

A case-driven fuzzy reasoning framework for emergency decision-making under interval probabilistic linguistic information

J. Zheng ¹, Y. M. Wang ², K. Zhang ³ and J. Q. Gao ⁴

^{1,4}Department of Electronics Information Science, Fujian Jiangxia University, Fujian 350108, PR China.

^{1,4}Research Institute for Data Analysis and Intelligent Decision Making in Fujian Jiangxia University, Fujian Jiangxia University, Fuzhou Fujian 350108, PR China.

²Institute of Decision Science, Fuzhou University, Fujian 350116, PR China.

³College of Information and Intelligent Transportation, Fujian Chuanzheng Communications College, Fuzhou 350007, PR China.

zhengjing80@fjxxu.edu.cn, ymwang@fzu.edu.cn, zhangkai@fjccpc.edu.cn, gaojianqing@fjxxu.edu.cn

Abstract

Case-driven fuzzy reasoning (CDFR) enhances emergency response efficiency by leveraging historical experience and evaluation information. However, existing CDFR models lack a systematic framework for multi-source information fusion and fail to adequately address the fuzziness regarding information reliability and inter-group consensus. To bridge this gap, this paper proposes a CDFR framework for emergency decision-making under interval probabilistic linguistic information. The reasoning process commences with fuzzy case retrieval to establish the decision context. Multi-source information is then pre-processed through a reliability measure and consensus-driven adjustment mechanism to ensure the credibility and consistency of the evaluation information. Furthermore, attribute weights are derived via the IPLTS-embedded DEMATEL method, and group-wise evaluation information is then fused using the IPLTSWG operator. Finally, an interval-based GLDS approach is proposed to generate the final ranking, which preserves the uncertainty of the original information throughout the reasoning chain. The practicability of the proposed framework is demonstrated through a case study of public health emergency response.

Keywords: Case-driven fuzzy reasoning, multi-group collaboration, emergency response, interval probabilistic linguistic term sets, DEMATEL, GLDS.

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1 Introduction

Case-driven fuzzy reasoning (CDFR) derives emergency decisions from historical case experience and fuzzy information via a structured inference process [35]. In emergency settings, time pressure and information uncertainty make rapid decision-making a major challenge. CDFR addresses this by structuring the reasoning from case retrieval to final ranking as a traceable process [30], enabling timely conclusions under compromised conditions. By embedding fuzzy information processing into the case-driven reasoning pipeline, the approach accommodates imprecision and incompleteness inherent in real-world data while preserving the logical consistency of the inference chain. This makes CDFR particularly suited to complex emergency scenarios.

However, existing CDFR models predominantly rely on expert knowledge, largely overlooking real-time public opinion on social media. As emergencies grow increasingly complex, public reactions have become a critical factor in crisis response. While incorporating public participation could enhance decision quality [11, 32], the noise, subjectivity, and uncertainty of user-generated content pose serious challenges to information reliability, an aspect that existing

CDFR frameworks are ill-equipped to handle. Thus, leveraging public wisdom without a robust reliability mechanism may introduce significant risks, necessitating a multi-source evaluation framework that effectively integrates public and expert inputs. To bridge this gap, this study develops a CDFR framework that effectively integrates multi-group evaluations while ensuring information trustworthiness. Specifically, three fundamental challenges must be addressed.

(1) The primary challenge lies in ensuring the reliability and consistency of multi-source fuzzy information fusion. While methods like attribute extraction and sentiment analysis can reveal public preferences to some extent [29], they often fail to quantify subjective evaluations precisely and interpretably. The Probabilistic Linguistic Term Set (PLTS) provides an alternative by representing multi-level sentiments and handling information incompleteness probabilistically [6], enabling nuanced opinion capture under ambiguity. However, inherent gaps and biases in public knowledge still limit the reliability of such opinions. Thus, models integrating public views must incorporate credibility weighting mechanisms to address source reliability. Additionally, multi-group decision-making often involves conflicting evaluations, necessitating a consistency-reaching processing (CRP) to align divergent viewpoints and enhance collective judgment reliability [7, 25]. Therefore, an information preprocessing model that jointly addresses sentiment reliability and evaluation consistency is essential for dual reliability assurance.

(2) The second challenge is to derive attribute weights and subsequently fuse group-wise evaluation information under a fuzzy environment. Real-world decision attributes are often interdependent, complicating the assessment process. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is particularly suited for identifying and visualizing causal relationships among criteria. DEMATEL has been successfully applied in diverse domains, including public health [25], barriers examination [19], and influence factor evaluation [15]. To better handle the ambiguity and imprecision inherent in group assessments, this study represents the direct-influence matrix using interval Probabilistic Linguistic Term Sets (IPLTSs). However, the integration of IPLTSs with DEMATEL—particularly in simplifying the weighting process and ensuring robustness—remains underexplored. Thus, further investigation is needed to develop an effective weighting mechanism within this hybrid framework. Once the attribute weights are determined, the evaluation information within each group must be further fused to generate a comprehensive group-level assessment.

(3) The third challenge is to fuse the multi-source evaluation information and rank historical cases effectively under interval-probabilistic uncertainty. Existing ranking methods, such as ELECTRE [23], VIKOR [9], and TODIM [18], often permit full compensation among attributes, which masks critical weaknesses and leads to less realistic rankings. In contrast, the GLDS method [36] is inherently non-compensatory and offers greater fairness and robustness in evaluation. However, the standard GLDS framework lacks an inherent mechanism to handle the uncertainty and fuzziness commonly encountered in real-world group decision-making. To bridge this gap, this study enhances the GLDS method by integrating interval-valued theory to formulate the dominance degree function, thereby enabling a global multi-source aggregation of all group-level results. However, this also increases the difficulty in determining the group weights and the global scores in this situation. Therefore, this necessitates an optimization algorithm for parameter calibration to improve the stability and reliability of aggregating multi-group evaluations.

To overcome these challenges, this study proposes a novel fuzzy CDFR model that integrates multi-source fuzzy information, aiming to generate more robust emergency alternatives. The contributions of this study are summarized as follows:

(1) Development of a fuzzy CDFR framework integrating multi-source fuzzy information. This framework is designed to generate emergency alternatives by conducting fuzzy reasoning based on retrieved similar historical cases and multi-source evaluation information. By accounting for the uncertainty, reliability, and consistency inherent in multi-source evaluations, this mechanism ensures more effective and stable reasoning outcomes while maintaining a traceable chain from case retrieval to final ranking.

(2) Proposal of a multi-source fuzzy information pre-processing mechanism. This mechanism is proposed to address the reliability and consistency issues in public opinions and expert evaluations. Through reliability-aware weighting of public inputs and consensus-driven calibration of multi-source evaluation information, the mechanism ensures effective reasoning outcomes.

(3) Extension of the IPLTS-DEMATEL for intra-group information fusion. The DEMATEL method is extended to the IPLTS environment to support attribute weight determination under fuzzy interdependencies. Based on the derived weights, the pre-processed evaluation information within each group is further fused to generate comprehensive group-level assessments. This ensures that the fused results not only capture the interdependencies among attributes, but also reflect the collective judgments within each group more reliably.

(4) Enhancement of the GLDS model with uncertainty preservation for multi-source fusion. This study enhances GLDS by integrating interval-valued theory to formulate the dominance degree function, enabling it to handle uncertainty effectively. Furthermore, an optimization algorithm is embedded for parameter calibration, which improves the stability and reliability of aggregating multi-group evaluations for final alternative selection.

The remainder of this paper is structured as follows: Section 2 introduces some preliminary concepts. Section 3

presents the proposed CDFR model integrating public wisdom. Section 4 presents a case study that was conducted to validate the proposed decision support framework. Section 5 discusses the results to verify the superiority of the proposal. Finally, Section 6 summarizes the conclusions of this study.

2 Literature review

In this section, previous studies on CDFR and group decision-making with fuzzy reasoning are reviewed.

2.1 Case-driven fuzzy reasoning

CDFR leverages historical experience and evaluation information to support emergency decision-making with an interpretable reasoning process [30, 35]. In case retrieval, to address the fuzziness and incompleteness commonly presented in real-world data, fuzzy theory has been introduced to handle heterogeneous information [3]. However, these methods often rely on single-dimensional similarity measures, whereas recent work has improved matching accuracy through multi-faceted evaluations such as bidirectional projection [35, 37] and machine learning [31]. In reasoning generation, existing studies have gradually integrated information fusion [33, 36] and behavioral theories [33, 37]. Nevertheless, despite these advancements, the reasoning process remains largely dependent on expert knowledge and fails to effectively utilize the vast and real-time public opinion available on social media [11, 32]. Consequently, existing CDFR models have yet to form a complete reasoning chain from multi-source information to final decisions, making it difficult to cope with the simultaneous challenges of information diversity and uncertainty in emergency scenarios.

2.2 Group decision making with fuzzy reasoning

Group decision-making is widely applied in emergency contexts, where multiple stakeholders participate in assessments to prioritize response alternatives [26]. Given the inherent uncertainty of emergencies, group decision-making often involves a process of fuzzy reasoning. A critical issue in this reasoning process is the CRP, which ensures that individual evaluations are aggregated into collective judgments with acceptable consensus [25]. With the advancement of information technologies, the participant pool has expanded from domain experts to the general public, and public opinions from social media have been shown to significantly influence crisis dynamics and enhance decision legitimacy [11, 32]. To represent such fuzzy inputs, Probabilistic Linguistic Term Sets (PLTSs) have been employed to capture subjective sentiments and handle incomplete information [6]. Within the CDFR framework, case selection has benefited from group decision-making based on expert assessments [33, 36]. However, existing CDFR studies remain confined to expert inputs and have not addressed the integration of public opinions, nor the dual challenges of information reliability and consensus reaching. In contrast, this study develops a GDM framework within CDFR that jointly tackles public opinion incorporation, reliability assurance, and consistency reaching in case selection.

2.3 Research gaps and motivation

Based on the above review, three research gaps are identified. First, existing CDFR frameworks lack mechanisms for incorporating multi-source information. Second, group decision-making fails to simultaneously address information reliability and the CRP. Third, none of the existing studies handle multi-source information integration, reliability, consistency, and uncertainty within a unified CDFR framework. Table 1 summarizes the research gaps addressed by this study.

Table 1: Summary of research gaps in literature review studies

References	Multi-source information integration	Reliability	Consistency	Uncertainty
CDFR with fuzzy similarity [36, 37]	—	—	—	✓
CDFR with machine learning [17, 32]	—	—	—	✓
CDFR with behavioral theories [34, 36]	—	—	—	✓
Group decision making under PLTS [4, 8, 28]	✓	—	—	✓
Group decision making with CRP [11, 25]	✓	—	✓	✓
This study	✓	✓	✓	✓

To address these gaps, this study proposes a CDFR framework that conducts a complete fuzzy reasoning process from case retrieval and multi-source information pre-processing, through attribute weight inference and intra-group fusion, to uncertainty-preserving ranking. This framework unifies the four key stages of emergency decision-making

into a coherent and traceable inference chain, ensuring that case experience, information reliability, group consistency, and interval-probabilistic uncertainty are systematically handled.

3 Preliminaries

Definition 3.1. [28] Let $\Gamma = \{\ell_0, \dots, \ell_H\}$ be a linguistic set, where H is a finite positive integer. Then, the IPLTSs are defined as

$$IL(p) = \left\{ \ell_h [p^{hL}, p^{hU}] \mid \ell_h \in \Gamma, 0 \leq p^{hL} \leq p^{hU}, \sum_{h=1}^{\#IL(p)} p^{hL} \leq 1 \right\},$$

where $[p^{hL}, p^{hU}]$ indicates the interval probabilities in the linguistic term ℓ_h and $\#IL(p)$ is the number of linguistic terms in $IL(p)$. If $p^{hL} = p^{hU}$, then IPLTS becomes PLTS.

IPLTS operations require a uniform number of linguistic terms. Therefore, IPLTSs with fewer terms must be extended to match the length of others.

Definition 3.2. [20] Suppose $IL_1(P)$ and $IL_2(P)$ are any two IPLTSs, and $\#IL_1(p)$ and $\#IL_2(p)$ are the respective numbers of linguistic terms. If $\#IL_1(p) > \#IL_2(p)$, then $IL_2(P)$ should add $\#IL_1(p) - \#IL_2(p)$ linguistic terms to make the number of linguistic terms the same as that of $IL_1(P)$. The added linguistic terms are the least ones in $IL_2(P)$, and their corresponding probabilities are zero.

Definition 3.3. [13] Suppose $IL(p) = \{\ell_h [p^{hL}, p^{hU}] \mid h = 1, 2, \dots, \#IL(p)\}$ is an IPLTS and L_h is a subscript of the linguistic term ℓ_h . The crisp IPLTS score is expressed as

$$E(IL(p)) = \sum_{h=1}^{\#IL(p)} \frac{L_h p_h^L + L_h p_h^U}{\#IL(p)}. \quad (1)$$

Definition 3.4. [13] Suppose $IL(p) = \{\ell_h [p^{hL}, p^{hU}] \mid h = 1, 2, \dots, \#IL(p)\}$ is an IPLTS and L_h is a subscript of the linguistic term ℓ_h . The interval IPLTS score is expressed as

$$E(IL(p)) = \left[\sum_{h=1}^{\#IL(p)} \frac{L_h p_h^L}{\#IL(p)}, \sum_{h=1}^{\#IL(p)} \frac{L_h p_h^U}{\#IL(p)} \right]. \quad (2)$$

Information aggregation of the IPLTS is essential for multi-attribute decision making, which must not only reduce information loss but also consider consistency and non-virtual preference values to ensure the validity of the decision results. To achieve this aim, the following aggregation operator was proposed [13].

Definition 3.5. [13] Let $IL_i(p) = \{\ell_{h_i} [p_i^{h_iL}, p_i^{h_iU}] \mid h = 1, 2, \dots, \#IL_i(p)\}$ ($i = 1, 2, \dots, n$) be an IPLTS, where Γ_i and $[p_i^{h_iL}, p_i^{h_iU}]$ are the i th linguistic term set and its interval probability, respectively, in $IL_i(p)$. Then, the IPLTSWG aggregation operator is defined as

$$\begin{aligned} \text{IPLTSWG}_\lambda(IL_1(p), \dots, IL_n(p)) &= (IL_1(p))^{\lambda_1} \otimes (IL_1(p))^{\lambda_2} \otimes \dots \otimes (IL_1(p))^{\lambda_n} \\ &= \bigcup_{l_{h_1} \in \Gamma_1} \left\{ [\gamma_{h_1}^{\lambda_1 p_1^{h_1L}}, l_{h_1}^{\lambda_1 p_1^{h_1U}}] \right\} \otimes \bigcup_{l_{h_2} \in \Gamma_2} \left\{ [\gamma_{h_2}^{\lambda_2 p_2^{h_2L}}, l_{h_2}^{\lambda_2 p_2^{h_2U}}] \right\} \otimes \dots \otimes \bigcup_{l_{h_n} \in \Gamma_n} \left\{ [\gamma_{h_n}^{\lambda_n p_n^{h_nL}}, l_{h_n}^{\lambda_n p_n^{h_nU}}] \right\}, \end{aligned}$$

where r_{h_i} is the linguistic value of the linguistic term l_{h_i} , h_i is the subscript of the linguistic term l_{h_i} , and $\gamma_{h_i} = h_i / \#IL(P_I)$, λ_i is the weight of the i th decision maker, and $\sum_{i=1}^n \lambda_i = 1$.

4 The proposed case-driven fuzzy reasoning framework

This section presents a fuzzy reasoning framework for emergency decision-making under IPLTS environments. The reasoning process begins with case retrieval, which identifies similar historical cases and establishes the decision context for subsequent information acquisition and pre-processing. Multi-source information is then refined through reliability-aware weighting and consensus-driven adjustment. Subsequently, the pre-processed information is fused at the group level, and the final ranking is obtained through the interval-based GLDS method. The overall architecture of the proposed framework is depicted in Figure 1. For convenience, the notations used in this study are listed in Table A1.

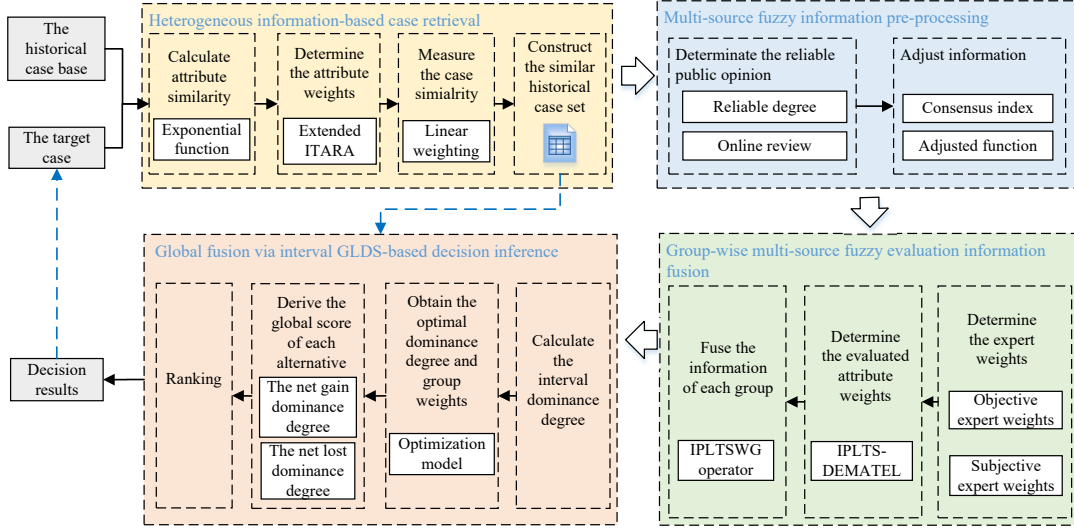


Figure 1: Flowchart of the proposed CDFR framework

4.1 Heterogeneous information-based case retrieval

This section proposes an indifference threshold-based case-similarity measurement which considers the influence of data dispersion on uncertainty.

Suppose the historical cases C_i ($i = 1, 2, \dots, n$) and target case C_0 are presented by a set of attributes $X = \{X_j \mid j = 1, 2, \dots, m\}$, where a_{ij} indicates the value of the attribute X_j regarding case C_i and a_{0j} denotes the value of the attribute X_j regarding case C_0 . In this study, a_{ij} and a_{0j} were expressed using an IPLTS and interval number, i.e., $a_{ij} = \{\ell_k [p_{k,ij}^L, p_{k,ij}^U]\}$, $a_{ij} = [a_{ij}^-, a_{ij}^+]$. The importance of attribute X_j is denoted as w_j^P , such that $0 \leq w_j^P \leq 1$ and $\sum_{j=1}^m w_j^P = 1$.

First, the attribute distance between a_{ij} and a_{0j} is obtained by

$$d(a_{0j}, a_{ij}) = \sqrt{(a_{0j}^- - a_{ij}^-)^2 + (a_{0j}^+ - a_{ij}^+)^2}, \quad (3)$$

$$d(a_{0j}, a_{ij}) = \sqrt{\frac{\sum_{k=1}^{\#h} ((\ell_k p_{k,0j}^L - \ell_k p_{k,ij}^L)^2 + (\ell_k p_{k,0j}^U - \ell_k p_{k,ij}^U)^2)}{\#h}}. \quad (4)$$

Then, the attribute similarity between historical case C_0 and historical case C_i regarding attribute X_j is measured by

$$S_{0ij} = \exp \left(-\frac{d(a_{0j}, a_{ij})}{\max_i \{d(a_{0j}, a_{ij})\}} \right). \quad (5)$$

Furthermore, an extension of the Indifference Threshold-based Attribute Ratio Analysis (ITARA) method [10] is proposed to determine attribute weights. ITARA is based on the logic that a wider distribution of attribute values indicates greater uncertainty and thus higher importance [10]. However, the original ITARA is limited to numerical data and cannot handle heterogeneous information. To overcome this limitation while preserving objectivity, this study extends ITARA to a heterogeneous environment, while keeping the indifference threshold data-driven. The extended procedure is presented as follows.

Step 1: The positive ideal solution (PIS) a_j^+ and negative ideal solution (NIS) a_j^- are determined.

If a_{ij} is an IPLTS, the PIS and NIS can be obtained by

$$a_j^+ = \begin{cases} \max_i \{E(a_{ij})\}, & \text{for benefit attribute} \\ \min_i \{E(a_{ij})\}, & \text{for cost attribute} \end{cases}, \text{ and } a_j^- = \begin{cases} \min_i \{E(a_{ij})\}, & \text{for benefit attribute} \\ \max_i \{E(a_{ij})\}, & \text{for cost attribute} \end{cases}. \quad (6)$$

If a_{ij} is an interval number, the PIS can be obtained by

$$a_j^+ = \max_i \left\{ \frac{a_{ij}^- + a_{ij}^+}{2} \right\}, \text{ and } a_j^- = \min_i \left\{ \frac{a_{ij}^- + a_{ij}^+}{2} \right\}. \quad (7)$$

Step 2: The distances between the attributes and the PIS and NIS $d(a_{ij}, a_j^+)$ and $d(a_{ij}, a_j^-)$ are calculated according to Eqs. (3) and (4), respectively. The closeness of each attribute is obtained as

$$CD_{ij} = (1 - d(a_{ij}, a_j^+) + d(a_{ij}, a_j^-)) / 2. \quad (8)$$

Step 3: A considerable deviation ρ_{ij} is defined as

$$\rho_{ij} = \begin{cases} CD_{ij} - \lambda_j, & \text{for } CD_{ij} > \lambda_j \\ 0, & \text{for } CD_{ij} \leq \lambda_j \end{cases}. \quad (9)$$

where $\lambda_j = (\frac{1}{n} \sum_{i=1}^n CD_{ij})$ denotes the indifference threshold. The mean λ_j serves as a data-driven benchmark of the average deviation on attribute X_j . When $CD_{ij} > \lambda_j$, the deviation indicates above-average dispersion and is retained as informative for weight assignment; otherwise, it is treated as negligible. The mean is chosen as the cutoff because it represents the central tendency of the observed deviations for a given attribute. In the ITARA framework, this choice is considered optimal in the sense that it maximizes the discriminatory information retained from the data while minimizing the influence of random fluctuations, without requiring any subjective parameters.

Step 4: The attribute weights are assigned according to l_p -metric measurement as follows:

$$w_j^P = \left(\sum_{i=1}^{n-1} \rho_{ij}^p \right)^{1/p} / \sum_{j=1}^m \left(\sum_{i=1}^{n-1} \rho_{ij}^p \right)^{1/p}. \quad (10)$$

where p is a parameter of the l_p -metric, and the attribute weights satisfy $\sum_{j=1}^m w_j^P = 1$, and $w_j^P > 0$.

Furthermore, according to the simple additive weighting method, case similarity S_i between historical case and target case is defined as the weighted sum of the attribute similarities:

$$S_i = \sum_{j=1}^m w_j^P S_{0ij}. \quad (11)$$

where $S_i \in [0, 1]$. A larger S_i indicates a higher degree of similarity between the historical case and the target case, implying that the corresponding solution is more informative for generating the alternative for the target case.

Finally, a set of similar historical cases is established. The decision-makers give thresholds β based on their own experience and expertise to identify the similar historical case set, where $\min_i \{S_i\} < \beta < \max_i \{S_i\}$. A higher β yields stricter screening for high-confidence scenarios, while a lower β expands candidate cases for data-sparse conditions. Experts determine the specific value by balancing retrieval precision and candidate sufficiency. If $S_i > \beta$, the historical case C_i would be selected into the similar historical case set. Then, the set of alternatives $D = \{D_u \mid u = 1, 2, \dots, U\}$ is constructed, where each D_u is the alternative corresponding to a historical case C_i with $S_i > \beta$, and the selected cases are renumbered consecutively from 1 to U .

4.2 Multi-source fuzzy information pre-processing

This section develops a multi-source fuzzy information pre-processing mechanism for the IPLTS environment. It refines public opinions and expert evaluations through reliability-aware processing and consensus-driven adjustment, thereby ensuring the validity of the fused fuzzy evaluation information. The processing tracks for public-review and expert information are shown in Table 2.

4.2.1 Acquisition of reliable fuzzy public opinions

Online reviews play a pivotal role in decision-making by aggregating user experiences and providing valuable insights [27, 29, 39]. However, the extracted evaluation information is often incomplete. Therefore, incorporating data reliability into a decision-making framework is essential [4].

The transformation of online reviews into PLTS involves the following steps:

Table 2: Workflow distinction between public-review information and expert information

Processing stage	Public-review information	Expert information
Source	Non-professional users	Domain experts
Raw data type	Natural language text	IPLTS
Core characteristics	Massive volume, high subjectivity, semantic ambiguity	Small volume, high authority, rigorous logic, strong reference value
Preprocessing method	Text mining, sentiment analysis, transformed into IPLTS	IPLTSWG
Reliability improvement	Reliability, CRP	CRP

Step 1: Attribute extraction. Online reviews are collected via a Python crawler and pre-processed by removing irrelevant, duplicated, and default entries. Candidate attributes are first identified based on literature and expert knowledge. Both the pre-processed reviews and the candidate attribute terms are then vectorised using a pre-trained BERT model. The cosine similarity between each review vector and each candidate attribute vector is computed, and each review is assigned to the candidate attribute with the highest similarity score. The candidate attributes are then ranked according to the frequency of reviews assigned to them, and the top-ranked ones are selected to form the core attribute set $T = \{T_1, T_2, \dots, T_Q\}$.

Step 2: Sentiment classification. For each review classified under attribute T_q , sentiment analysis is conducted using SnowNLP. Each review receives a sentiment score $\psi \in [0, 1]$ and is mapped to one of five linguistic levels in the predefined term set $\Gamma = \{\ell_0(\text{very bad}), \ell_1(\text{bad}), \ell_2(\text{neutral}), \ell_3(\text{good}), \ell_4(\text{very good})\}$ according to the rule [11]. Specifically, a sentiment score is assigned to ℓ_k if it falls within the interval $[k/5, (k+1)/5]$.

Step 3: Conversion to PLTS. For each alternative D_u under attribute T_q , let N_{uq} be the total number of reviews classified under T_q , and $N_{k,uq}$ be the number of these reviews assigned to the linguistic level ℓ_k . The probability $p_{k,uq}$ is then computed as $p_{k,uq} = N_{k,uq}/N_{uq}$. Then, the online reviews of alternative D_u with respect to attribute T_q is converted into a PLTS as $e_{uq} = \{\ell_h(p_{k,uq})\}$, where $p_{k,uq} \geq 0$ and $\sum_{k=0}^4 p_{k,uq} = 1$.

The similarity between the online and expert evaluation information can determine the reliability of the online evaluation information. On this basis, the online evaluation information is measured.

Definition 4.1. [4] Let $E = (e_{uq})_{U \times Q} = \{\ell_{uq}^h(p_{uq}^h)\}_{U \times Q}$ be the online review matrix obtained by sentiment analysis, and let $R^k = (r_{uq}^k)_{U \times Q} = (\ell_{uq}^{kh}[p_{uq}^{khL}, p_{uq}^{khU}])_{U \times Q}$ be the evaluated information matrix of the k th expert, where $k = \{1, 2, \dots, K\}$. The reliability of alternative D_u regarding attribute T_q is measured by

$$RL_{uq} = \left(\sum_{k=1}^K \exp(-d_{uq}^k) \right) / K, \quad (12)$$

where d_{uq}^k is the distance between the public and the k th expert's evaluated information regarding attribute T_q and

is obtained by $d_{uq}^k = \sqrt{\sum_{h=1}^{\#IP} \left(\left(\frac{\ell_h p_{uq}^{hL} - \ell_h^k p_{uq}^{khL}}{\tau} \right)^2 + \left(\frac{\ell_h p_{uq}^{hU} - \ell_h^k p_{uq}^{khU}}{\tau} \right)^2 \right)}$. A higher RL_{uq} indicates stronger agreement

between public and expert opinions, making the online review information more trustworthy and thus more influential in the aggregation process.

Furthermore, according to the operator described in a previous study [13], the comprehensive information on online reviews is obtained by

$$\bar{e}_{uq} = RL_{uq} e_{uq} = \bigcup_{\{\ell_{uq}^h[p_{uq}^{hL}, p_{uq}^{hU}]\} \in e_{uq}} \{\ell_{uq}^{RL_{uq}h}, RL_{uq} p_{uq}^h\}. \quad (13)$$

According to the above steps, we can analyze the complexity of reliable public opinion determination. The main cost lies in preprocessing (attribute extraction and sentiment classification), with complexity $O(N \cdot D \cdot (L^2 + M))$, where N is the number of reviews, L is the average text length, D is the embedding dimension, and M is the number of candidate attributes. This scales linearly with N . After conversion to a $U \times Q$ PLTS matrix, the subsequent reliability computation becomes $O(K \cdot U \cdot Q)$, independent of N . Thus, the framework is scalable for large-scale online reviews.

4.2.2 Consensus-driven evaluation information adjustment

In group decision-making, divergent expertise among decision-makers often leads to conflicting evaluations. Achieving consensus is crucial to reconcile these conflicts and align collective outcomes with individual preferences. This alignment is quantitatively assessed using similarity-based consistency measures.

Definition 4.2. Let $R^k = (r_{uq}^k)_{U \times Q}$ be the evaluated information matrix of the k th expert; the CI of every expert is defined as

$$CI(E^k) = 1 - \frac{1}{UQ(K-1)} \sum_{u=1}^U \sum_{q=1}^Q \sum_{\substack{g=1 \\ g \neq k}}^K d(r_{uq}^k, r_{uq}^g). \quad (14)$$

where $d(r_{uq}^k, r_{uq}^g)$ represents the distance between expert E^k and E^g regarding the q th attribute of the u th alternative.

Evidently, $0 \leq CI(E^k) \leq 1$ can be proven. A smaller value of $CI(E^k)$ means that the evaluated information of the expert E^k is more consistent with that of other experts. Suppose ρ ($0 < \rho < 1$) is the predefined acceptable CI threshold. If $CI(E^k) > \rho$, the CI is considered to have been reached. If $CI(E^k) < \rho$, the CI has not been reached, and the evaluated information of expert E^k should be adjusted to achieve a higher level. In general, the parameter ρ is determined by all experts during the decision-making process.

Suppose that the ℓ th-round evaluated information of expert E^k is $r_{uq}^{k\ell}$. If the evaluated information has not reached the CI, the adjusted information can be gained as follows:

$$r_{uq}^{k(\ell+1)} = \theta r_{uq}^{k\ell} + (1 - \theta) r_{uq}^{\ell*}. \quad (15)$$

where $r_{uq}^{\ell*}$ denotes the evaluation of the experts with the minimum CI at the ℓ th round, and parameter θ is the consensus control parameter. The number of iterations required to reach consensus is governed by three factors: the acceptable CI threshold ρ , the consensus control parameter θ , and the initial divergence among experts. A stricter ρ or a larger θ tends to increase the iteration count, while higher initial consensus reduces it. A larger θ means slower but steadier adjustments; a smaller θ means faster adjustments but may cause the expert's opinion to swing past the target and lose its individuality. The adjustment of θ depends on the trade-off between convergence speed and the preservation of individual expertise. In practice, a smaller θ is preferable when rapid consensus is needed, while a larger θ better preserves expert diversity in more deliberative settings.

Proposition 4.3. (Convergence of consensus adjustment). Under the adjustment mechanism in Eq. (15), the group disagreement strictly decreases at each iteration and terminates in finite steps for any given threshold $\rho > 0$.

Proof. Let $\Delta_\ell = \max_{u,q,k} |r_{uq}^{k,\ell} - \bar{r}_{uq}^\ell|$, where $\bar{r}_{uq}^\ell$ is the group mean. Since $r_{uq}^{\ell+1}$ is a convex combination of r_{uq}^ℓ and the most consistent expert's evaluation, $\Delta_{\ell+1} \leq \Delta_\ell$. Unless consensus is reached, at least one evaluation moves strictly toward the mean, so $\Delta_{\ell+1} < \Delta_\ell$ for $\Delta_\ell > \rho$. As $\Delta_\ell \geq \rho$ and is decreasing, it converges. Given $\rho > 0$, there exists a finite ℓ^* such that $\Delta_{\ell^*} \leq \rho$, i.e., the process terminates in finite steps. $\square$

4.3 Group-wise multi-source fuzzy evaluation information fusion

This subsection develops a group-specific evaluation fusion model comprising three stages: expert weighting, attribute weighting, and information fusion.

4.3.1 Determination of the expert weights

The weights of experts are determined through an integration of their self-evaluations and the level of consistency in their evaluation information.

The importance of each expert is estimated by IPLTS, i.e., $\gamma^k = \{\ell_h^k[p^{khL}, p^{khU}]\}$. Then, the objective expert weights are given by

$$w_k^o = \sum_{h=1}^{\#IL(p)} \frac{\ell_h^k p^{khL} + \ell_h^k p^{khU}}{\#IL(p)}. \quad (16)$$

Furthermore, the subjective expert weights based on the CI are defined as

$$w_k^s = \frac{\exp(-CI(E^k))}{\sum_{k=1}^K \exp(-CI(E^k))}. \quad (17)$$

Finally, the expert weights are determined according to the subjective and objective weights by

$$w_k = \frac{w_k^o w_k^s}{\sum_{k=1}^K w_k^o w_k^s}. \quad (18)$$

Accordingly, the objective weight reflects experts' self-perceived competence, while the subjective weight reflects their alignment with the group consensus. Combined multiplicatively, the resulting weights account for both individual self-assessment and collective consistency.

4.3.2 Attribute weights determination via IPLTS-DEMATEL

This subsection introduces the DEMATEL methodology to capture the intricate interconnections among diverse criteria under IPLTS environments.

Step 1: A matrix $A_{Q \times Q}^k = [a_{qt}^k]_{Q \times Q} = \{\ell_{qth}^k [p_{qt}^{khl}, p_{qt}^{khu}]\}_{Q \times Q}$ of direct relations is derived from the experts. The experts provide the degree of influence by making pairwise comparisons between attributes to construct a direct relationship matrix $A_{Q \times Q}^k$ (where Q is the number of attributes). The degree of influence is measured using IPLTS.

Step 2: The direct relations from the experts are integrated by using the IPLTSWG operator, and the group direct influence matrix is obtained.

$$B = (b_{qt})_{Q \times Q} = [b_{qt}^-, b_{qt}^+] = IPLTSWG_{w_k}(a_{qt}^1, \dots, a_{qt}^K) = \left(\sum_h \prod_{w_k} \ell_{qth}^{k(w_k p_{qt}^{khl})}, \sum_h \prod_{w_k} \ell_{qth}^{k(w_k p_{qt}^{khu})} \right). \quad (19)$$

Step 3: The normal distribution matrix $G = (g_{qt})_{Q \times Q}$ of direct relations is obtained. Assuming that ζ follows a normal distribution within the interval $[b_{qt}^-, b_{qt}^+]$, according to probability theory, the normal distribution value can be obtained by

$$g_{qt} = \int_{b_{qt}^-}^{b_{qt}^+} \frac{\zeta}{b_{qt}^+ - b_{qt}^-} d\zeta. \quad (20)$$

Step 4: Matrix G is normalized. The normalized matrix $\bar{G} = (\bar{g}_{qt})_{Q \times Q}$ can be calculated by

$$\bar{g}_{qt} = g_{qt} / \sum_{q=1}^Q g_{qt}. \quad (21)$$

Step 5: The total relation matrix T is computed. The total relation matrix $T = (t_{qt})_{Q \times Q}$ is obtained by

$$T = \bar{G}(I - \bar{G})^{-1}, \quad (22)$$

where I denotes the identity matrix. The element t_{qt} indicates the indirect influences of attribute T_q on attribute T_t .

Step 6: The sums of the rows and columns of matrix T are computed. The sums of the rows and columns are represented by M and D , respectively, and can be computed by

$$M = [m_q]_{Q \times 1} = \sum_{t=1}^Q t_{qt}. \quad (23)$$

$$D = [d_q]_{1 \times Q} = \sum_{t=1}^Q t_{qt}, \quad (24)$$

where m_q is the degree of influential impact given by attribute T_q to all other attributes, and d_q is the degree of influential impact received by attribute T_q from all other attributes.

Step 7: The attribute weights are determined. The importance degree of attribute T_q can be obtained by

$$\sigma_q = \sqrt{(m_q + d_q)^2 + (m_q - d_q)^2}. \quad (25)$$

Then, the evaluated attribute weights w_q^R can be determined by

$$w_q^R = \sigma_q / \sum_{q=1}^Q \sigma_q. \quad (26)$$

where w_q^R reflects the interdependencies and causal relationships among attributes. These weights will serve as the input for the subsequent aggregation stage, ensuring that the interaction information is preserved throughout the decision-making process. A higher w_q^R indicates greater importance of the corresponding attribute, which should be prioritized in practice.

To illustrate the effectiveness of the IPLTS-DEMATEL algorithm, an example is presented below.

Example 4.4. Suppose there are 3 attributes: heat (X_1), shortness of breath (X_2), and fatigue (X_3). The direct relation matrix and the pairwise comparison matrix are given as follows:

$$DR = \begin{bmatrix} \{\ell_0[0, 0]\} & \{\ell_3[0.7, 0.9]\} & \{\ell_2[0.6, 0.8]\} \\ \{\ell_0[0, 0]\} & \{\ell_0[0, 0]\} & \{\ell_1[0.5, 0.7]\} \\ \{\ell_0[0, 0]\} & \{\ell_0[0, 0]\} & \{\ell_0[0, 0]\} \end{bmatrix}, \quad AHP = \begin{bmatrix} 1 & 2 & 5 \\ 1/2 & 1 & 3 \\ 1/5 & 1/3 & 1 \end{bmatrix}.$$

From the AHP matrix, X_1 is the best attribute and X_3 is the worst. The BO vector is $\{1, 2, 5\}$ and the OW vector is $\{5, 3, 1\}$. The attribute weights are determined by IPLTS-DEMATEL, AHP and BWM as follows: $w_{DR} = \{0.606, 0.358, 0.036\}$, $w_{AHP} = \{0.582, 0.309, 0.109\}$, $w_{BWM} = \{0.54, 0.29, 0.17\}$. All methods identify X_1 as the most important attribute. However, DEMATEL assigns X_1 a notably higher weight than AHP and BWM do. This difference arises because DEMATEL captures the causal relationships among attributes— X_1 drives both X_2 and X_3 , and as the root cause, it should carry greater weight in the decision. In contrast, AHP and BWM assume attribute independence and thus treat driving factors and accompanying symptoms on an equal footing. As a result, it overestimates the importance of X_3 and underestimates the weight of X_1 . This confirms that DEMATEL's ability to account for interdependencies yields a more reasonable weight distribution aligned with the actual causal structure. At the same time, the consistent ranking across all three methods demonstrates that the weighting result is not an artifact of any single methodological construction.

4.3.3 Intra-group evaluation information fusion

With the attribute weights determined, the information for each group should be aggregated. In emergency decision-making, a severely low performance on any single attribute may render the entire alternative infeasible; therefore attributes should not compensate for one another. The IPLTSWG operator meets this requirement through its geometric aggregation logic, as the failure of one key dimension cannot be compensated by satisfactory performance in others. To prevent such compensatory effects, the IPLTSWG operator is employed, as its geometric aggregation mechanism inherently penalizes extremely low values and ensures that poor performance on critical attributes is not masked by superior performance elsewhere. By contrast, the IPLTSWA operator permits trade-offs among attributes; it is incompatible with the non-compensatory logic required in emergency settings. Accordingly, the IPLTSWG operator is adopted to fuse the group-wise evaluation information. The comprehensive information of the k th expert regarding alternative D_u can be obtained using the IPLTSWG operator as follows:

$$EI_u^k = IPLTSWG_{w_q^R}(r_{u1}^k, \dots, r_{uQ}^k) = \left(\prod_h \sum_{w_q^R} \ell_{uq}^{kh(w_q^R p_{uq}^{khL})}, \prod_h \sum_{w_q^R} \ell_{uq}^{kh(w_q^R p_{uq}^{khU})} \right). \quad (27)$$

Comprehensive information on online reviews regarding alternative D_u can be obtained by

$$PI_u = IPLTSWG_{w_q^R}(e_{u1}, \dots, e_{uQ}) = \left(\prod_h \sum_{w_q^R} \ell_{uq}^h(w_q^R p_{uq}^h), \prod_h \sum_{w_q^R} \ell_{uq}^h(w_q^R p_{uq}^h) \right). \quad (28)$$

where EI_u^k and PI_u are the IPLTSs.

Remark 4.5. The IPLTS-DEMATEL procedure analyzes the interrelationships among criteria and determines a weight vector that already encodes these interdependencies. The IPLTSWG aggregation then applies this weight vector to synthesize the performance of each alternative; it does not re-model the interactions, as they have already been captured in the weights. This two-stage paradigm, i.e., determining weights through interaction analysis and then aggregating alternative performances under these weights, is standard in DEMATEL-based multi-attribute decision-making. Explicitly reintroducing criterion interactions at the aggregation stage would risk double-counting the effects already accounted for. Thus, the interaction information is implicitly preserved through the weights throughout the decision process.

To further illustrate the advantages of the proposed two-stage paradigm, an example is presented below.

Example 4.6. Based on Example 4.4, this example further demonstrates how different weighting schemes and different aggregation operators affect the final ranking of alternatives when evaluation information is expressed as IPLTS. Consider three alternatives C_1, C_2, C_3 evaluated on attributes X_1, X_2 and X_3 , the matrix is shown as follows:

$$\begin{bmatrix} C_1 & \left[\begin{array}{ccc} \{\ell_3[0.7, 0.9]\} & \{\ell_3[0.6, 0.8]\} & \{\ell_2[0.5, 0.7]\} \\ \{\ell_4[0.8, 1]\} & \{\ell_3[0.7, 0.9]\} & \{\ell_1[0.4, 0.6]\} \\ \{\ell_2[0.6, 0.8]\} & \{\ell_3[0.5, 0.7]\} & \{\ell_3[0.6, 0.8]\} \end{array} \right] \\ C_2 & \\ C_3 & \end{bmatrix}.$$

Using the different weights obtained from Example 4.4 and applying IPLTSWA and IPLTSWG to aggregate the decision matrix, the results are shown in Table 3.

Table 3: Decision-making results based on different weights and aggregation operator

	AHP	BWM	The proposed method
IPLTSWA	$C_2 > C_1 > C_3$	$C_2 > C_1 > C_3$	$C_2 > C_1 > C_3$
IPLTSWG	$C_1 > C_2 > C_3$	$C_1 > C_2 > C_3$	$C_1 > C_2 > C_3$

As shown in Table 3, C_2 ranks first under IPLTSWA across all three weighting schemes, while C_1 ranks first under IPLTSWG. The reason is that C_1 achieves the highest score on X_2 , the most heavily weighted attribute, while the lower weight assigned to X_3 by DEMATEL reduces the penalty on C_1 's weakness. This confirms that DEMATEL's captured interdependencies and IPLTSWG's penalty mechanism jointly determine the final ranking.

4.4 Global fusion via interval GLDS-based decision inference

This subsection performs the global multi-source fusion via the proposed interval GLDS framework, which directly operates on the IPLTS outputs obtained from the group-wise steps. The uncertainty is retained through interval-valued dominance degrees, whose bounds serve as constraints in the subsequent optimization model. This ensures that the obtained weights and dominance degrees are derived under interval uncertainty rather than being compressed into crisp values. Suppose the aggregated information of each group forms the final decision matrix $Z = [z_{ug}]_{U \times (K+1)}$.

Step 1: The dominance degree function is proposed according to arithmetic algebra for interval values, which is defined as

$$df_g(D_u, D_v) = [df_g^-(D_u, D_v), df_g^+(D_u, D_v)] = [\max\{0, \phi_{ug}^- - \phi_{vg}^+\}, \max\{0, \phi_{vg}^- - \phi_{ug}^+\}]. \quad (29)$$

where $[\phi_{ug}^-, \phi_{ug}^+]$ and $[\phi_{vg}^-, \phi_{vg}^+]$ are the interval score values of the comprehensive information of decision-making entities z_{ug} and z_{vg} , respectively. In contrast to conventional dominance measures that reduce interval inputs to crisp values, the dominance function in Eq. (29) preserves the interval form throughout the evaluation process: its lower and upper bounds capture the best-case and worst-case dominance scenarios, respectively. This interval-valued output maintains the spectrum of uncertainty inherent in the original evaluations, rather than compressing it into a single-point estimate.

Step 2: The group weights and the dominance degree are determined. With the interval-valued dominance degrees established, an optimization model is required to determine the group weights and the precise dominance degree. To preserve the uncertainty captured by Eq. (29), the interval bounds can serve as constraints. This ensures the dominance degree feasible, propagates uncertainty, and prevents the bounds from over-constraining group weights, allowing the data range to drive weight determination. Meanwhile, although minimizing the weighted dominance deviation ensures decision consistency, it may induce severe weight polarization. To overcome this, the Shannon entropy of the weight distribution is integrated as a regularization term. This design balances minimizing evaluation deviations with maximizing of weight dispersion via $\lambda \in [0, 1]$. Based on this, an optimization model is constructed as follows:

$$\begin{aligned} \min \quad & (1 - \lambda) \sum_{U=1}^U \sum_{v=1}^U \sum_{g=1}^{K+1} w_g^G df_g(D_u, D_v) + \lambda \sum_{g=1}^{K+1} w_g^G \ln(w_g^G); \\ \text{s.t.} \quad & \sum_{g=1}^{K+1} w_g^G = 1; \\ & 0 \leq w_g^G \leq 1; \\ & df_g(D_u, D_v) \leq df_g^+(D_u, D_v); \\ & df_g(D_u, D_v) \geq df_g^-(D_u, D_v); \\ & 0 < \lambda \leq 1. \end{aligned} \quad (\text{Model-1})$$

The objective function integrates both the minimization of dominance degree deviations and the information entropy of the weight distribution. By incorporating information entropy, the model ensures that attributes with smaller evaluation deviations receive larger weights while effectively preventing severe weight polarization. Thus, a robust and consensus-driven weight distribution is achieved. The parameter λ governs this trade-off. The group weights w_g^G satisfy $0 \leq w_g^G \leq 1$ and $\sum_{g=1}^{K+1} w_g^G = 1$, ensuring theoretical feasibility and numerical stability. By solving this convex optimization model, the precise dominance degree $df_g(D_u, D_v)$ and group weight w_g^G are obtained.

Properties of Model 1: Model-1 is a convex optimization problem with a non-empty and compact feasible region, which guarantees several desirable properties: (1) convexity, ensuring that any locally optimal solution is globally optimal; (2) existence of at least one optimal solution; and (3) stability of the obtained group weights against small perturbations in the dominance degree inputs. Regarding uniqueness, due to the strict convexity introduced by the information entropy term (when $\lambda > 0$), the optimization problem ensures a unique optimal group weight vector. Detailed proofs are provided in Appendix A.

Step 3: The overall dominance flow alternative D_u over D_v is defined as

$$df(D_u, D_v) = \sum_{g=1}^{K+1} w_g^G df_g(D_u, D_v). \quad (30)$$

Step 4: The net GLDS $DS_1(D_u)$, $DS_2(D_u)$ can be derived by

$$DS_1(D_u) = \sum_{v=1}^U df^N(D_u, D_v), \quad (31)$$

$$DS_2(D_u) = \max_v df^N(D_u, D_v). \quad (32)$$

where $df^N(D_u, D_v) = df(D_u, D_v) / \sqrt{\sum_{u=1}^U \sum_{v=1}^U (df(D_u, D_v))^2}$ is the normalized overall dominance flow.

The corresponding rank set $A_1 = \{\gamma_1(D_1), \gamma_1(D_2), \dots, \gamma_1(D_U)\}$ is generated according to the descending order of $DS_1(D_U)$. The corresponding rank set $A_2 = \{\gamma_2(D_1), \gamma_2(D_2), \dots, \gamma_2(D_U)\}$ is obtained according to the ascending order of $DS_2(D_u)$.

Step 5: The global score for each alternative is derived by

$$GS_u = DS_1^N(D_u) \cdot \frac{m - \gamma_1(D_u) + 1}{m(m+1)/2} - DS_2^N(D_u) \cdot \frac{\gamma_2(D_u)}{m(m+1)/2}, \quad (33)$$

where $DS_l^N(D_u) = DS_l(D_u) / \sqrt{\sum_{u=1}^U (DS_l(D_u))^2}$, $l = \{1, 2\}$, and GS_u synthesizes the positive and negative performances of each alternative, ensuring that critical deficiencies are not overlooked while strengths are duly recognized.

According to the rank in descending order of GS_u , the most appropriate historical case is obtained, and the decision-maker can draw references from the alternative historical case to make decisions.

For the convenience of understanding, the flowchart of the proposed model is shown in Figure 2, and the procedure of the proposed CDFR integrating public wisdom is summarized as follows:

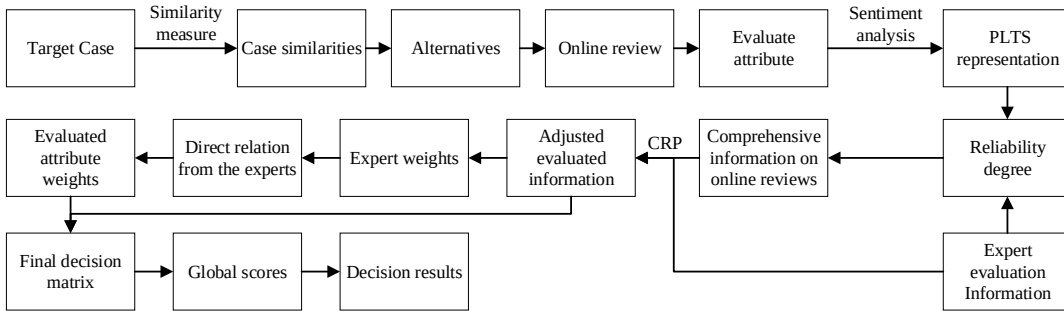


Figure 2: Flowchart of the proposed model

Phase 1: Based on Eqs. (3)-(11), the similarities between the target case and each historical case are computed, and the set of similar historical cases is subsequently constructed, from which the initial alternatives are derived.

Phase 2: Online reviews are collected and preprocessed, and represented using PLTS. Subsequently, their reliabilities are measured via Eq. (12), based on which the comprehensive online review information is obtained through Eq. (13). The adjusted evaluation information is then derived from Eqs. (14)-(15).

Phase 3: Expert weights are first derived from Eqs. (16)-(18). Subsequently, the direct influence relations among experts are obtained via Eq. (19), followed by the determination of attribute weights through Eqs. (20)-(26). Finally, the aggregated decision matrix is generated using Eqs. (27)-(28).

Phase 4: The global scores are computed using Model-1 and Eqs. (30)-(33), and the optimal alternative is subsequently identified by ranking the global scores in descending order. Accordingly, the final decision result is obtained.

4.5 Theoretical properties of the interval-based GLDS Method

This section formally proves the dual-uncertainty preservation property of the interval-based GLDS method proposed in Section 4.4.

Proposition 4.7. *Let $\varphi_{ig} = [\varphi_{ig}^-, \varphi_{ig}^+]$ be the interval score of the IPLTS evaluation. Let $\Phi : \varphi_{ig} \rightarrow [df^-, df^+]$ be the interval dominance mapping defined by Eq. (29), and let $\Psi : [df^-, df^+] \rightarrow (df_g(D_u, D_v), w)$ be the optimization mapping defined by Model-1. The composite mapping $\Psi \circ \Phi$ preserves both the interval structure and the probabilistic semantics of the IPLTS inputs.*

Proof. For two interval scores $[a^-, a^+]$ and $[b^-, b^+]$, Eq. (29) yields $df^- = \max\{0, a^- - b^+\}$, $df^+ = \max\{0, a^+ - b^-\}$. Three cases are distinguished:

- (1) If $a^- \geq b^+$, then $df^-, df^+ > 0$;
- (2) If $a^- < b^+$ and $a^+ > b^-$, then $df^- = 0$, $df^+ > 0$;
- (3) If $a^+ \leq b^-$, then $df^- = df^+ = 0$.

Thus, the interval form is preserved in all cases without scalar compression. Since interval scores derive from the interval probabilities, and Eq. (29) operates on these scores without modifying the probability, $[df^-, df^+]$ inherits the probabilistic semantics of the input. Since Model-1 strictly enforces the interval constraint $df_g(D_u, D_v) \in [df_g^-, df_g^+]$, the optimal solution inherently respects this bound, thereby transmitting the probabilistic semantics with the interval structure to the optimal solution. $\square$

Remark 4.8. *Extending the GLDS method to the IPLTS environment broadens its applicability in complex fuzzy decision contexts. The proposed GLDS extension is achieved via the coordinated design of the interval dominance mapping and the convex optimization model. This synergy effectively mitigates weight polarization while strictly preserving dual uncertainty through interval constraints, thereby ensuring strong robustness.*

5 Case study

To demonstrate the efficacy of the proposed fuzzy CDFR model, a case study aimed at providing a drug selection alternative for patients exhibiting mild symptoms was conducted. Subsequently, sensitivity and comparative analyses were undertaken to highlight the innovation of our proposed method.

5.1 Case background and data source

As the novel coronavirus continues to mutate and spread, outbreaks continue to occur in some areas despite increased global vaccination rates. However, the harm of the new coronavirus to the human body is also diminishing, and many cases are mild. As a result, many people can select drugs based on collected historical cases, online reviews, and their doctors' recommendations. For mild COVID-19, the main symptoms are fever (X_1), cough (X_2), shortness of breath (X_3), sputum production (X_4), and fatigue (X_5) [36]. Considering the uncertainty and the interval range of time, the attribute X_1 is represented as interval numbers, and the other attributes are presented as IPLTSs. The set of linguistic variables is $\{\text{Normal(N)}, \text{Little Serious(LS)}, \text{Serious(S)}, \text{Very Serious(VS)}, \text{Extremely Serious(ES)}\}$. Ten historical cases were collected via questionnaire survey and are listed in Table 4. Four main drugs are available for patients: Bunofen (M_1), Lianhuaqingwen capsule (M_2), Ritonavir(M_3), and Ribavirin(M_4) [21].

Table 4: Information of the historical cases and the target case

	X_1	X_2	X_3	X_4	X_5
C_1	[38.5, 39]	{S[0.7, 0.8], VS[0.1, 0.2]}	{LS[0.3, 0.4], S[0.5, 0.6]}	{S[0.6, 0.7], VS[0.2, 0.3]}	{N[0.6, 0.7], LS[0.25, 0.3]}
C_2	[38.2, 38.9]	{LS[0.3, 0.4], S[0.5, 0.6]}	{S[0.5, 0.6], VS[0.3, 0.4]}	{LS[0.5, 0.6], S[0.3, 0.4]}	{LS[0.3, 0.4], S[0.5, 0.6]}
C_3	[38.3, 40.1]	{N[0.1, 0.2], LS[0.7, 0.8]}	{VS[0.7, 0.8], ES[0.1, 0.2]}	{N[0.2, 0.3], LS[0.6, 0.7]}	{S[0.2, 0.3], VS[0.6, 0.7]}
C_4	[37.9, 38.8]	{VS[0.4, 0.6], ES[0.3, 0.4]}	{S[0.1, 0.2], VS[0.7, 0.8]}	{VS[0.45, 0.6], ES[0.35, 0.4]}	{VS[0.4, 0.6], ES[0.3, 0.4]}
C_5	[38.6, 41]	{LS[0.5, 0.6], S[0.3, 0.4]}	{S[0.5, 0.6], VS[0.3, 0.4]}	{LS[0.2, 0.3], S[0.6, 0.7]}	{N[0.6, 0.7], LS[0.2, 0.3]}
C_6	[38.4, 40]	{S[0.6, 0.7], VS[0.2, 0.3]}	{VS[0.5, 0.6], ES[0.3, 0.4]}	{LS[0.4, 0.5], VS[0.4, 0.5]}	{LS[0.3, 0.4], S[0.5, 0.6]}
C_7	[38.7, 40.3]	{N[0.2, 0.3], LS[0.6, 0.7]}	{VS[0.4, 0.6], ES[0.2, 0.4]}	{VS[0.8, 0.9], ES[0.05, 0.1]}	{S[0.2, 0.3], VS[0.6, 0.7]}
C_8	[38.3, 41]	{VS[0.75, 0.8], ES[0.1, 0.2]}	{S[0.2, 0.4], VS[0.5, 0.6]}	{LS[0.2, 0.3], VS[0.6, 0.7]}	{VS[0.5, 0.6], ES[0.3, 0.4]}
C_9	[38.6, 39.7]	{VS[0.8, 0.9], ES[0.05, 0.1]}	{LS[0.2, 0.3], S[0.6, 0.7]}	{LS[0.45, 0.6], VS[0.3, 0.4]}	{N[0.4, 0.5], LS[0.4, 0.5]}
C_{10}	[38.2, 39.5]	{LS[0.25, 0.4], S[0.5, 0.6]}	{VS[0.6, 0.7], ES[0.2, 0.3]}	{VS[0.6, 0.7], ES[0.2, 0.3]}	{LS[0.6, 0.7], S[0.2, 0.3]}
C_0	[38.6, 39.8]	{VS[0.7, 0.85], ES[0.1, 0.15]}	{S[0.3, 0.4], S[0.5, 0.6]}	{LS[0.55, 0.65], VS[0.3, 0.35]}	{S[0.8, 0.9], VS[0.05, 0.1]}

5.2 CDFR model integrating public wisdom

This section outlines the steps involved in the proposed model for choosing an appropriate drug. The calculation procedure consists of four phases. Phase 1 constructs a similar historical case set by computing attribute similarities and case similarities. Phase 2 processes public opinions and expert evaluations to ensure information reliability and consistency. Phase 3 generates comprehensive evaluated information for each decision-making group. Phase 4 derives the collective evaluation information, determines the final ranking, and identifies the optimal drug as the recommended decision outcome.

Phase 1: Heterogeneous information-based case retrieval

First, the attribute similarities S_{0ij} were calculated using Eqs. (3)–(5). Then, the attribute weights were determined according to the extended IRARA methods in Eqs. (6)–(10). Next, the case similarity S_i was measured using Eq. (11). At this intermediate stage, the computed case similarities are $\{0.6913, 0.5492, 0.4281, 0.5999, 0.5152, 0.6489, 0.4512, 0.6661, 0.7943, 0.5375\}$. With the case similarity threshold set as $\zeta = 0.6$, the similar historical case set was obtained as $D = \{C_1, C_6, C_8, C_9\}$, corresponding drug alternatives were indicated as $\{M_1, M_2, M_3, M_4\}$.

Phase 2: Multi-source fuzzy information pre-processing

Step 2.1: Acquisition of reliable fuzzy public opinions.

(1) Determine the evaluation attributes. First, collect and preprocess the public opinion data. Public opinion data were extracted from the JD.com e-commerce platform, yielding 1071, 1601, 292, and 744 raw reviews for Bunofen (M_1), Lianhuaqingwen capsule (M_2), Ritonavir (M_3), and Ribavirin (M_4), respectively. Then, the data preprocessing is carried out, including eliminating duplicate and irrelevant textual reviews, segmenting words, and removing stop words, and so on. After preprocessing, the number of effective data for Bunofen (M_1), Lianhuaqingwen capsule (M_2), Ritonavir (M_3), and Ribavirin (M_4) were 405, 294, 102, and 159, respectively. Next, guided by a prior study [21], we defined six topics along with their extended descriptions. Furthermore, the BERT model in conjunction with cosine similarity analysis was employed to identify the most relevant evaluation attributes. Finally, the evaluation attributes are determined as antiviral activity (T_1), cooling (T_2), cough relief (T_3), and the ease of breathing (T_4).

(2) Transform into PLTS. Sentiment analysis is conducted to construct the decision-making matrix. The number of reviews for each drug across each evaluated attribute was determined using a classification method. Additionally, the SnowNLP sentiment analysis tool was employed to categorize these reviews into linguistic terms, defined as ℓ_0 = very bad, ℓ_1 = bad, ℓ_2 = fair, ℓ_3 = good, and ℓ_4 = very good. Subsequently, the results from the sentiment analysis were converted into a PLTS in Section 3.2.1. At this intermediate stage, the resulting evaluation matrix is presented in Table 5.

Table 5 shows that M_1 and M_2 receive predominantly high sentiment ratings, with ℓ_4 exceeding 0.8 across all attributes. It indicates that these two drugs are perceived more favorably by patients than M_3 and M_4 .

(3) Determine the evaluation information by experts. According to the symptoms and alternatives of similar historical cases, three experts provided their evaluations; the evaluation information is shown in Tables A2, A3, and A4.

Table 5: Evaluation information from online reviews

	T_1	T_2	T_3	T_4
M_1	$\{\ell_0(0.0619), \ell_1(0.0223), \ell_2(0.0421), \ell_3(0.0396), \ell_4(0.8342)\}$	$\{\ell_0(0.0588), \ell_1(0.0176), \ell_2(0.0588), \ell_3(0.0647), \ell_4(0.8000)\}$	$\{\ell_0(0.0638), \ell_1(0.0255), \ell_2(0.0298), \ell_3(0.0213), \ell_4(0.8596)\}$	$\{\ell_0(0.0594), \ell_1(0.0223), \ell_2(0.0421), \ell_3(0.0396), \ell_4(0.8366)\}$
M_2	$\{\ell_0(0.0306), \ell_1(0.0136), \ell_2(0.0204), \ell_3(0.0952), \ell_4(0.8401)\}$	$\{\ell_0(0.0423), \ell_1(0.0212), \ell_2(0.0212), \ell_3(0.1005), \ell_4(0.8148)\}$	$\{\ell_0(0.0095), \ell_2(0.0190), \ell_3(0.0857), \ell_4(0.8857)\}$	$\{\ell_0(0.0308), \ell_1(0.0137), \ell_2(0.0205), \ell_3(0.0959), \ell_4(0.8390)\}$
M_3	$\{\ell_0(0.1068), \ell_1(0.0388), \ell_2(0.0777), \ell_3(0.2427), \ell_4(0.5340)\}$	$\{\ell_0(0.1000), \ell_1(0.0600), \ell_2(0.1000), \ell_3(0.3000), \ell_4(0.4400)\}$	$\{\ell_0(0.1154), \ell_1(0.0192), \ell_2(0.0577), \ell_3(0.1731), \ell_4(0.6346)\}$	$\{\ell_0(0.1078), \ell_1(0.0392), \ell_2(0.0784), \ell_3(0.2353), \ell_4(0.5392)\}$
M_4	$\{\ell_0(0.1013), \ell_1(0.0633), \ell_2(0.0886), \ell_3(0.1899), \ell_4(0.5570)\}$	$\{\ell_0(0.1038), \ell_1(0.0660), \ell_2(0.1038), \ell_3(0.1887), \ell_4(0.5377)\}$	$\{\ell_0(0.0926), \ell_1(0.0556), \ell_2(0.0556), \ell_3(0.1852), \ell_4(0.6111)\}$	$\{\ell_0(0.1013), \ell_1(0.0633), \ell_2(0.0886), \ell_3(0.1899), \ell_4(0.5570)\}$

(4) **Obtain reliable online public opinion.** The reliability of the four drugs was calculated for each evaluated attribute by Eq. (12). The resulting reliability values are shown in Table 6. Then, online reviews that integrate reliability were obtained by Eq. (13).

Table 6: Reliability of the online reviews

	T_1	T_2	T_3	T_4
M_1	0.4271	0.4582	0.4160	0.3936
M_2	0.3815	0.4254	0.4463	0.4125
M_3	0.5142	0.4840	0.3847	0.4028
M_4	0.3893	0.5021	0.5929	0.5187

Table 6 shows that reliability values vary considerably across different drugs and attributes, indicating that the reliability of information sources differs.

Step 2.2 Consensus-driven evaluation information adjustment. The CI of every participant was computed by Eq. (14). At this intermediate stage, the initial CI values are: $CI(E^1) = 0.8853$, $CI(E^2) = 0.7872$, $CI(E^3) = 0.8191$, and $CI(E^4) = 0.8566$. Because the CI threshold was set as $\rho = 0.8$, $CI(E^2) < \rho$, the evaluated information of expert E^2 was adjusted according to Eq. (15) with parameter $\theta = 0.5$. The adjusted evaluated information of expert E^2 is presented in Table 7. Then, the CI of every participant was recalculated as follows: $CI(E^1) = 0.8706$, $CI(E^2) = 0.8923$, $CI(E^3) = 0.8846$, and $CI(E^4) = 0.8624$. Because $CI(E^k) > \rho$, the participants reached a consensus. It means convergence is reached in one iteration.

Table 7: Adjusted evaluated information of expert E^2

	T_1	T_2	T_3	T_4
M_1	$\{\ell_1[0.05, 0.1], \ell_2[0.05, 0.1], \ell_3[0.1, 0.2], \ell_4[0.7, 0.8]\}$	$\{\ell_2[0.15, 0.25], \ell_3[0.1, 0.2], \ell_4[0.6, 0.7]\}$	$\{\ell_1[0.05, 0.1], \ell_2[0.05, 0.1], \ell_3[0.3, 0.4], \ell_4[0.5, 0.65]\}$	$\{\ell_1[0.025, 0.05], \ell_2[0.025, 0.05], \ell_3[0.1, 0.2], \ell_4[0.775, 0.9]\}$
M_2	$\{\ell_2[0.05, 0.1], \ell_3[0.15, 0.25], \ell_4[0.725, 0.825]\}$	$\{\ell_1[0.05, 0.1], \ell_2[0.075, 0.15], \ell_3[0.075, 0.15], \ell_4[0.75, 0.775]\}$	$\{\ell_1[0.025, 0.05], \ell_2[0.05, 0.1], \ell_3[0.075, 0.15], \ell_4[0.775, 0.865]\}$	$\{\ell_2[0.075, 0.15], \ell_3[0.1, 0.2], \ell_4[0.8, 0.875]\}$
M_3	$\{\ell_1[0.15, 0.25], \ell_2[0.2, 0.3], \ell_3[0.1, 0.25], \ell_4[0.45, 0.6]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.2, 0.25], \ell_3[0.2, 0.3], \ell_4[0.4, 0.525]\}$	$\{\ell_2[0.175, 0.25], \ell_3[0.275, 0.375], \ell_4[0.5, 0.65]\}$	$\{\ell_1[0.05, 0.1], \ell_2[0.2, 0.3], \ell_3[0.15, 0.3], \ell_4[0.5, 0.6]\}$
M_4	$\{\ell_0[0.05, 0.1], \ell_1[0.1, 0.2], \ell_2[0.15, 0.25], \ell_3[0.1, 0.2], \ell_4[0.5, 0.6]\}$	$\{\ell_0[0.05, 0.1], \ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.15, 0.25], \ell_4[0.525, 0.6]\}$	$\{\ell_2[0.15, 0.25], \ell_3[0.15, 0.25], \ell_4[0.6, 0.7]\}$	$\{\ell_1[0.05, 0.1], \ell_2[0.2, 0.3], \ell_3[0.2, 0.25], \ell_4[0.475, 0.65]\}$

Table 7 presents the adjusted evaluation information of expert E^2 , where higher linguistic terms receive increased interval probabilities, indicating that the evaluation is effectively guided toward the group consensus.

Phase 3: Group-wise fuzzy evaluation information fusion. Three decision makers self-evaluated their respective importance, with the result being $\{S_2[0.2, 0.3], S_3[0.2, 0.3], S_4[0.5, 0.6]\}$, $\{S_2[0.2, 0.3], S_3[0.6, 0.7], S_4[0.1, 0.2]\}$, $\{S_3[0.2, 0.3], S_4[0.7, 0.8]\}$. Then, according to Eqs. (16)–(18), the decision-maker weights are determined as $\{0.3410,$

0.3040, 0.3550}. Next, the experts' direct relations matrix is provided in Tables A5, A6, and A7. Furthermore, applying Eqs. (19)–(26), the evaluated attribute weights are determined as $\{0.2696, 0.2647, 0.2669, 0.1988\}$. Finally, the comprehensive assessment information is calculated using Eqs. (27)–(28) and converted into interval numbers through the interval scoring function. At this intermediate stage, the resulting comprehensive evaluation matrix is presented in Table 8.

Table 8: Comprehensive evaluated information

	T_1	T_2	T_3	T_4
D ₁	[6.8064, 7.6650]	[7.6014, 8.9409]	[6.7033, 7.6146]	[6.7177, 7.4370]
D ₂	[7.1236, 7.9864]	[7.6348, 8.2923]	[6.6794, 7.5848]	[6.7877, 7.5811]
D ₃	[7.4616, 8.2465]	[7.5803, 8.3178]	[6.5265, 7.5944]	[6.8327, 7.5021]
D ₄	6.8663	7.5870	6.9134	6.7040

Table 8 shows that D₁, D₂, and D₃ exhibit relatively similar evaluations across all attributes, while D₄ scores consistently lower than the other three on every attribute, indicating a clear distinction between D₄ and D₁–D₃.

Phase 4: Alternative ranking inference via interval-valued GLDS. Based on the comprehensive evaluation information obtained in Table 5, the degrees of interval dominance were calculated using Eq. (29). Subsequently, an optimal model was developed to ascertain the group weights and degrees of dominance using Model-1, and the group weights were determined as $\{0.3395, 0.4000, 0.2107, 0.0499\}$. Then, the net GLDSs, $DS_1(D_n)$ and $DS_2(D_n)$ were derived using Eqs. (30)–(32). Finally, the total scores for each alternative were obtained using Eq. (3). The final results are summarized in Table 9.

Table 9: Fusion results of every alternative

	$DS_1(D_u)$	$DS_2(D_u)$	GS_u
M ₁	0.9829	0.6709	0.2590
M ₂	0.0618	0.0506	-0.0028
M ₃	0.0000	0.0000	0.0000
M ₄	0.8934	0.6835	0.1997

According to the global score GS_u in Table 9, the four drugs were ranked as $M_1 > M_4 > M_3 > M_2$. The results indicate that the Bunofen capsule is the most suitable therapeutic choice for the patient based on the comprehensive evaluation of historical cases, online reviews, and expert assessments. Thus, M₁ (Bunofen capsule) is recommended as the best therapeutic option for the patient.

6 Comparative analysis

The superiority of the proposed model was assessed from three viewpoints: (1) utilization of a combination of online reviews and expert evaluations; (2) effect of the degree of reliability for online reviews in fuzzy environment, and (3) superiority of the novel GLDS method.

6.1 Employing the combination of online reviews and expert evaluations

Previous research has mainly concentrated on utilizing expert evaluation information to choose the most appropriate historical case [33, 38, 34]. However, with the progression of information technology, a wealth of valuable data can be obtained from the Internet and has been seamlessly integrated into multi-criteria decision-making processes [11, 29]. This information offers valuable insights into various alternatives across different criteria or other pertinent aspects, which are the users' actual experiences and can help improve decision effectiveness. In contrast, this study focused on a hybrid evaluation, combining both expert evaluations and public reviews. To highlight the advantages of using the combined evaluation approach, we undertook a comparative analysis by employing the proposed decision analysis independently to expert evaluations and online reviews.

(1) Utilization of expert evaluations

The determination of attribute weights and aggregation of expert information are consistent with the original text. When generating collective evaluation information, online evaluations are not integrated, and only the evaluation information of multiple experts is considered. First, the expert weights and degree of dominance were determined by applying the optimization model in Model-1. Then, by applying the GLDS method, the global score of each alternative was obtained: $GS_1 = 0.0896$, $GS_2 = -0.0260$, $GS_3 = 0$, and $GS_4 = 0.0067$. From the global scores, we ranked the alternatives as $M_1 > M_4 > M_3 > M_2$. Hence, we selected an alternative to the M_1 case to support decision-making.

(2) Utilization of online reviews

The determination of attribute weights is consistent with the original proposed method. Then, the public evaluation information is obtained according to Eq. (28). Furthermore, the global scores were then obtained by the GLDS as $GS_1 = 0.0586$, $GS_2 = 0.1260$, $GS_3 = 0$, and $GS_4 = 0$, and the rank of the alternatives was $M_2 > M_1 > M_3 = M_4$.

In summary, the outcomes derived from utilizing expert evaluations in the decision-making process were $M_1 > M_4 > M_3 > M_2$; the decisions arrived at through the analysis of online reviews were $M_2 > M_1 > M_3 = M_4$.

The results show that decisions vary significantly depending on the information source. Online reviews alone selected M_2 , whereas both expert judgments and the proposed method chose M_1 . This divergence arises from the limitations of single-source data: expert opinions lack public perspective, while online reviews, though reflecting user experience, are subjective and non-professional. In contrast, although the proposed method aligns with experts on M_1 , it achieves a much higher global score (0.2590) compared to the standalone expert evaluation (0.0896). Thus, the proposed multi-source fusion framework provides a more comprehensive and reliable decision-making basis.

6.2 Effect of the degree of reliability for online reviews

To demonstrate the effect of the degree of reliability of online reviews, the scores of online review information were analyzed under different degrees of reliability. The weights assigned to attributes and the methods used for information fusion were consistent with those employed in the proposed method. Suppose that the reliability degree of every attribute is identical and is set from 0.1 to 0.9 in increments of 0.2. The scores of the online reviews for the alternatives are shown in Figure 3.

Figure 2 clearly demonstrates that, depending on varying degrees of reliability, notable discrepancies emerge in the scores and ranking outcomes of the alternatives. When the reliability level was set at 0.1, the first-ranked alternative was M_3 , and when the reliability degree was increased to 0.3, the first-ranked alternative changed to M_2 . Furthermore, with the increase in reliability degree, the score values of alternatives increased, except for alternative M_3 . The reason for this difference is that the reliability degree was integrated into the evaluation. With the increase in reliability degree, the online review was closer to and more consistent with the expert evaluations. Consequently, the evaluation information of online reviews is more credible. However, some of the existing studies [8, 12, 17, 39] introduced evaluation of online reviews into the decision-making problem without considering the degree of reliability, which may amplify the impact of extreme opinions and unprofessional comments. In contrast, the proposed decision framework considering the degree of reliability, can avoid erroneous comments and ensure decision quality.

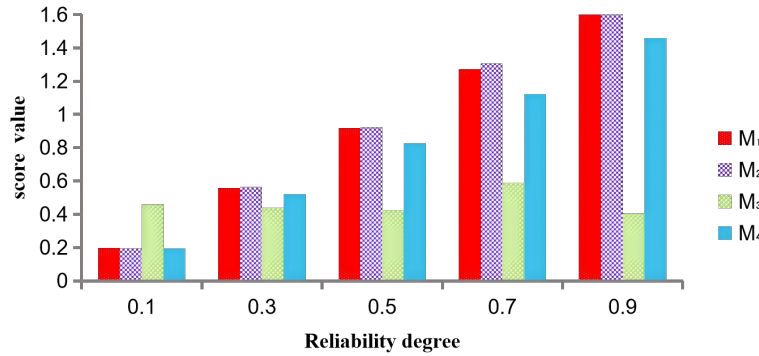


Figure 3: Online review information score with different reliability degree

6.3 Superiority of the novel GLDS method

To demonstrate the superiority of the novel GLDS method, we compared it with L-GLDS[16], Z-GLDS[36], TODIM, VIKOR and TOPSIS. Group weights were set as the average weights and the weights determined in this study. The results are presented in Table 10 and Figure 4.

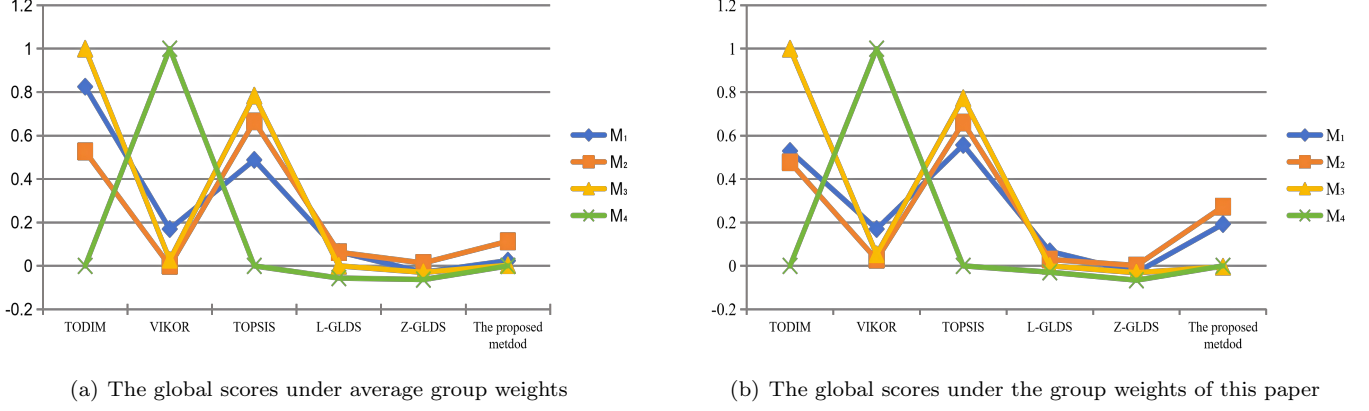


Figure 4: Global scores of different methods

Table 10: Results of different method comparison

Weights	Methods	M ₁	M ₂	M ₃	M ₄
The average group weights	L-GLDS	0.0651(1)	0.0626(2)	0.0001(3)	-0.0561(4)
	Z-GLDS	-0.0296(2)	0.0132(1)	-0.0299(3)	-0.0621(4)
	TODIM	0.8250(2)	0.5270(3)	1.0000(1)	0.0000(4)
	VIKOR	0.1696(2)	0.0005(4)	0.0278(3)	1.0000(1)
	TOPSIS	0.4880(3)	0.6650(2)	0.7840(1)	0.0000(4)
The group weights of this paper	The proposed method	0.0241(2)	0.1131(1)	0.0029(3)	0.0000(4)
	L-GLDS	0.0696(1)	0.0373(2)	-0.0130(3)	-0.0311(4)
	Z-GLDS	-0.0359(3)	0.0004(1)	-0.0347(2)	-0.0659(4)
	TODIM	0.5530(2)	1.0000(1)	0.1960(3)	0.0000(4)
	VIKOR	0.6557(3)	0.0000(4)	1.0000(1)	0.9600(2)
	TOPSIS	0.3840(2)	1.0000(1)	0.0500(4)	0.0530(3)
	The proposed method	0.2590(1)	-0.0028(4)	0.0000(3)	0.1997(2)

Table 10 and Figure 4 reveal markedly different rankings among the six methods under identical weights. Among GLDS approaches, the optimal choices of L-GLDS and Z-GLDS remain consistently locked across different weights. In contrast, the proposed method selects M_2 under average weights but logically shifts to M_1 when applying our optimized weights. This divergence arises because L-GLDS and Z-GLDS directly convert dominance degrees into crisp values, while the proposed method treats them as optimization variables under interval constraints, strictly preserving the dual uncertainty of the evaluation boundaries. More importantly, since the given weights in our model are inherently optimized based on the dominance degrees, they exhibit stronger logical cohesion with the interval-valued evaluation process. Consequently, the proposed model enables truly data-driven reasoning, adapting its optimal selection based on the underlying information.

As for the other classical methods, the proposed method yields optimal choices that consistently diverge from TODIM, TOPSIS, and VIKOR under both the average weights and the proposed weights. This divergence stems from their fundamentally distinct decision logics: TODIM is based on loss aversion under prospect theory, TOPSIS measures the geometric distance to the ideal solution, and VIKOR seeks a compromise between group utility and individual regret. In contrast, the proposed approach not only ensures robust and impartial rankings, but also strictly preserves the uncertainty inherent in the evaluation information. Therefore, the proposed method guarantees fairness and information completeness in uncertain decision-making scenarios.

6.4 Sensitivity analysis

In the collective evaluation information generation process, the group weights are vital for the results. Therefore, a sensitivity analysis of group weights would improve confidence in the robustness of the results. To examine weight sensitivity, we tested five group weight vectors: (0.3, 0.3, 0.3, 0.1), (0.25, 0.25, 0.25, 0.25), (0.5, 0.2, 0.2, 0.1), (0.1, 0.2, 0.2, 0.5), and (0.1, 0.4, 0.4, 0.1). The resulting global scores are shown in Table 11.

Group weights	GS_1	GS_2	GS_3	GS_4
0.3,0.3,0.3,0.1	0.1923	0.2727	-0.0041	0.0000
0.25,0.25,0.25,0.25	0.0241	0.1131	0.0029	0.0000
0.5,0.2,0.2,0.1	0.1313	0.3836	-0.0045	0.0000
0.1,0.2,0.2,0.5	0.0638	0.5098	-0.009	0.0000
0.1,0.4,0.4,0.1	0.2819	0.1502	-0.0036	0.0000

As can be seen from Table 11, GS_4 consistently scores zero and ranks last across all weight sets, while GS_3 always obtains negative scores and ranks third. GS_1 and GS_2 occupy the top two positions: GS_2 ranks first under weight sets (0.3, 0.3, 0.3, 0.1), (0.5, 0.2, 0.2, 0.1), (0.1, 0.2, 0.2, 0.5), and equal weights (0.25, 0.25, 0.25, 0.25); GS_1 takes first only when weights are (0.1, 0.4, 0.4, 0.1). Thus, the best alternative varies only between GS_1 and GS_2 , never falling below second place. This confirms that the proposed method is insensitive to weight changes and yields stable rankings across different weight configurations.

Furthermore, to verify the rationality of the selected threshold $\eta = 0.6$, we conducted a sensitivity analysis by varying the threshold from 0.55 to 0.75 at intervals of 0.05. The results are shown in Table 12.

Threshold	0.55	0.60	0.65	0.70	0.75
Number of similar cases	7	4	3	2	1

The results in Table 12 show that when the threshold increases from 0.60 to 0.65, the number of similar cases decreases from 4 to 3; when it decreases to 0.55, the number increases to 7. Both changes are smooth and moderate. However, when the threshold exceeds 0.70, the number of similar cases drops sharply to 2 or fewer, indicating insufficient information. These observations confirm that 0.6 lies in a stable region, and our choice is reasonable and robust.

Finally, to evaluate the sensitivity of the parameter λ in Model-1, five representative values {0.1, 0.3, 0.5, 0.7, 0.9} are tested. By solving Model-1 for each setting, the corresponding group weights and GLDS scores are obtained, as presented in Table 13.

λ	w	GS_1	GS_2	GS_3	GS_4
0.1	{0.1860,0.8115,0.0025,0.0000}	0.4435(1)	0.0000(3)	0.0000(3)	0.0280(2)
0.3	{0.3565,0.5223,0.1171,0.0041}	0.3104(1)	-0.0004(4)	0.0000(3)	0.1418(2)
0.5	{0.3395,0.4000,0.2107,0.0499}	0.2590(1)	-0.0028(4)	0.0000(3)	0.1997(2)
0.7	{0.3005,0.3224,0.2450,0.1321}	0.4017(1)	-0.0054(4)	0.0000(3)	0.1130(2)
0.9	{0.2649,0.2698,0.2512,0.2141}	0.4477(1)	-0.0069(4)	0.0000(3)	0.0983(2)

From Table 13, the weights evolve from severe polarization at $\lambda = 0.1$ to near-uniformity at $\lambda = 0.9$, confirming the effect of entropy regularization. Furthermore, the final ranking remains strictly $GS_1 > GS_4 > GS_3 > GS_2$, proving strong robustness.

6.5 Discussion

To further verify the novelty of our model, we compare it with several representative MCDM studies that are closely related to our methodology. Demir [5] and Rouhani-Tazangi et al. [22] employ grey numbers and fuzzy decision maps for healthcare MCDM problems, yet their approaches are expert-dependent and neglect public opinion, whereas our model integrates online reviews with expert inputs. Alodhaibi et al. [1] and Shahid and Tahir [24] develop fuzzy aggregation frameworks but do not consider information source credibility, which our model explicitly addresses through

reviewer reliability measures incorporated during information aggregation. Basuri et al. [2] combine entropy-VIKOR with generalized fuzzy numbers, but rely on pre-defined memberships and lack interval-valued support, while our interval-based GLDS accommodates such inputs.

From the preceding comparative analysis, the proposed fuzzy reasoning framework exhibits the following commendable merits:

(1) Traditional approaches often rely on a single information source, which may introduce bias. By contrast, the proposed framework reasons over multi-source fuzzy information to capture public sentiment and professional judgment synergistically. This multi-source information fusion yields a more balanced and dependable assessment of the alternatives.

(2) Online reviews vary greatly in credibility, and unverified comments can distort outcomes. By incorporating reliability measures for online reviewers, our approach filters out erroneous feedback, thereby reinforcing the validity of the final decision results.

(3) The classical GLDS prevents poor performance on any single attribute from being compensated by others, but often operates under crisp data. Our interval-theory-based GLDS extends this framework to handle uncertainty, ensuring both fairness across attributes and completeness of the information used.

(4) Overall, the proposed method harnesses both public wisdom and professional expertise through multi-source information integration, makes full use of available case data, and remains intuitive and easy to implement in practice.

(5) The proposed framework consists of several interconnected components that together form a complete decision-making workflow: retrieving similar historical cases to construct a case base; processing online public reviews with credibility filtering; determining attribute weights via IPLTS-DEMATEL; evaluating alternatives under uncertainty via the interval-based GLDS method; and synthesizing final performance scores via the IPLTSWG operator. Since these components are domain-independent, the framework is applicable not only to emergency response contexts such as emergency supplier selection and plan generation but also to broader multi-attribute decision-making problems, including site selection for energy storage power stations.

7 Conclusion

In this study, a CDFR framework integrating multi-source fuzzy information is proposed. A case application of a public health emergency demonstrates the feasibility and applicability. Additionally, the superiority of the proposed model is verified through detailed comparative analysis with other methods. The results indicate that the proposed framework effectively generates reliable emergency alternatives by systematically incorporating public wisdom and expert evaluations while maintaining decision reliability and reasoning traceability. The main advantages of the proposed model are summarized as follows:

(1) To better handle the uncertainty and fuzziness inherent in multi-source framework, a two-stage information preprocessing mechanism is developed. It jointly addresses the reliability of public opinions and the consistency of evaluations, thereby ensuring the validity of the evaluation information for the subsequent fuzzy reasoning process.

(2) To make the attribute weights more comprehensive and reliable, an extended IPLTS-DEMATEL method is proposed, which not only handles the ambiguity and imprecision of group evaluations, but also visualizes the causal relationships among attributes, providing a solid foundation for the subsequent aggregation and ranking stages.

(3) To ensure the results are more robust and realistic, an interval-based GLDS method is developed. By integrating the interval dominance degree function and embedding an optimization model for parameter determination, this method effectively preserves the interval and probabilistic uncertainty of the original information throughout the reasoning chain.

Despite the above contributions, this study still has certain limitations that inform future research directions. First, the consensus mechanism assumes uniform preference adjustment willingness across groups, which may be unrealistic when stakeholder interests diverge; more flexible mechanisms accommodating heterogeneous behaviors will be developed. Second, the current sentiment extraction approach is relatively basic; advanced NLP techniques will be explored to better capture and represent public opinions from unstructured online data.

Appendix A: Proofs of Properties of Model-1

Property 1 Existence. The feasible region of Model-1 is nonempty and bounded since all constraints are linear. The objective function is continuous; thus, by the Extreme Value Theorem, at least one optimal solution exists.

Property 2 Convexity and global optimality. All constraints are linear, making the feasible region convex. Since the entropy term is strictly convex, Model-1 is a strictly convex optimization problem, ensuring that any local optimum

is globally optimal.

Property 3 Uniqueness and stability. The strict convexity ensures a unique optimal group weight vector w_g^G . Meanwhile, the interval constraints guarantee the uniqueness of the optimal dominance degree df_g . According to convex optimization sensitivity analysis, small perturbations in the input bounds cause continuous changes in this unique optimal solution, demonstrating the model's strong robustness.

Appendix B

Table A1: Notation in our study

Acronyms		Symbols	
CDFR	Case-driven fuzzy reasoning	d_{uq}^k	The distance between the public and the k th expert
IPLTS	Interval probabilistic linguistic term set	RL_{uq}	The reliability of D_u regarding T_q
DEMATEL	Decision-making trial and evaluation laboratory	$\bar{e}_{uq}$	The comprehensive information on online reviews
GLDS	Gained and lost dominance score	E^k	The k th expert
CRP	Consistency reaching processing	$CI(E^k)$	The CI of E^k
ITARA	Indifference threshold-based attribute ratio analysis	$d(r_{uq}^k, r_{uq}^g)$	The evaluated attribute distance between expert E^k and E^g
IPLTSWG	Interval probabilistic linguistic term set weighted geometry	ρ	The acceptable CI threshold
PIS	The positive ideal solution	$r_{uq}^{k\ell}$	The ℓ th-round evaluated information of E^k
NIS	The negative ideal solution	∂	The consensus control parameter
CI	Consistency index	γ^k	The self-evaluated importance of E^k
Symbols		w_k^o	The objective expert weights
C_i	The i th historical case	w_k^s	The subjective expert weights
C_0	The target case	w_k	The expert weights
X_j	The j th attribute	a_{qt}^k	The direct relations among T_q
a_{ij}	The value of X_j regarding C_i	b_{qt}	The group direct influence
w_j^p	The importance of X_j	g_{qt}	The normal distribution value of direct relations
ρ_{ij}	The considerable deviation	$\bar{g}_{qt}$	The normalized g_{qt}
a_j^-	The NIS of attribute	T	The total relation matrix
$d(a_{0j}, a_{ij})$	The attribute distance	M	The sums of the rows of T
S_{0ij}	The attribute similarity	D	The sums of the columns of T
a_j^+	The PIS of attribute	σ_q	The importance degree of attribute T_q
$\bar{C}D_{ij}$	The closeness of each attribute	w_q^R	The evaluated attribute weights
λ_j	The indifference threshold	ET_u^k	The comprehensive information of E^k
S_i	The case similarity	PI_u	The comprehensive information on online reviews
ξ	The thresholds of similar historical case	$df_g(D_u, D_v)$	The dominance degree function
D_u	The u th similar historical case	w_g^G	The group weights
T_q	The q th evaluation attribute	$df(D_u, D_v)$	The overall dominance-flow
e_{uq}	The evaluation value of online review	$DS_1(D_u)$	The net gain dominance score
r_{uq}^k	The evaluation value of the k th expert	$DS_2(D_u)$	The net lost dominance score
		GS_u	The global score for each alternative

Table A2: Evaluated information of expert 1

	T_1	T_2	T_3	T_4
M_1	$\{\ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.6, 0.7]\}$	$\{\ell_2[0.2, 0.3], \ell_3[0.1, 0.2], \ell_4[0.5, 0.6]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.3, 0.4], \ell_4[0.4, 0.5]\}$	$\{\ell_1[0.05, 0.1], \ell_2[0.05, 0.1], \ell_3[0.1, 0.2], \ell_4[0.7, 0.9]\}$
M_2	$\{\ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.7, 0.8]\}$	$\{\ell_2[0.05, 0.1], \ell_3[0.05, 0.1], \ell_4[0.8, 0.85]\}$	$\{\ell_1[0.05, 0.1], \ell_2[0.05, 0.1], \ell_3[0.05, 0.1], \ell_4[0.75, 0.83]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.8, 0.9]\}$
M_3	$\{\ell_1[0.2, 0.3], \ell_2[0.2, 0.3], \ell_3[0.1, 0.3], \ell_4[0.4, 0.6]\}$	$\{\ell_1[0.1, 0.2], \ell_2(0.2), \ell_3[0.2, 0.3], \ell_4[0.4, 0.5]\}$	$\{\ell_2[0.15, 0.2], \ell_3[0.25, 0.35], \ell_4[0.6, 0.7]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.2, 0.3], \ell_3[0.1, 0.3], \ell_4[0.5, 0.6]\}$
M_4	$\{\ell_0[0.1, 0.2], \ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.5, 0.6]\}$	$\{\ell_0[0.1, 0.2], \ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.5, 0.55]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.2, 0.3], \ell_4[0.6, 0.7]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.2, 0.3], \ell_3(0.2), \ell_4[0.45, 0.6]\}$

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Table A3: Evaluated information of expert 2

	T_1	T_2	T_3	T_4
M_1	$\{\ell_3[0.1, 0.2], \ell_4[0.8, 0.9]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.7, 0.8]\}$	$\{\ell_3[0.3, 0.4], \ell_4[0.6, 0.8]\}$	$\{\ell_3[0.1, 0.2], \ell_4[0.85, 0.9]\}$
M_2	$\{\ell_3[0.2, 0.3], \ell_4[0.75, 0.85]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.7]\}$	$\{\ell_2[0.05, 0.1], \ell_3[0.1, 0.2], \ell_4[0.8, 0.9]\}$	$\{\ell_2[0.05, 0.1], \ell_3[0.1, 0.2], \ell_4[0.8, 0.85]\}$
M_3	$\{\ell_1[0.1, 0.2], \ell_2[0.2, 0.3], \ell_3[0.1, 0.2], \ell_4[0.5, 0.6]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.2, 0.3], \ell_4[0.4, 0.55]\}$	$\{\ell_2[0.2, 0.3], \ell_3[0.3, 0.4], \ell_4[0.4, 0.6]\}$	$\{\ell_2[0.2, 0.3], \ell_3[0.2, 0.3], \ell_4[0.5, 0.6]\}$
M_4	$\{\ell_1[0.1, 0.2], \ell_2[0.2, 0.3], \ell_3[0.1, 0.2], \ell_4[0.5, 0.6]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.2, 0.3], \ell_4[0.55, 0.65]\}$	$\{\ell_2[0.2, 0.3], \ell_3[0.1, 0.2], \ell_4[0.6, 0.7]\}$	$\{\ell_2[0.2, 0.3], \ell_3[0.2, 0.3], \ell_4[0.5, 0.7]\}$

Table A4: Evaluated information of expert 3

	T_1	T_2	T_3	T_4
M_1	$\{\ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.75, 0.8]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.8, 0.9]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.7, 0.8]\}$	$\{\ell_1[0.05, 0.1], \ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.6, 0.7]\}$
M_2	$\{\ell_2[0.1, 0.2], \ell_3[0.2, 0.3], \ell_4[0.7, 0.8]\}$	$\{\ell_2[0.05, 0.1], \ell_3[0.1, 0.2], \ell_4[0.8, 0.85]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.05, 0.1], \ell_4[0.75, 0.85]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.15, 0.2], \ell_4[0.7, 0.8]\}$
M_3	$\{\ell_1[0.2, 0.3], \ell_2[0.2, 0.3], \ell_3[0.1, 0.2], \ell_4[0.4, 0.6]\}$	$\{\ell_1[0.2, 0.3], \ell_2[0.1, 0.2], \ell_3[0.3, 0.4], \ell_4[0.3, 0.5]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.1, 0.2], \ell_4[0.5, 0.7]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.2, 0.3], \ell_3[0.2, 0.3], \ell_4[0.5, 0.6]\}$
M_4	$\{\ell_2[0.2, 0.3], \ell_3[0.2, 0.3], \ell_4[0.5, 0.6]\}$	$\{\ell_2[0.2, 0.3], \ell_3[0.2, 0.3], \ell_4[0.55, 0.6]\}$	$\{\ell_2[0.1, 0.2], \ell_3[0.05, 0.1], \ell_4[0.6, 0.7]\}$	$\{\ell_1[0.1, 0.2], \ell_2[0.1, 0.2], \ell_3[0.2, 0.3], \ell_4[0.5, 0.6]\}$

Table A5: Direct relation matrix of D^1

	T_1	T_2	T_3	T_4
T_1		$\{HI[0.6, 0.7], VHI[0.3, 0.4]\}$	$\{LI[0.2, 0.3], EI[0.7, 0.8]\}$	$\{EI[0.5, 0.6], HI[0.4, 0.5]\}$
T_2	$\{LI[0.1, 0.2], EI[0.8, 0.9]\}$		$\{EI[0.3, 0.4], HI[0.6, 0.7]\}$	$\{LI[0.2, 0.3], EI[0.7, 0.8]\}$
T_3	$\{HI[0.7, 0.8], VHI[0.2, 0.3]\}$	$\{LI[0.4, 0.5], EI[0.5, 0.6]\}$		$\{EI[0.8, 0.9], HI[0.1, 0.2]\}$
T_4	$\{EI[0.6, 0.7], HI[0.3, 0.4]\}$	$\{HI[0.8, 0.9], VHI[0.1, 0.2]\}$	$\{EI[0.5, 0.6], HI[0.4, 0.5]\}$	

Table A6: Direct relation matrix of D^2

	T_1	T_2	T_3	T_4
T_1		$\{EI[0.5, 0.6], HI[0.4, 0.5]\}$	$\{EI[0.6, 0.7], HI[0.3, 0.4]\}$	$\{EI[0.4, 0.6], HI[0.5, 0.6]\}$
T_2	$\{EI[0.7, 0.8], HI[0.2, 0.3]\}$		$\{EI[0.4, 0.5], HI[0.6, 0.7]\}$	$\{EI[0.8, 0.9], HI[0.1, 0.2]\}$
T_3	$\{EI[0.3, 0.4], HI[0.6, 0.7]\}$	$\{EI[0.6, 0.7], HI[0.3, 0.4]\}$		$\{EI[0.7, 0.8], HI[0.2, 0.3]\}$
T_4	$\{EI[0.4, 0.5], HI[0.5, 0.6]\}$	$\{EI[0.1, 0.2], HI[0.8, 0.9]\}$	$\{LI[0.3, 0.4], EI[0.6, 0.7]\}$	

Table A7: Direct relation matrix of D^3

	T_1	T_2	T_3	T_4
T_1		$\{HI[0.6, 0.7], VHI[0.2, 0.4]\}$	$\{HI[0.7, 0.8], VHI[0.2, 0.3]\}$	$\{LI[0.1, 0.2], EI[0.8, 0.9]\}$
T_2	$\{LI[0.2, 0.3], EI[0.7, 0.8]\}$		$\{LI[0.5, 0.6], EI[0.4, 0.5]\}$	$\{EI[0.6, 0.7], HI[0.3, 0.4]\}$
T_3	$\{EI[0.5, 0.6], HI[0.4, 0.5]\}$	$\{EI[0.6, 0.7], HI[0.3, 0.4]\}$		$\{EI[0.4, 0.5], HI[0.5, 0.6]\}$
T_4	$\{HI[0.7, 0.8], VHI[0.2, 0.3]\}$	$\{HI[0.8, 0.9], VHI[0.2, 0.3]\}$	$\{EI[0.5, 0.6], HI[0.4, 0.5]\}$	

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used DeepSeek solely for polishing the English language. The authors reviewed and verified all AI-assisted output and took full responsibility for the accuracy, originality, validity, integrity, and scientific content of the manuscript. No generative AI or AI-assisted technology was used to generate, modify, fabricate, manipulate, or interpret the primary data, scientific results, statistical analyses, or conclusions reported in this manuscript.

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