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A Semantic–Preference Similarity Fusion Approach for Large-Scale Group Decision Making

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Abstract: *Large-scale group decision-making (LGDM) often relies on unified semantic scales, single-perspective clustering, and mean-based feedback adjustment, which can distort experts' intended preferences and lead to ranking instability during the consensus-reaching process. To overcome these limitations, this paper proposes a multi-stage semantic–preference fusion framework that integrates personalized individual semantics with order-preserving consensus regulation.First, a consistency-driven personalized individual semantic modeling mechanism is developed to calibrate each expert's numerical scale function, enhancing the additive consistency of fuzzy preference matrices while strictly preserving ordinal constraints. Second, a semantic–preference joint clustering strategy is introduced to reconstruct subgroup structures from dual perspectives by incorporating semantic merging, subgroup size reallocation, and preference migration, together with a hierarchical weighting scheme for aggregating intra-group and inter-group information. Third, a multi-level consensus measurement system is established at the individual, subgroup, and group levels, and an anchor-guided nonlinear feedback mechanism is designed to regulate bounded preference adjustments for low-consensus experts while minimizing the risk of order violations. Finally, numerical examples and comparative experiments demonstrate that the proposed method effectively improves consensus and ranking stability, thereby providing an interpretable and convergent framework for large-scale decision-making.*

Keywords: *Large-scale group decision making; Personalized individual semantics; Linguistic preference relations; Dual perspectives clustering; Order-preserving consensus reaching*

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I. Introduction

With the rapid development of digital technologies and intelligent systems, group decision making (GDM) has become a primary tool for solving complex decision problems in dynamic environments[1]. As decision problems grow in scope, the number of participating experts increases significantly, making large-scale group decision making (LGDM) an important research topic [2]. Involving experts from diverse backgrounds improves decision rationality, but it also introduces strong heterogeneity that complicates the consensus reaching process (CRP) [3]. Consequently, developing a unified LGDM framework that simultaneously handles semantic diversity, subgroup complexity, and ranking stability is necessary.

In practical LGDM applications, expert heterogeneity creates three closely related challenges. First, experts often interpret the same linguistic terms differently due to distinct cognitive backgrounds. Using a uniform numerical scale can therefore distort individual preference information [4]. Second, the complex structure of large expert panels makes subgroup clustering difficult. Similarity among experts depends on both observable preference scores and latent semantic interpretations, yet most existing clustering methods consider only a single perspective [5, 6]. Third, conventional CRP mechanisms focus mainly on numerical convergence while neglecting ordinal ranking stability. Forced linear adjustments can easily trigger ranking reversals, which reduces model interpretability and weakens expert trust in the final decision [7]. These issues suggest that semantic calibration, subgroup clustering, and order-preserving feedback regulation should be integrated into a coherent decision pipeline.

Quantifying individual cognitive differences in linguistic evaluations is essential for accurate preference modeling. Personalized individual semantics (PIS) models and data-driven learning approaches [7,8] have been widely used to derive expert-specific numerical scales. In addition, additive consistency is vital for maintaining logical transitivity in fuzzy preference matrices [9]. Although recent studies have incorporated consistency constraints into PIS modeling [10], consistency optimization is usually treated as an isolated preprocessing step. Most existing frameworks fail to maintain order-preserving constraints across subsequent

clustering and feedback stages, which means the logical transitivity gained during semantic calibration can be lost during later preference adjustments.

Dividing a large expert panel into smaller, homogeneous subgroups is a common strategy to reduce dimensionality and improve consensus efficiency [11]. Existing studies typically perform clustering based on preference similarity, trust relationships, or conflict networks [12]. However, these methods often suffer from a single-perspective limitation because they separate latent semantic cognition from explicit preference expression. Because experts' subjective semantic scales and objective preference scores are not aligned simultaneously, single-perspective clustering can distort subgroup formation and weight assignment, thereby weakening subsequent opinion aggregation.

The CRP serves as the core mechanism for resolving conflicts and reaching collective agreement. Most existing CRP models rely on minimum-adjustment optimization, trust evolution, or conflict management rules to modify inconsistent opinions [13]. Although recent models have begun to consider both cardinal and ordinal consensus [5], forced linear feedback remains widespread. Such mean-based linear adjustments often pull individual preferences toward an average value without bounding the adjustment trajectory, which can cause ranking reversals and reduce expert acceptance. Furthermore, because semantic calibration, subgroup clustering, and consensus feedback are usually designed separately, high consistency achieved in early stages is often disrupted during iterative feedback.

To overcome these limitations, an integrated framework named the Semantic–Preference Combined Multi-layer Consensus Model (SPCOM) is proposed. First, a consistency-driven PIS optimization model is constructed to calibrate individual numerical scales under strict monotonicity and ordinal constraints. Second, a three-stage semantic–preference joint clustering algorithm is designed. This algorithm establishes cognitive homogeneity through semantic merging, balances subgroup sizes via reallocation, and refines behavioral consistency through preference migration. Third, an anchor-guided nonlinear feedback mechanism is developed. High-consensus experts with strong similarity are selected as reference anchors, and low-consensus preferences are updated via convex combinations regulated by an adaptive weight.

The main contributions of this study are summarized as follows:

A consistency-driven PIS calibration mechanism: By embedding additive consistency maximization directly into numerical scale optimization, individual linguistic mappings maintain source-level logical transitivity without distorting ordinal preferences.

A three-stage semantic–preference joint clustering strategy: By combining semantic merging with preference-based migration, the proposed clustering algorithm unifies cognitive and behavioral dimensions, producing subgroups that are both semantically coherent and preference-consistent.

An anchor-guided nonlinear consensus regulation mechanism: By using dual-perspective reference anchors and a power-function retention weight, the feedback process achieves rapid convergence while mathematically preserving ordinal ranking stability.

The remainder of this paper is organized as follows. Section 2 introduces the preliminary concepts. Section 3 formulates the LGDM problem and details the SPCOM framework. Section 4 applies the proposed method to an electric van procurement case study. Section 5 presents comparative experiments and sensitivity analyses, and Section 6 concludes the paper.

II. Preliminary Knowledge

This section reviews the fundamental definitions of linguistic term sets, personalized semantic modeling, fuzzy preference relations, and similarity measures used throughout this study.

2.1 Linguistic Terms and Personalized Semantic Modeling

Definition 1. In large-scale group decision-making problems, experts often express their relative preferences over alternatives using linguistic terms. Let $S=\{s_0,s_1,\ldots,s_g\}$ be an ordered linguistic term set, where s_i denotes the i-th linguistic term and satisfies $s_0<s_1<\cdots<s_g$, $Neg(s_i)=s_{g-i}$.

To facilitate subsequent computations, linguistic terms need to be mapped onto a numerical interval. A numerical scale function $NS:S\rightarrow[0,1]$ is introduced, where $NS(s_i)$ denotes the numerical scale associated with the linguistic term s_i. The function is required to satisfy strict monotonicity.

$$0=NS(s_0)<NS(s_1)<\cdots<NS(s_g)=1 \quad (1)$$

Definition 2. Heterogeneous interpretations of identical linguistic terms among experts may render unified numerical scales prone to preference distortion . To mitigate this problem, a consistency-driven personalized semantic modeling approach is adopted. Specifically, the numerical scale $NS^{(k)}$ of expert d_k is optimized so as to maximize the consistency of his or her preference relations. The corresponding model is formulated as follows.`

Because experts interpret identical linguistic terms differently, a unified scale can distort individual judgments. In consistency-driven PIS modeling, the personalized numerical scale $NS^{(k)}$ for expert e_k is derived by maximizing the additive consistency index $CI\left(L^{(k)}\right)$ of the expert's linguistic preference matrix $L^{(k)}$:

$$\begin{aligned} &\max_{NS^{(k)}} \quad CI\left(L^{(k)}\right) \\ &\text{s.t.\&} NS^{(k)}(s_{i+1})\text{-}NS^{(k)}(s_i)\geq\lambda, \\ &NS^{(k)}(s_0)=0, NS^{(k)}\left(s_g\right)=1, \end{aligned} \tag{2}$$

whereλ>0 is a minimum spacing parameter that preserves the strict semantic order of linguistic terms.

2.2 Fuzzy Preference Relations and Additive Consistency

Definition 3. Let $X=\{x_0,x_1,\ldots,x_n\}$ be the set of alternatives. Expert d_k provides a linguistic preference relation matrix over X based on the linguistic term set S through pairwise comparisons.

$$\begin{aligned} &L^{(k)}=(l_{ij}^{(k)})_{n\times n}, l_{ij}^{(k)}\in S \\ &\text{s.t. } l_{ij}^{(k)}=\text{Neg}(l_{ji}^{(k)}), l_{ii}^{(k)}=s_{g/2}, \end{aligned} \tag{3}$$

where $l_{ij}^{(k)}$ denotes the preference degree of expert d_k for alternative x_i over x_j.

Definition 4. Using the personalized numerical scale $NS^{(k)}$, the linguistic preference relation is transformed into a fuzzy preference relation matrix as follows.

$$\begin{aligned} &F^{(k)}=(f_{ij}^{(k)})_{n\times n}, f_{ij}^{(k)}=NS^{(k)}(l_{ij}^{(k)}) \\ &\text{s.t. } f_{ij}^{(k)}+f_{ji}^{(k)}=1, f_{ii}^{(k)}=0.5 \end{aligned} \tag{4}$$

Definition 5. To assess the logical rationality of experts' judgments, the additive consistency index proposed by Herrera-Viedma et al. [35] is employed and defined as follows.

$$CI(L^{(k)})=1-\frac{4}{n(n-1)(n-2)}\sum_{i<j<k}\left|NS^{(k)}(l_{ij})+NS^{(k)}(l_{jk})-NS^{(k)}(l_{ik})-0.5\right| \tag{5}$$

when $CI(L^{(k)})\geq\theta_{CI}$, the expert's preference relation is considered to have acceptable consistency.

2.3 Semantic and Preference Similarity

Definition 6. Based on the semantic mapping values, the semantic similarity between experts i and j is defined as follows.

$$L_{i,j}^{sem}=1-\sqrt{\frac{1}{t(t-1)}\sum_{p\neq q}\left[E_i(A_p>A_q)-E_j(A_p>A_q)\right]^2} \tag{6}$$

where $E_i(A_p>A_q)$ and $E_j(A_p>A_q)$ denote the semantic mapping values given by experts i and j, respectively, for the ordered alternative pair $(A_p>A_q)$. Based on this definition, the semantic similarity matrix $L^{sem}=(L_{i,j}^{sem})_{k\times k}$ can be constructed, where k is the number of participating experts. Furthermore, the semantic degree of expert j is defined as $k_j^{sem}=\sum_{i=1}^{e}L_{ij}^{sem}$,where the self-similarity term $L_{i,i}^{sem}$is excluded from the computation.

Definition 7. Based on the fuzzy preference relations, the preference similarity between experts i and j is defined as follows.

$$F_{i,j}^{pref}=1-\sqrt{\frac{1}{t(t-1)}\sum_{p\neq q}\left[\frac{P_i(A_p>A_q)}{6}-\frac{P_j(A_p>A_q)}{6}\right]^2} \tag{7}$$

where $P_i(A_p>A_q)$ and $P_j(A_p>A_q)$ denote the preference scores provided by experts i and j, respectively, for the ordered alternative pair $(A_p>A_q)$. Based on this definition, the preference similarity matrix $F^{pref}=(F_{i,j}^{pref})_{k\times k,}$ can be constructed, where k is the number of participating experts. Furthermore, the preference degree of expert j is defined as $k_j^{pref}=\sum_{i=1}^{e}F_{ij}^{pref}$,where the self-similarity term $F_{i,i}^{pref}$ is excluded from the computation.

Definition 8. To comprehensively assess the aggregation level of an expert group from both semantic and preference perspectives, the overall group measures are defined in a normalized mean form:

$$Z=\sum_{i=1}^{k}k_i^{sem}, P=\sum_{i=1}^{k}k_i^{pref} \tag{8}\ (9)$$

High values of Z and P indicate strong semantic alignment and preference convergence across the group, whereas low values indicate the need for subgroup coordination and feedback adjustment.

III. Problem Description and Model Construction

Section 3 presents the large-scale group decision-making problem and the construction of the proposed model, detailing the decision scenario, modeling process, and key components of the framework in a structured manner.

3.1 Problem Description and Process Description

In LGDM, a panel of k experts $E=\{e_1,\ldots,e_k\}$ evaluates t alternatives $A=\{A_1,\ldots,A_t\}$ using a seven-level linguistic term set $S=\{s_0,\ldots,s_6\}$. Due to varying domain knowledge and cognitive habits, experts exhibit two distinct types of divergence: (1) semantic divergence, where identical linguistic terms correspond to different numerical perceptions; and (2) preference divergence, where experts assign different superiority ratings to the same pair of alternatives (A_p,A_q).

To resolve both divergences without causing ranking reversals, the SPCOM workflow is structured into five sequential stages, as illustrated in Fig. 1: (1) personalized semantic calibration, (2) dual-similarity computation, (3) three-stage semantic–preference joint clustering and hierarchical aggregation, (4) multi-level consensus measurement, and (5) anchor-guided nonlinear feedback adjustment.

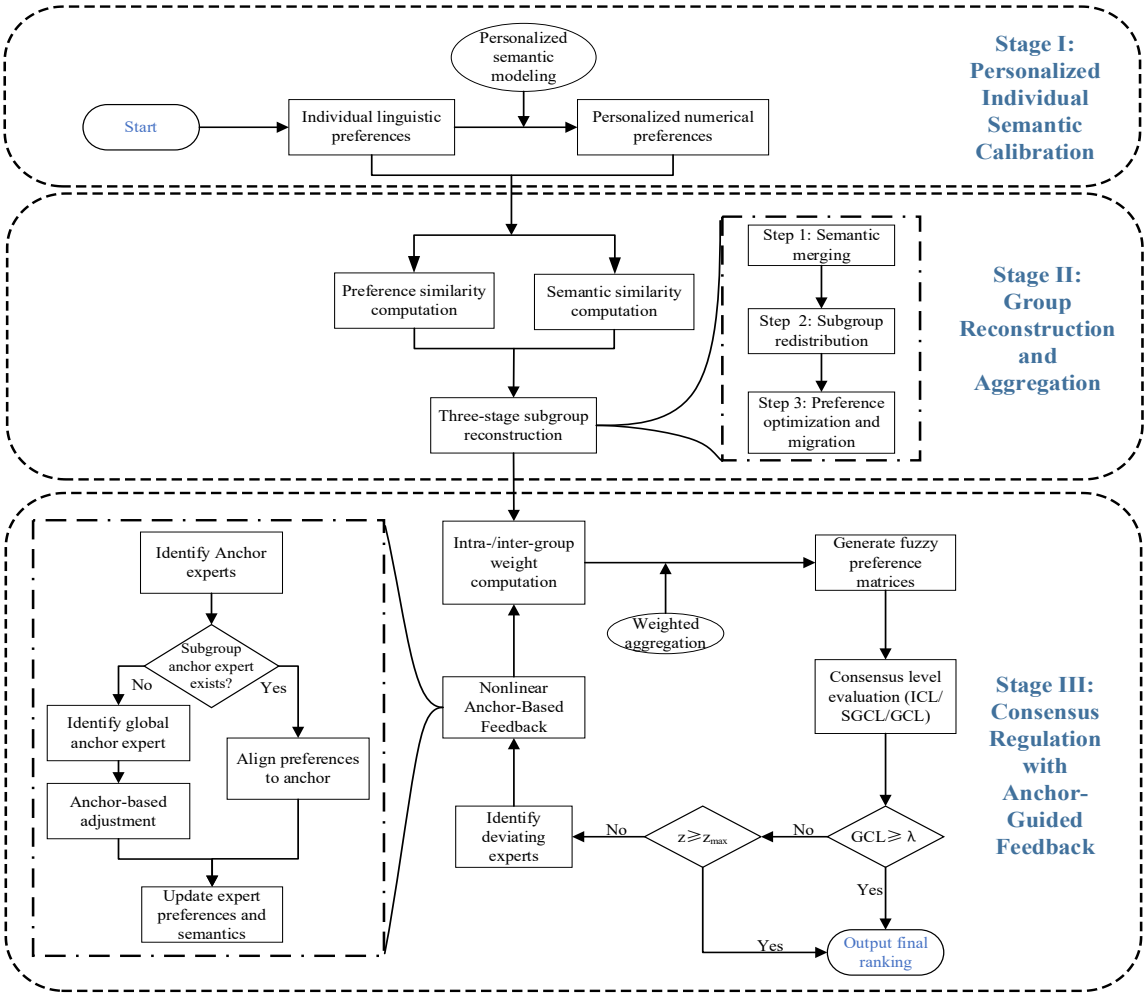


Fig. 1. Flowchart of the proposed semantic–preference combined multi-layer consensus model (SPCOM).

3.2 Personalized Semantic Assignment and Similarity Computation

To prevent preference distortion under a static linguistic scale, each expert's linguistic terms are mapped onto a personalized numerical scale. For the seven-level linguistic set $S=\{s_0,s_1,\ldots,s_{g-1}\}$, the boundary and neutral terms are fixed as anchors: *i.e.,* $NS(s_0)=0$, $NS(s_{g/2})=0.5$, $NS(s_6)=1$. The intermediate values NS_1, NS_2, NS_4, NS_5 are optimized by minimizing the additive consistency deviation across all triples of alternatives:

$$\min_{NS_1,NS_2,\ldots,NS_{g-2}} \left(\sum_{(i,j)\square\Omega} \left| NS(l_i)+NS(l_j)-NS(c_{ij})-0.5 \right| \right) \quad (10)$$

$$\text{s.t.} \quad NS_{min} \le NS_k \le NS_{max}, \quad NS_{k+1}-NS_k \ge \lambda, k=1,\ldots,g-2, \lambda > 0$$

where Ω denotes the set of ordered alternative triples and $\lambda > 0$ enforces strict monotonicity. By minimizing internal transitivity deviations, Eq. (10) calibrates each expert's scale $E_i(A_p>A_q)=NS(l_{pq}^{(i)})$ while preserving the original ordinal structure. Afterward, the similarity matrices L^{sem} and F^{pref} and the centrality indicators k^{sem} ,k^{pref}, Z, and P are calculated via Eqs. (6)–(9).

3.3 Three-Stage Semantic–Preference Joint Clustering and Weighting

To integrate latent cognitive similarity with observable preference similarity, a three-stage joint clustering strategy is developed, as detailed in Algorithm 1 (Table 1). First, experts with high semantic similarity are merged to establish cognitive homogeneity. Second, undersized clusters are reallocated to satisfy cardinality bounds [m, M]. Third, individual experts migrate across subgroups based on preference similarity to improve behavioral consistency.

Table 1. Three-Stage Semantic–Preference Joint Clustering Algorithm.

Algorithm 1. Three-Stage Semantic–Preference Joint Clustering

Step 1. Initialization

Treat all experts as independent individuals and construct the initial set of subgroups $H=\{H_1,H_2,\ldots,H_m\}$.

Then,compute the semantic similarity between each pair of subgroups.

Step 2. Semantic Merging

For any two subgroups $H_a,H_b \in H$,their semantic similarity is computed as follows.

$$sim^{sem}(H_a,H_b)=|H_a|^{-1}|H_b|^{-1}\sum_{i\square H_a}\sum_{j\square H_b} L_{ij}^{sem} \quad (11)$$

If $sim^{sem}(H_a,H_b) \ge T$ and $|H_a|+|H_b| \le M$, then merge H_a and H_b,and update H.

Step 3. Size Reallocation

For any subgroup H whose size is smaller than m, its members are reassigned to the subgroup with the highest semantic similarity, while ensuring that the size of the resulting subgroup does not exceed M.

Step 4. Individual Migration Optimization

For any expert e_i , if the preference similarity $sim^{pref}(e_i, H_t)$ with another subgroup H_t is higher than that with the original subgroup, and the migration does not violate the size constraints, then the expert is reassigned to the new subgroup in order to further improve overall preference consistency.

Step 5. Output

The final output is an optimized subgroup partition $\{H_1,H_2,\ldots,H_G\}$, which provides a foundation for subsequent consensus adjustment.

Once the G subgroups $\{H_1, \ldots, H_G\}$ are formed, a hierarchical weighting scheme is applied.

Definition 9. In the weight design, intra-group weights are determined by a weighted aggregation of semantic degree and preference degree, so as to reflect the representativeness of each individual within the subgroup.

$$w_i^{(g)}=\alpha\times\frac{k_i^{sem}}{\sum_{j\in H_g} k_j^{sem}}+(1-\alpha)\times\frac{k_i^{pref}}{\sum_{j\in H_g} k_j^{pref}}, i\in H_g, \quad (12)$$

Inter-group weights are assigned according to the aggregation level of each subgroup.

$$\varphi_g=\beta\frac{|H_g|}{k}+\eta\frac{\sum_{i\square H_g} k_i^{pref}}{P}+(1-\beta-\eta)\frac{\sum_{i\square H_g} k_i^{sem}}{Z}, g=1,\ldots,G, \quad (13)$$

where $\alpha,\beta,\eta \in [0,1]$ are weight adjustment factors. Based on the above weight design, a weighted aggregation is first performed within each subgroup to obtain the fuzzy preference matrix of that subgroup.

$$F^{SG_g}=\sum_{i\square H_g} w_i^{(g)} F^{(i)}, g=1,\ldots,G. \quad (14)$$

In Eq.(14),$F^{(i)}$ denotes the individual fuzzy preference matrix of expert e_i,and $w_i^{(g)}$represents the intra-group weight. To ensure that opinions within the group are aggregated into an overall preference in a differentiated manner, the subgroup-level results are then integrated at the inter-group level according to the inter-group weights φ_g, yielding the overall fuzzy preference matrix.

$$F^G=\sum_{g=1}^{G}\varphi_g F^{SG_g} \quad (15)$$

3.4 Multi-Level Consensus Measurement

After preference aggregation, consensus is evaluated at the individual, subgroup, and group levels using the normalized mean absolute deviation [16]. For any two preference matrices $A=(a_{pq})$ and $B=(b_{pq})$, the distance function \psi(A, B) is defined as:

$$\psi(A,B)=\frac{1}{t(t\text{-}1)}\sum_{p\neq q}|a_{pq}\text{-}b_{pq}| \quad (16)$$

$$ICL^i=1\text{-}\psi(F^{(i)},F^G)$$

Accordingly, the individual consensus level (ICL^i), subgroup consensus level ($SGCL^g$), and overall group consensus level (GCL) are calculated as:

$$\begin{aligned} ICL^i&=1\text{-}\psi(F^{(i)},F^G),\\ SGCL^g&=1\text{-}\psi(F^{SG_g},F^G),\\ GCL&=\sum_{g=1}^{G}\varphi_g SGCL^g \end{aligned} \quad (17)$$

3.5 Anchor-Guided Nonlinear Consensus Reaching Process

If GCL <γ, an iterative feedback process is activated (z = 0, 1, ... , z_{max}) until GCL≥γ or z = z_{max}. In each iteration, the expert with the lowest consensus degree, denoted as e_{min}, is selected for adjustment. To avoid boundary oscillations caused by discrete similarity distributions, a tolerance ε = 0.05 is introduced, meaning that any expert satisfying $ICL(e_{aim})\geq\gamma-\varepsilon$ = 0.85 qualifies as a candidate anchor expert. Depending on whether a qualified anchor exists inside the target expert's subgroup, one of two adjustment strategies is executed:

Intra-group alignment: If the subgroup containing e_{min} includes at least one candidate anchor with ICL≥0.85, the candidate having the highest semantic similarity with e_{min} is selected as e_{aim}. The preference matrix of e_{min} is directly aligned with that of e_{aim}, after which hierarchical weights and aggregated matrices are updated.

Global semantics-first, preference-second nonlinear adjustment: If no expert within e_{min} 's subgroup satisfies ICL≥0.85, the anchor expert e_{aim} is selected from the entire expert panel E among all experts with ICL≥0.85 based on maximum similarity with e_{min} . First, the personalized semantic vector $NS(e_{min})\}$ is updated toward $NS(e_{aim})$, and the fuzzy preference matrix $F^{e_{min}}$ is then fused with $F^{e_{min}}$ via a convex combination:

$$\begin{aligned} NS_{e_{min}}^{new}&=NS_{e_{min}}+\zeta_i\Gamma\left(NS_{aim}\text{-}NS_{e_{min}}\right)\\ \forall p\neq q:f_{e_{min}}^{new}(A_p>A_q)&=\zeta_i f_{e_{min}}^{old}(A_p>A_q)+\left(1\text{-}\zeta_i\right)f_{aim}(A_p>A_q) \end{aligned} \quad (18)$$

where $\Gamma>0$ is a scaling factor and $\zeta_i\in(0,1]$ is the adaptive original preference weight determined by the expert's semantic centrality:

$$\zeta_i=max\left(\zeta_{min},\left(\frac{k_i^{sem}}{\max\limits_j k_j^{sem}}\right)^{\delta}\right) \quad (19)$$

Here, ζ_{min} is the lower bound of information retention and \delta is the nonlinear adjustment coefficient (set to ζ_{min} = 0.2, δ= 1.2, Γ= 1.0 based on preliminary simulations). In Eq. (18), ζ_i acts as an information retention factor: experts with higher semantic centrality retain more of their initial evaluations, whereas peripheral experts shift more strongly toward the anchor.

Proposition 1 (Ordinal Stability Condition): For any alternative pair (k_p, k_q), let f_{pq}^{old} be the preference value of the target expert and f_{pq}^{aim} be that of the anchor expert. If both experts share the same preference directionality (i.e., $(f_{pq}^{old}$ - 0.5)$(f_{pq}^{aim}$ - 0.5) > 0), then the updated preference f_{pq}^{old} derived from the convex combination in Eq. (18) is guaranteed to preserve the original ordinal rank.

Proof: Since $f_{pq}^{new}=\zeta_i f_{pq}^{old}+(1\text{-}\zeta_i) f_{pq}^{aim}$ and ζ_i in (0, 1], the value of f_{pq}^{new} is a monotonic interpolation between f_{pq}^{old} and f_{pq}^{aim}. If both initial values are greater than (or less than) 0.5, their convex combination must necessarily fall on the same side of the neutral threshold. Consequently, the trajectory of adjustment remains within the original decision cone, strictly maintaining the experts' comparative logic and mitigating the risk of ranking reversals.

Following each adjustment round, the model recomputes the individual and group consensus measures to monitor the convergence.

IV. Case Study

To verify the practicality and effectiveness of the SPCOM framework, a real-world case study involving the procurement of electric light commercial vehicles (e-LCVs) for European urban logistics is conducted.

4.1 Experimental Design and Data

Driven by the European Green Deal and the "Fit for 55" emissions reduction package, an integrated European logistics enterprise plans to electrify its last-mile urban delivery fleet. Four mainstream automobile manufacturers have submitted candidate electric van models, denoted as $A=\{A_1, A_2, A_3, A_4\}$, which differ in driving range, payload capacity, charging compatibility, intelligent systems, and life-cycle cost. Twenty experts $E=\{e_1,\ldots,e_{20}\}$ from fleet management, technical R&D, operations scheduling, finance, sustainability, and external research institutes were invited to evaluate the four candidates.

Each expert performed pairwise comparisons among the four alternatives using the seven-level linguistic term set $S=\{s_0$*:very poor,* s_1*:poor,* s_2*:slightly poor,* s_3*:fair,* s_4*:good,* s_5*:very good,* s_6*:excellent*$\}$, encoded as integer indices {0,1,2,3,4,5,6}. Because fuzzy preference matrices are reciprocal with diagonal entries fixed at 0.5, only the six upper-triangular entries are required. Table 2 presents the initial linguistic evaluation indices for a subset of experts.

Table 2. Original Linguistic Evaluation Index Table for Experts'Pairwise Comparisons of Alternatives (Partial; see Appendix A1).

Alternative Pairwise / Comparison Expert	A_2 for A_1	A_3 for A_1	A_4 for A_1	A_3 for A_2	A_4 for A_2	A_4 for A_3
e_1	3	4	4	2	3	0
e_2	4	6	6	6	5	5
e_3	3	2	0	6	3	2
e_4	2	4	3	5	0	5
e_5	4	3	3	1	3	3
…	…	…	…	…	…	…
e_{16}	5	5	6	3	2	2
e_{17}	3	3	3	0	5	0
e_{18}	1	1	0	1	6	5
e_{19}	5	6	4	5	6	6
e_{20}	0	6	1	4	5	6

4.2 Personalized Semantic Value Computation

Using the consistency-driven optimization model in Eq. (10) with fixed anchors $NS(s_0) = 0$, $NS(s_3) = 0.5$, and $NS(s_6) = 1$, the personalized numerical scales $NS(e_k)$ for all 20 experts are obtained, as partially shown in Table 3. Clear differences appear across intermediate terms (s_1, s_2, s_4, s_5), confirming that the PIS model captures individual cognitive nuances.

Table 3. Personalized Semantic Mapping Results of Experts (Partial; see Appendix A2).

e_k	$NS_0^{(k).0}$	$NS_1^{(k).0}$	$NS_2^{(k).0}$	$NS_3^{(k).0}$	$NS_4^{(k).0}$	$NS_5^{(k).0}$	$NS_6^{(k).0}$
e_1	0	0.1	0.25	0.5	0.617	0.667	1
e_2	0	0.15	0.2	0.5	0.6	0.667	1
e_3	0	0.333	0.383	0.5	0.833	0.883	1
e_4	0	0.1	0.45	0.5	0.6	0.75	1
e_5	0	0.333	0.383	0.5	0.55	0.75	1
…	…	…	…	…	…	…	…
e_{16}	0	0.333	0.383	0.5	0.6	0.667	1
e_{17}	0	0.15	0.2	0.5	0.55	0.75	1
e_{18}	0	0.167	0.299	0.5	0.6	0.667	1
e_{19}	0	0.1	0.45	0.5	0.6	0.667	1
e_{20}	0	0.1	0.25	0.5	0.55	0.75	1

4.3 Decision-Making Process

For clarity, the superscript (z) in **Step $1^{(z)}$.–Step $5^{(z)}$.** denotes the z-th consensus adjustment round, where

z=0 corresponds to the initial state.

Step 1$^{(0)}$. Using Eq. (4), each expert's linguistic assessments are mapped into fuzzy preference matrices $F^{(k,0)}$. For instance, the upper-triangular matrices for experts e_1–e_4 are:

$$F^{1,0}=\begin{pmatrix} 0.5 & 0.5 & 0.667 & 0.617 \\ Null & 0.5 & 0.5 & 0.667 \\ Null & Null & 0.5 & 0.667 \\ Null & Null & Null & 0.5 \end{pmatrix} \quad F^{2,0}=\begin{pmatrix} 0.5 & 0.5 & 0.667 & 0.15 \\ Null & 0.5 & 0 & 0.2 \\ Null & Null & 0.5 & 0.2 \\ Null & Null & Null & 0.5 \end{pmatrix}$$

$$F^{3,0}=\begin{pmatrix} 0.5 & 0.833 & 0.883 & 1 \\ Null & 0.5 & 0.333 & 0.5 \\ Null & Null & 0.5 & 0.333 \\ Null & Null & Null & 0.5 \end{pmatrix} \quad F^{4,0}=\begin{pmatrix} 0.5 & 1 & 1 & 0 \\ 0 & 0.5 & 0.45 & 0.5 \\ Null & Null & 0.5 & 0.5 \\ Null & Null & Null & 0.5 \end{pmatrix}$$

Step 2$^{(0)}$. (Similarity computation): Pairwise semantic similarities L^{sem} and preference similarities F^{pref} are calculated using Eqs. (6) and (7), as shown in Tables 4 and 5.

Table 4. Semantic Similarity Matrix of Experts (Partial; see Appendix A3).

	e_1	**e_2**	**e_3**	**e_4**	**e_5**	**…**	**e_{16}**	**e_{17}**	**e_{18}**	**e_{19}**	**e_{20}**
e_1	0.5	0.610	0.718	0.634	0.686	…	0.819	0.676	0.655	0.843	0.763
e_2	Null	0.5	0.572	0.644	0.749	…	0.670	0.646	0.559	0.659	0.624
e_3	Null	Null	0.5	0.571	0.591	…	0.675	0.513	0.464	0.768	0.579
e_4	Null	Null	Null	0.5	0.618	…	0.538	0.584	0.556	0.629	0.501
e_5	Null	Null	Null	Null	0.5	…	0.739	0.676	0.623	0.752	0.694
…	…	…	…	…	…	…	…	…	…	…	…
e_{16}	Null	Null	Null	Null	Null	…	0.5	0.687	0.655	0.838	0.828
e_{17}	Null	Null	Null	Null	Null	…	Null	0.5	0.522	0.679	0.756
e_{18}	Null	Null	Null	Null	Null	…	Null	Null	0.5	0.628	0.564
e_{19}	Null	Null	Null	Null	Null	…	Null	Null	Null	0.5	0.720
e_{20}	Null	Null	Null	Null	Null	…	Null	Null	Null	Null	0.5

Table 5. Preference Similarity Matrix of Experts (Partial; see Appendix A4).

	e_1	**e_2**	**e_3**	**e_4**	**e_5**	**…**	**e_{16}**	**e_{17}**	**e_{18}**	**e_{19}**	**e_{20}**
e_1	0.5	0.935	0.953	0.939	0.948	…	0.970	0.946	0.943	0.973	0.961
e_2	Null	0.5	0.929	0.940	0.959	…	0.944	0.941	0.927	0.943	0.937
e_3	Null	Null	0.5	0.929	0.932	…	0.946	0.919	0.910	0.961	0.930
e_4	Null	Null	Null	0.5	0.937	…	0.923	0.930	0.926	0.939	0.916
e_5	Null	Null	Null	Null	0.5	…	0.957	0.946	0.937	0.959	0.949
…	…	…	…	…	…	…	…	…	…	…	…
e_{16}	Null	Null	Null	Null	Null	…	0.5	0.948	0.943	0.973	0.971
e_{17}	Null	Null	Null	Null	Null	…	Null	0.5	0.920	0.947	0.960
e_{18}	Null	Null	Null	Null	Null	…	Null	Null	0.5	0.938	0.928
e_{19}	Null	Null	Null	Null	Null	…	Null	Null	Null	0.5	0.954
e_{20}	Null	Null	Null	Null	Null	…	Null	Null	Null	Null	0.5

Step 3$^{(0)}$. (Joint clustering and hierarchical aggregation): Setting T = 0.75, m = 3, and M = 6 in Algorithm 1 partitions the 20 experts into four balanced subgroups of five members each, as listed in Table 6.

Table 6. Expert Clustering Results and Subgroup Weights.

Expert Subgroup	Number of Experts	Expert Members	Overall Weight of Expert Subgroup
H1	5	e_1,e_7,e_9,e_{17},e_{18}	0.232
H2	5	e_2,e_5,e_{10},e_{13},e_{16}	0.272
H3	5	e_3,e_{12},e_{14},e_{19},e_{20}	0.246
H4	5	e_4,e_6,e_8,e_{11},e_{15}	0.250

Using Eqs. (12)–(15), the initial subgroup preference matrices F^{SG_g} are obtained as:

$$F^{SG_{1,0}}=\begin{pmatrix} 0.5 & 0.434 & 0.481 & 0.266 \\ Null & 0.5 & 0.434 & 0.653 \\ Null & Null & 0.5 & 0.585 \\ Null & Null & Null & 0.5 \end{pmatrix} F^{SG_{2,0}}=\begin{pmatrix} 0.5 & 0.667 & 0.631 & 0.298 \\ Null & 0.5 & 0.376 & 0.245 \\ Null & Null & 0.5 & 0.347 \\ Null & Null & Null & 0.5 \end{pmatrix}$$

$$F^{SG_{3,0}}=\begin{pmatrix}0.5 & 0.417 & 0.770 & 0.629\\ Null & 0.5 & 0.456 & 0.579\\ Null & Null & 0.5 & 0.453\\ Null & Null & Null & 0.5\end{pmatrix}\quad F^{SG_{4,0}}=\begin{pmatrix}0.5 & 0.270 & 0.348 & 0.168\\ Null & 0.5 & 0.537 & 0.496\\ Null & Null & 0.5 & 0.628\\ Null & Null & Null & 0.5\end{pmatrix}$$

Aggregating the four subgroups yields the initial collective group preference matrix F^G:

$$F^{G}=\begin{pmatrix}0.5 & 0.452 & 0.560 & 0.340\\ Null & 0.5 & 0.449 & 0.485\\ Null & Null & 0.5 & 0.499\\ Null & Null & Null & 0.5\end{pmatrix}$$

Step 4$^{(0)}$. Based on the overall fuzzy preference matrix F^G, Eqs.(16)–(20) are applied to compute the ICL, SGCL, and GCL, so as to evaluate the degree of opinion aggregation. The results of individual consensus levels are illustrated in Fig. 2.In this case study, the overall consensus threshold is set toγ=0.9. The initial results indicate that the overall consensus level is GCL=0.873＜γ. Therefore, the process proceeds to Step 5 to initiate the adjustment procedure.

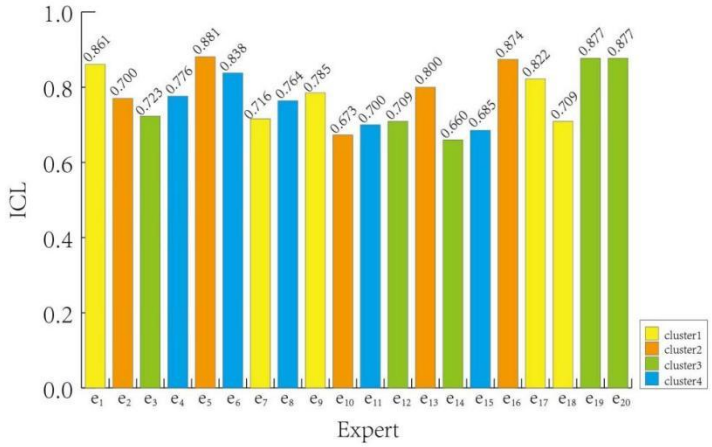


Fig. 2. Distribution of ICL.

Step 5$^{(0)}$. First, the expert with the lowest individual consensus level, denoted as e_{min}, is identified and selected as the initial adjustment target. As shown in Fig. 2,e_{min} corresponds to expert e_{14}.According to the clustering results in Table 6, this expert belongs to subgroup H_4. Therefore, the adjustment process first searches for an anchor expert e_{aim} within subgroup H_4. Expert e_{20} is identified as a suitable anchor, since $ICL^{e_{20}}$ exceeds 0.85 and, as indicated in Table 5, e_{20} exhibits the highest semantic similarity with expert e_{14} among the candidate set. Based on these criteria, expert e_{20} is selected as the anchor expert, and the preferences of e_{14} are directly aligned with those of e_{20}.After the adjustment, the fuzzy preference matrix of expert e_{15} is given as follows.

$$F^{14,1}=F^{20,0}=\begin{pmatrix}0.5 & 0 & 0.55 & 0.55\\ Null & 0.5 & 0.5 & 0.5\\ Null & Null & 0.5 & 0.5\\ Null & Null & Null & 0.5\end{pmatrix}$$

Recomputing the hierarchical weights gives $w_{e_4}^{(4,1)}$=0.192，$w_{e6}^{(4,1)}$=0.195，$w_{e_8}^{(4,1)}$=0.218，$w_{e_{11}}^{(4,1)}$=0.196，$w_{e_{15}}^{(4,1)}$=0.199, , and subgroup weights φ_1^1=0.248，φ_2^1=0.259，φ_3^1=0.248，φ_4^1=0.245 .The updated individual consensus level reaches 0.879 > 0.85, and the group consensus rises to $GCL^{(1)}$ =0.879 < 0.90, requiring a second iteration.

Step 5$^{(1)}$-Step 4$^{(2)}$.(Round 2 adjustment): Next, expert e_{10} in subgroup H_2 exhibits the lowest consensus (ICL_{10}^0= 0.673). Within H_2, expert e_5 satisfies ICL_5^0= 0.881 > 0.85 and shares the highest semantic similarity with e_{10}. Applying intra-group alignment updates $F^{10,2}$ to match $F^{5,0}$:

$$F^{10,2}=F^{5,0}=\begin{pmatrix}0.5 & 0 .5 & 0.5 & 0.333\\ Null & 0.5 & 0.383 & 0\\ Null & Null & 0.5 & 0.55\\ Null & Null & Null & 0.5\end{pmatrix}$$

Recalculating the weights yields $w_{e2}^{(2,2)}$=0.199，$w_{e5}^{(2,2)}$=0.202，$w_{e10}^{(2,2)}$=0.186，$w_{e_{13}}^{(2,2)}$=0.196，$w_{e_{16}}^{(2,2)}$=0.217，φ_1^2=0.247，φ_2^2=0.256，φ_3^2=0.253，φ_4^2=0.244 .After Round 2, ICL_{10}^2=0.883>0.85, while GCL^2=0.881<0.90.

Step 5$^{(2)}$-Step 4$^{(2)}$.(Round 3 adjustment): In the third round, expert $e_{11} \in H_4$ has the lowest consensus degree. Because no member in H_4 satisfies ICL≥0.85, a global anchor is selected from the full candidate set $e_1, e_5, e_{16}, e_{19}, e_{20}$=. Using Eqs. (15) and (16), the personalized semantic scale is updated to $NS_1^{(14),\ 3}$=0.286， $NS_2^{(14),\ 3}$=0.397， $NS_4^{(14),\ 3}$=0.6， $NS_5^{(14),\ 3}$=0.7236, and the preference matrix of e_{11} is fused with the anchor expert e_{19} to obtain:

$$F^{11,3}=\begin{pmatrix} 0.5 & 0 & 0.573 & 0.507 \\ Null & 0.5 & 0.533 & 06 \\ Null & Null & 0.5 & 0.6 \\ Null & Null & Null & 0.5 \end{pmatrix}$$

Updating the weights yields$w_{e4}^{(4,3)}$ =0.193，$w_{e6}^{(4,3)}$ =0.198，$w_{e8}^{(4,3)}$ =0.217，$w_{e_{11}}^{(4,3)}$ =0.195， $w_{e_{15}}^{(4,3)}$ =0.197, φ_1^3=0.247， φ_2^3=0.258， φ_3^3=0.252， φ_4^3=0.243 。The updated individual consensus reaches 0.857 > 0.85, and the overall group consensus reaches GCL^3 = 0.907 > 0.90, terminating the CRP after only three rounds.

Table 7. Evolution of consensus measures across iterative rounds.

	GCL	$SGCL_1$	$SGCL_2$	$SGCL_3$	$SGCL_4$
Round 0	0.873	0.882	0.878	0.885	0.849
Round 1	0.879	0.880	0.874	0.883	0.875
Round 2	0.881	0.879	0.887	0.880	0.878
Round 3	0.907	0.902	0.905	0.904	0.918

As shown in Table 8, GCL increases monotonically from 0.873 to 0.907 within three rounds, while all subgroup consensus levels exceed 0.90. Minor fluctuations in unadjusted subgroups occur because any local preference update shifts the global reference matrix F^G via Eq. (12). These results confirm that SPCOM efficiently coordinates heterogeneous linguistic evaluations to support procurement decisions.

5 Discussion

To further evaluate the performance of SPCOM, comparative experiments and parameter sensitivity analyses are conducted against two representative benchmark models: MSCOM [14] (which focuses on consistency-based preference adjustment) and PBCM [15] (which employs multi-stage consensus optimization with linear shrinkage). Table 8 summarizes the structural differences among the three methods.

Table 8. Comparative Analysis of Different Group Decision-Making Methods.

Method Comparison	Type of Evaluation Information	Mechanism Comparison of Large-Scale Group Consensus Models	Semantic Information Considered	Multi-view Joint Learning	Multi-stage Consensus Optimization	Direct Consensus Output
Reference [14]	Linguistic preference relations	Consistency adjustment and aggregation	×	×	×	√
Reference [15]	Hierarchical linguistic preference information	Multi-stage optimization model	×	×	√	√
Proposed Method	Probabilistic linguistic semantic information	Strong semantic–preference joint learning	√	√	√	√

For fair comparison, all three models were tested under identical experimental settings (k = 20, t = 4, g = 6, z_{max}= 10) across 500 independent simulation runs under three consensus thresholds (γ = 0.90, 0.92, 0.95). Figs. 3 and 4 illustrate the trajectories of average ICL and GCL across iterations.

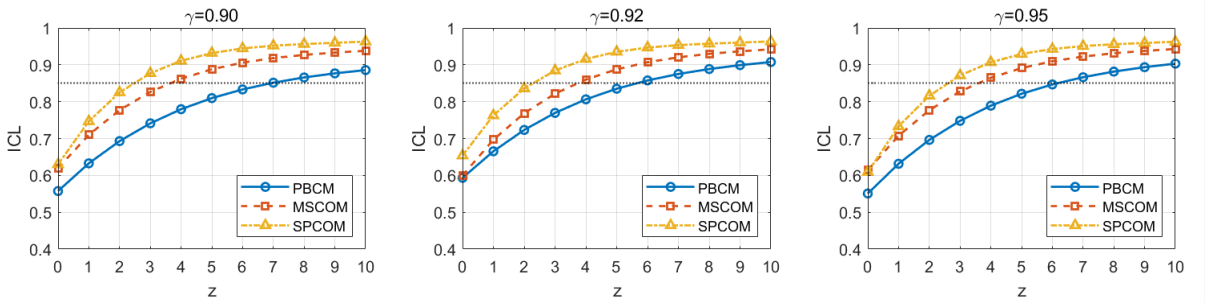


Fig. 3. ICL with an Expert Consistency Threshold of 0.85.

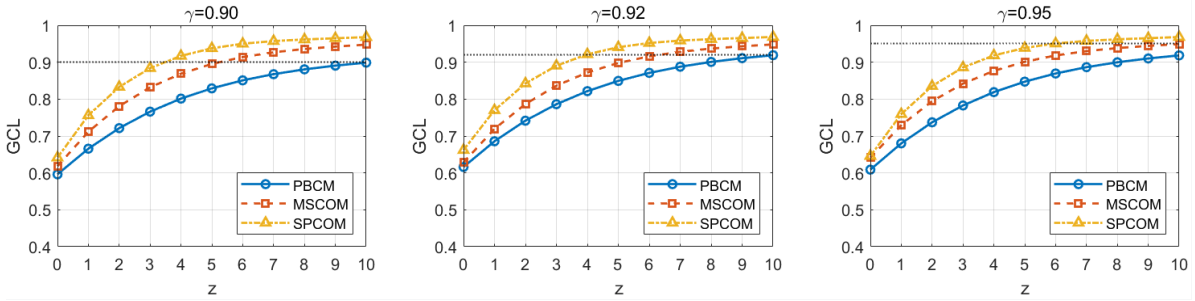
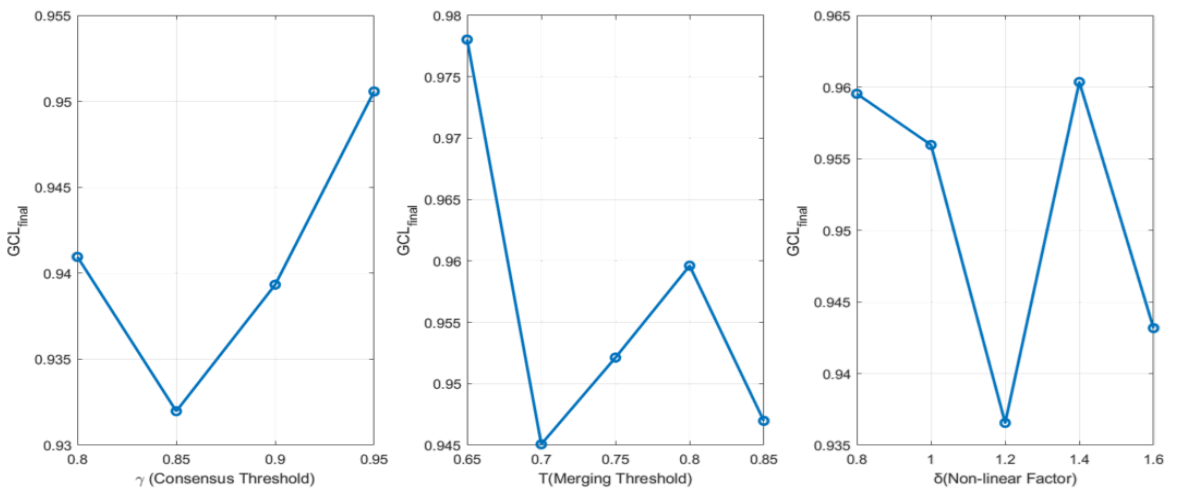


Fig. 4. GCL an Expert Consistency Threshold of 0.85.

As shown in Figs. 3 and 4, although all three methods improve consensus as iterations proceed, SPCOM consistently achieves a steeper convergence curve and a higher final GCL under all three thresholds ($\gamma = 0.90$, 0.92, 0.95). While MSCOM achieves moderate convergence speed, it exhibits local fluctuations, whereas PBCM converges more slowly and reaches a lower terminal consensus level. By calibrating personalized semantics prior to joint clustering and anchor-guided feedback, SPCOM eliminates cognitive bias early in the pipeline and reaches high-quality agreement in fewer rounds.

Meanwhile, this study conducts sensitivity analysis only on the consensus threshold γ, the clustering merging threshold T, and the nonlinear adjustment coefficient δ. This choice is motivated by the fact that these three parameters directly govern the core mechanisms of the model γ determines the condition for consensus achievement, T controls the subgroup structure, and δ regulates the original preference weight during preference iteration. Other parameters, such as m and M, are structural or secondary tuning parameters and do not directly affect the fundamental operating principles of the algorithm. Therefore, they are not included in the sensitivity analysis.



(a)Variation of GCL with the consensus threshold γ (b) Variation of GCL with the clustering merging threshold T (c)Variation of GCL with the nonlinear adjustment coefficient δ

Fig. 5. Sensitivity Analysis of Key Parameters on the Final Group Consensus Level.

Figure 5 reports the stability results of the model under different parameter settings. It can be observed that variations in the three parameters lead to slight changes in consensus speed and convergence level, while the overall trends remain consistent. As γ increases, the convergence process becomes slightly slower; however,

the final GCL remains at a relatively high level. When T is below 0.70, excessive subgroup merging may occur, resulting in temporary fluctuations in GCL. In contrast, the model exhibits more stable behavior when T lies in the range of 0.75 to 0.80. The effect of δ shows a typical nonlinear pattern: insufficient adjustment occurs at low values, whereas local oscillations may appear at high values. The most stable convergence is achieved at moderate adjustment levels.

Overall, parameter variations do not alter the final ranking structure, nor do they weaken the advantage of SPCOM in rapidly achieving a high consensus level. These results indicate that the proposed model has good robustness. Moreover, the optimal parameter ranges identified in the sensitivity analysis are highly consistent with the parameter settings used in the case study, further confirming the rationality of the experimental design and the reliability of the proposed method.

VI. Conclusion

This paper presented the SPCOM framework to address semantic distortion, single-perspective clustering, and ranking instability in LGDM. First, a consistency-driven PIS optimization model was formulated to calibrate individual numerical scales while maintaining additive consistency and ordinal transitivity. Second, a three-stage semantic–preference joint clustering algorithm and hierarchical weighting method were developed to construct subgroups that are both cognitively and behaviorally coherent. Third, an anchor-guided nonlinear feedback mechanism was designed to guide low-consensus experts toward reference anchors via bounded convex combinations, theoretically guaranteeing ordinal stability. Application to an urban logistics electric van procurement problem and 500 simulation experiments verified that SPCOM reaches consensus (GCL = 0.907) within three rounds and outperforms existing benchmark models in both convergence speed and stability.

Despite these advantages, several limitations merit future investigation. First, SPCOM assumes complete pairwise preference matrices; extending the model to handle incomplete evaluations via consistency-preserving matrix completion is an important next step. Second, strategic or non-cooperative behaviors are not explicitly modeled during feedback regulation. Future work will incorporate behavioral game mechanisms and generative simulation models to dynamically calibrate the preference retention weight ζ_i in dynamic, heterogeneous decision environments.

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Statements and Declarations

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Declaration of interest statement

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted. We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work.

Author contributions

Xiuli Geng: Writing – original draft, Visualization, Resources, Methodology, Investigation, Funding acquisition, Conceptualization.

Zexi Lin: Writing–original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Data availability

The initial data for the case study has been given in the paper and appendix.