under pressure and risk in EDM scenarios. As a result, the decision process and outcomes are more aligned with real-world needs, offering more effective decision support for emergency management.

Although this study has made significant progress in the LGEDM field, several future research directions remain. First, this paper primarily focuses on static decision-making scenarios, whereas real-world emergencies are often highly dynamic. Therefore, future research could consider developing dynamic LGEDM models, incorporating a time series analysis to more accurately describe the evolution of experts' preferences in emergency environments. Second, while the Louvain algorithm has been used for expert clustering, computational complexity remains a challenge when dealing with large datasets. Future work could explore more efficient clustering methods, such as deep learning-based intelligent clustering strategies, to further improve the model's computational efficiency and scalability. Additionally, this study primarily uses PLTSs for information representation, but the information in emergency situations often comes from diverse sources, including multi-source heterogeneous data such as text, sensor data, and social media information. Therefore, future research could integrate natural language processing techniques and multimodal data fusion methods to enhance the model's adaptability and intelligence in complex information environments.

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Data Availability Statement: The original data presented in this study are openly available in a publicly accessible repository at https://github.com/Joy-618/dataset (accessed on 13 February 2025).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Louvain Algorithm

The Louvain algorithm is an efficient community detection method designed to identify community structures within a graph by maximizing its modularity. Modularity is a metric that quantifies the strength of community divisions, with higher values indicating better-defined communities. The Louvain algorithm is widely applied in a complex network analysis due to its efficiency and strong performance in detecting community structures.

The algorithm operates iteratively and consists of two main stages: (1) modularity optimization stage—the algorithm adjusts community assignments by moving nodes within the graph to maximize modularity; (2) once no further significant modularity improvements can be achieved, the detected communities are collapsed into supernodes, forming a new, reduced graph. The modularity optimization process is then repeated on this new graph. The pseudocode for the Louvain algorithm is shown in Algorithm A1.

Algorithm A1. Louvain Algorithm.

Input: Graph G, threshold ε
Output: Community structure C

```
Initialize each node as its own community
repeat
  for each node v in G do
    for each neighbor w of node v do
      Compute the modularity gain if node v joins the community of w
    end for
    Move node v to the community that maximizes modularity gain
  end for
  Aggregate communities into supernodes to form a new graph
  If modularity improves < ε then
    exit
  end if
until no further modularity improvement occurs
return C
```

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