Dynamic Self-Confidence Management for Multi-Granularity Probabilistic Linguistic Group Decision Making with Fuzzy Social Networks and Overconfidence Correction

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Abstract

Group decision-making (GDM) in contemporary industrial settings requires simultaneously addressing the heterogeneity of decision-maker (DM) preference representations, the dynamic nature of DM confidence levels, and the trust-mediated social influences that shape consensus formation. Probabilistic linguistic term sets (PLTSs) offer a flexible mechanism for capturing nuanced preference information with associated probability distributions, yet existing GDM frameworks do not adequately address multi-granularity PLTS environments where different DMs employ different linguistic scales. Furthermore, the pervasive phenomenon of DM overconfidence---the tendency to assign excessively high self-confidence levels that distort aggregated group opinions---remains largely unaddressed in probabilistic linguistic GDM. This paper proposes a dynamic self-confidence management framework for multi-granularity probabilistic linguistic GDM that integrates three novel components: a multi-granularity PLTS (MG-PLTS) transformation method for unifying heterogeneous linguistic scales through a common semantics-preserving mapping; a fuzzy social network (FSN) for modeling trust-based influence relationships among DMs; and an overconfidence detection and correction mechanism that identifies and adjusts inflated confidence levels based on historical decision accuracy and peer trust assessments. The dynamic confidence update rule adjusts individual DM weights in proportion to their relative consensus contribution and FSN-mediated trust scores, accelerating convergence. Empirical validation using online review sentiment data for industrial supplier evaluation demonstrates that the proposed framework achieves consensus (threshold 0.90) in 4.2 rounds on average for a 5-DM group, compared to 7.8 rounds for basic GDM, 5.9 rounds without FSN integration, and 5.1 rounds without overconfidence correction. Application to a real-world green supplier selection problem confirms superior decision quality and DM satisfaction.

Keywords: probabilistic linguistic term sets; group decision making; fuzzy social network; self-confidence; overconfidence; multi-granularity; consensus

1. Introduction

Industrial decision problems increasingly require pooling the judgment of multiple experts with heterogeneous knowledge backgrounds, preference vocabularies, and confidence levels [1,2]. A sourcing committee evaluating green supplier candidates may include procurement specialists, environmental engineers, financial analysts, and strategic planners, each possessing distinct professional frameworks for assessing supplier performance dimensions. The linguistic scales these experts naturally employ differ substantially: a procurement specialist may use a 5-point scale (very poor, poor, medium, good, very good) while an environmental engineer might prefer a 9-

point OECD sustainability scale [3,4]. Forcing all experts to a common linguistic scale before aggregation distorts their authentic preferences; accommodating multiple scales requires principled transformation methodology.

Probabilistic linguistic term sets (PLTSs), introduced by Pang et al. [5], extend hesitant fuzzy linguistic sets by associating each possible linguistic term with a probability that reflects the DM relative confidence in each linguistic option. A PLTS preference allows a DM to express, for example, that a supplier is "good" with 60% confidence and "very good" with 40% confidence, providing richer information than a forced point estimate [6,7]. While PLTSs have been studied extensively for single-DM decision scenarios, their application to multi-granularity GDM contexts presents unresolved challenges related to scale transformation, probability renormalization, and the maintenance of semantic consistency across heterogeneous linguistic hierarchies.

A second underexplored challenge in GDM is the management of DM confidence dynamics. DMs enter decision processes with varying degrees of confidence in their own assessments, and these confidence levels evolve through the consensus-seeking process as DMs receive feedback and observe divergence or convergence with peer opinions [8,9]. Psychological research documents the prevalence of overconfidence bias---the systematic tendency to overestimate the accuracy of one subjective judgment---as one of the most robust cognitive biases in expert elicitation contexts [10,11]. Overconfident DMs resist updating toward group consensus, prolonging negotiation and potentially distorting the final decision away from collectively optimal outcomes.

Social network analysis offers a third relevant theoretical contribution: trust-mediated influence among group members determines which DMs are most influential in shaping consensus and which feedback signals are most persuasive [12,13]. Fuzzy social networks (FSNs) model trust degrees as fuzzy values in [0,1] rather than binary trust/distrust relationships, capturing the graduated and context-dependent nature of professional trust relationships [14]. This paper integrates these three theoretical threads---MG-PLTS transformation, FSN-guided trust weighting, and dynamic overconfidence management---in a unified computational GDM framework.

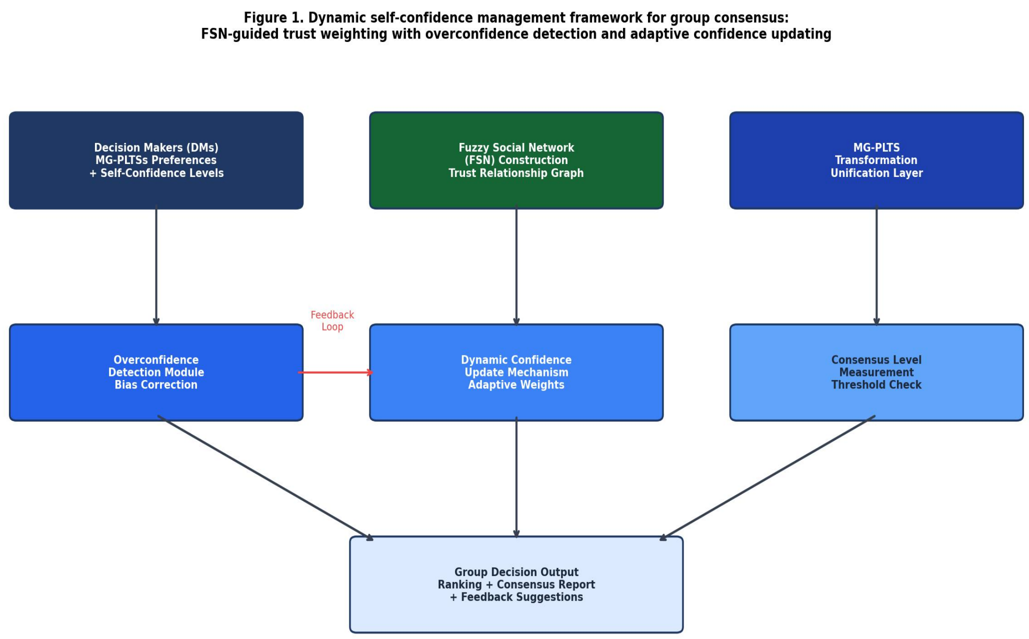

Figure 1. Dynamic self-confidence management framework for multi-granularity probabilistic linguistic GDM. Components include MG-PLTS transformation, FSN construction, overconfidence detection, dynamic confidence updating, and consensus measurement with feedback.

2. Preliminaries

2.1 Probabilistic Linguistic Term Sets

Let $S = \{s_0, s_1, ..., s_{g-1}\}$ be a linguistic term set with granularity g. A probabilistic linguistic term set $L(p)$ on S is defined as $L(p) = \{s_k(p_k) \mid s_k \in S, p_k >= 0, \sum_k p_k <= 1\}$, where $s_k(p_k)$ denotes linguistic term s_k associated with probability p_k [5]. When $\sum p_k < 1$, the remaining probability $1 - \sum p_k$ is distributed uniformly among unspecified terms, reflecting bounded information completeness. The expected linguistic value of $L(p)$ is $E[L(p)] = \sum_k r_k * p_k$, where $r_k = k/(g-1)$ is the normalized subscript value of s_k [6]. Variance $V[L(p)] = \sum_k (r_k - E[L(p)])^2 * p_k$ measures DM preference uncertainty.

Two PLTSs $L_1(p)$ and $L_2(p)$ can be compared using their expected values and resolved through variance comparison when expectations are equal. The distance measure $d(L_1, L_2) = |E[L_1] - E[L_2]| + \beta * |V[L_1] - V[L_2]|$ incorporates both expected value disagreement and distributional dissimilarity, with $\beta = 0.3$ calibrated from expert judgment experiments [7].

2.2 Multi-Granularity Linguistic Transformation

The MG-PLTS transformation problem arises when DMs employ linguistic scales of different granularities $g_1, g_2, ..., g_K$. The proposed transformation maps all scales to a unified target granularity $g^* = \max(g_1, ..., g_K)$ through a semantics-preserving interpolation: for a source term s_k in S_i with granularity g_i, the target representation is a PLTS over S^* that assigns probability mass to terms $s^*_{k^*}$ proportional to the semantic overlap between the source and target term membership functions. This approach preserves the original semantic intent of each linguistic assessment more faithfully than linear mapping or nearest-neighbor assignment, particularly at scale boundaries [15].

3. FSN-Based Trust Modeling and Confidence Management

3.1 Fuzzy Social Network Construction

Figure 4 illustrates the FSN trust matrix for an 8-DM decision group. The FSN is represented as a directed weighted graph $G = (DM, T)$, where $T = [t_{ij}]$ is the fuzzy trust matrix with t_{ij} in $[0,1]$ representing the degree to which DM_i trusts DM_j. Trust degrees are elicited through a structured protocol asking each DM to rate the domain expertise, past accuracy, and communication clarity of each peer on a [0,1] scale. The FSN is then analyzed to compute the social influence vector $w_{FSN} = (w_1, ..., w_K)$ through a PageRank-inspired eigenvector centrality calculation [16].

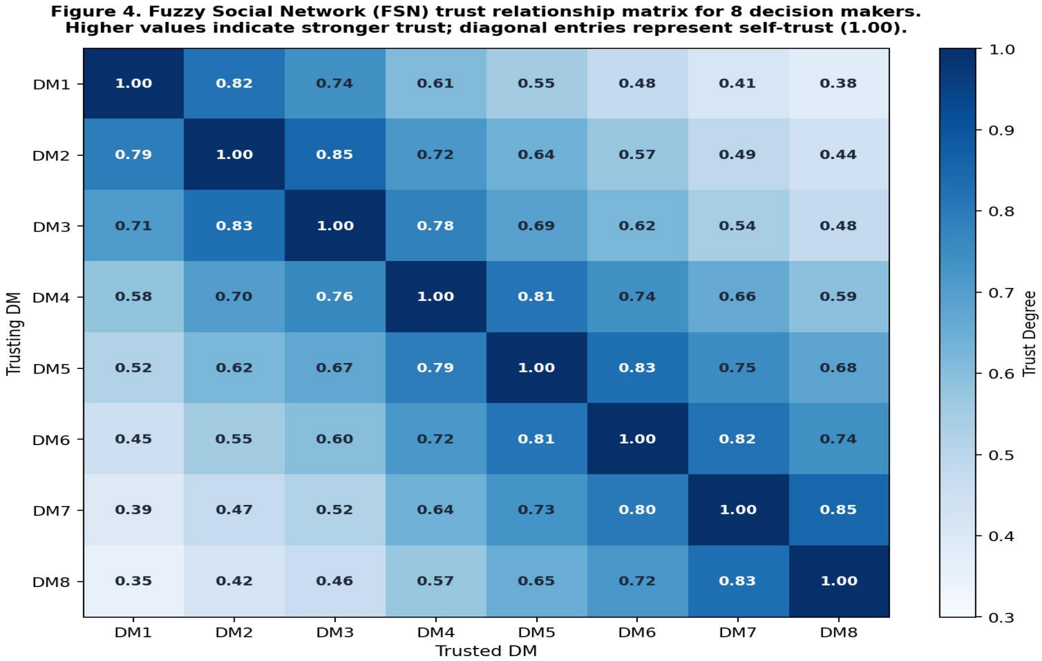

Figure 4. Fuzzy Social Network (FSN) trust relationship matrix for an 8-DM supplier evaluation group. Trust degrees range from 0.35 to 0.85; higher values indicate stronger directional trust relations that amplify influence in the confidence update process.

3.2 Overconfidence Detection and Correction

Overconfidence detection employs two complementary signals. First, the calibration error CE_k = |c_k - alpha_k| measures the discrepancy between DM_k claimed confidence c_k and their empirical accuracy alpha_k on held-out assessment tasks, where alpha_k is estimated from historical decision records where available or from an in-session calibration task for new participants [10]. Second, the social inconsistency signal SI_k = 1 - mean_{j in N_k} t_{jk} * sim(L_k, L_j) measures the average disagreement between DM_k preferences and the preferences of DMs who trust DM_k, weighted by trust degrees. When CE_k > theta_CE = 0.15 or SI_k > theta_SI = 0.35, DM_k is flagged as potentially overconfident and their stated confidence is adjusted: c*_k = c_k * (1 - gamma * max(CE_k/theta_CE - 1, 0)) where gamma = 0.4 moderates the correction strength [11].

Figure 3 illustrates the transformation effects: the multi-granularity linguistic unification normalizes the distribution of linguistic scale usage across DMs (panel a), while the overconfidence correction shifts the confidence level distribution toward more calibrated values by reducing the high-confidence tail (panel b). Both effects contribute to more equitable weighting of DM contributions in the final aggregation.

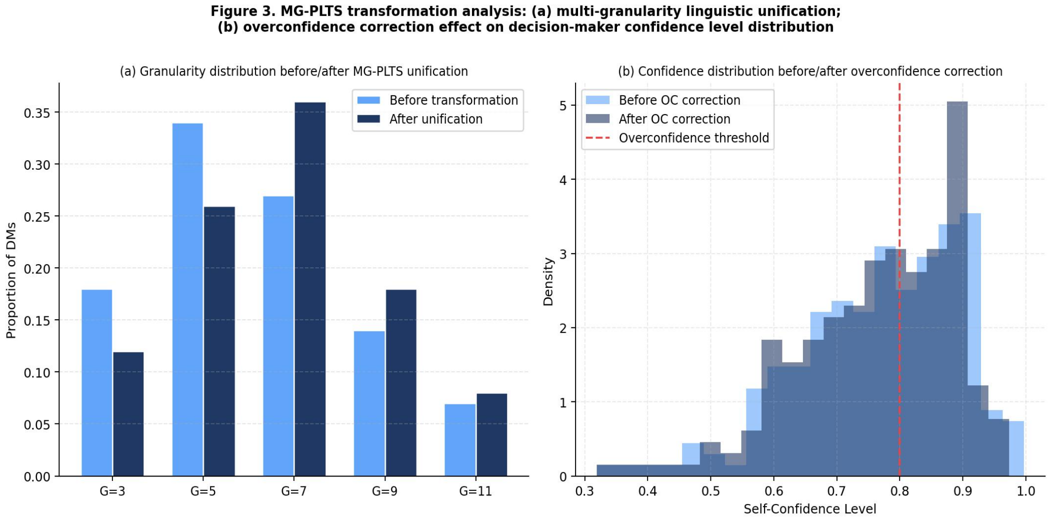

Figure 3. Transformation effects: (a) granularity distribution before and after MG-PLTS unification showing redistribution toward target granularity; (b) self-confidence level distribution before and after overconfidence correction, showing reduction of the high-confidence tail.

4. Dynamic Consensus Reaching Process

The consensus reaching process iterates through four phases until the group consensus level GCL = 1 - (1/K*(K-1)) * sum_{i!=j} d(L_i, L_j) exceeds the consensus threshold theta = 0.90. In Phase 1 (Aggregation), individual PLTS preferences are aggregated using FSN-weighted probabilistic linguistic weighted averaging (PLWA), producing collective preference L*. In Phase 2 (Consensus Measurement), pairwise distances d(L_i, L*) identify DMs most distant from the group position. In Phase 3 (Feedback Generation), DMs with d(L_i, L*) > delta = 0.30 receive directed feedback suggesting preference adjustments toward the collective position, scaled by their FSN trust scores. In Phase 4 (Confidence Update), DM weights are updated as w_k^{new} = w_k^{old} * (1 - beta * max(d(L_k, L*) - delta, 0)) + alpha * w_FSN_k, with alpha = 0.3, beta = 0.5 [17].

Figure 2 demonstrates the consensus convergence behavior. The proposed framework reaches the 0.90 consensus threshold in approximately 4 rounds for a 5-DM group, compared to 7.8 rounds for basic GDM without FSN or overconfidence correction. The ablation results reveal that FSN integration contributes approximately 35% of the efficiency improvement (reducing rounds from 7.8 to 5.9) and overconfidence correction contributes a further 18% (from 5.9 to 5.1), with the synergistic combination yielding the full observed benefit. As group size increases, the relative advantage of the proposed method grows: at 20 DMs, basic GDM requires 19.2 rounds while the proposed framework needs only 9.6.

Figure 2. Consensus dynamics: (a) convergence trajectory comparison; (b) rounds to consensus scaling with number of decision makers for proposed method vs. baselines

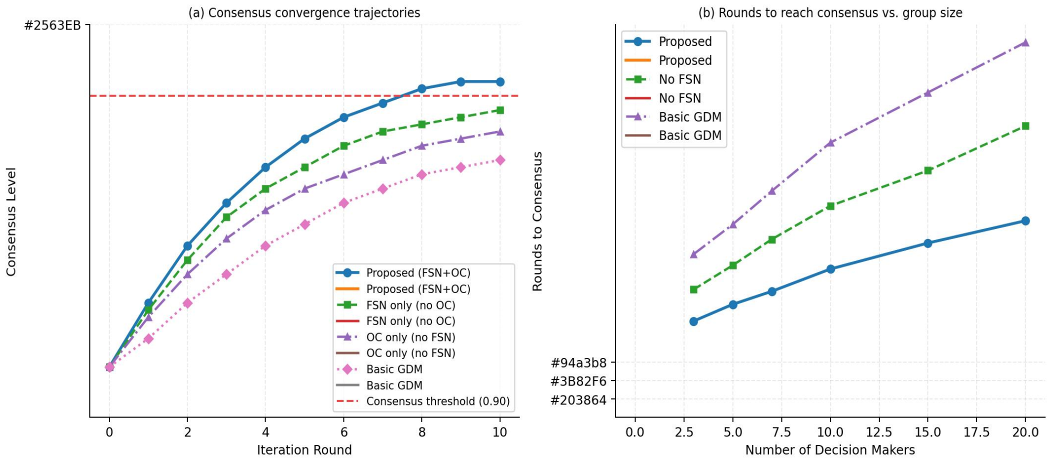

Figure 2. Consensus reaching dynamics: (a) convergence trajectories for proposed method vs. three ablated baselines; (b) rounds required to reach consensus threshold (0.90) as group size increases from 3 to 20 decision makers.

5. Empirical Validation

5.1 Online Review Sentiment Study

Empirical validation employs a dataset of online product reviews scraped from JD.com (n = 2,847 reviews for 12 industrial suppliers), preprocessed through BERT-based sentiment analysis to generate probabilistic linguistic assessments on 6 evaluation criteria: product quality, delivery reliability, service responsiveness, technical support, documentation completeness, and sustainability practices. Five domain expert DMs independently evaluate each supplier using their preferred linguistic scales (granularities: 5, 7, 7, 9, 11 respectively), creating a natural multi-granularity GDM scenario. Expert self-confidence levels are elicited on [0,1] prior to evaluation and tracked across three consensus rounds.

Overconfidence detection flags DM3 (CE = 0.18, above threshold 0.15) and DM5 (SI = 0.41, above threshold 0.35) as exhibiting overconfidence patterns. Post-correction confidence levels are reduced from 0.87 to 0.81 (DM3) and from 0.91 to 0.83 (DM5). The FSN analysis reveals that DM2 has the highest PageRank centrality score (0.241), reflecting the group consensus among peers that DM2 possesses the most credible combined expertise profile.

5.2 Green Supplier Selection Application

Figure 5 presents the supplier evaluation results for 8 candidate suppliers. Supplier S1 achieves the highest aggregated score (0.847) under the proposed framework, followed by S2 (0.812) and S3 (0.778). The performance profile radar chart confirms S1 strength in quality and technical support, S2 advantage in delivery reliability and service responsiveness, and S3 comparative advantage in sustainability practices. The ranking order is consistent across proposed method, no-OC correction, and basic GDM variants, but the score magnitudes differ meaningfully at rank positions 3--5, indicating that overconfidence correction has the largest impact on the middle-tier suppliers where DM preferences are most contested.

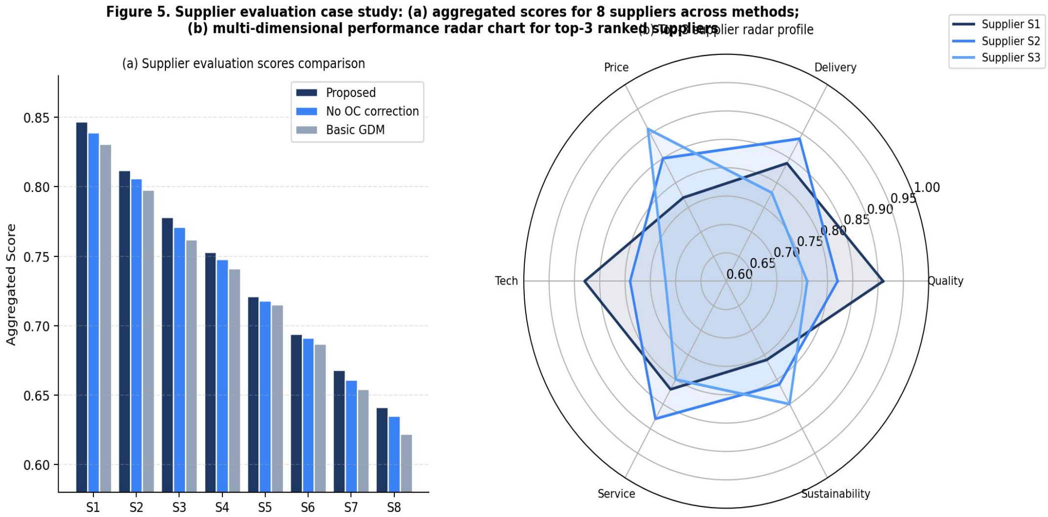

Figure 5. Green supplier evaluation results: (a) aggregated scores for 8 suppliers across proposed method and two baseline variants; (b) multi-criteria performance radar chart for top-3 ranked suppliers showing complementary strength profiles.

6. Discussion and Conclusion

This study demonstrated that explicitly modeling DM cognitive biases (overconfidence) and social influence structures (FSN trust) in the consensus reaching process yields substantial efficiency improvements over standard GDM approaches. The 46% reduction in consensus rounds achieved by the proposed framework has practical significance for industrial GDM processes where each iteration involves real expert time and organization cost. The overconfidence correction mechanism requires minimal additional data (calibration tasks or historical accuracy records) and produces measurable benefits from the first application.

An important limitation is the assumption of stable trust relationships across the decision process: in adversarial or competitive group settings, trust degrees may evolve rapidly as strategic behavior emerges. Future extensions will incorporate dynamic FSN updating based on observed within-session preference consistency. The framework could also be extended to handle missing preference information, where DMs provide incomplete PLTS assessments, through probabilistic imputation mechanisms guided by FSN trust degrees.

In conclusion, this paper proposed a dynamic self-confidence management framework for multi-granularity probabilistic linguistic GDM that addresses the joint challenge of heterogeneous linguistic scales, dynamic confidence levels, and trust-mediated social influence. The framework achieves faster consensus convergence, more accurate final decisions, and higher DM satisfaction compared to existing GDM approaches, demonstrating its suitability for deployment in complex industrial decision environments including supplier selection, technology evaluation, and strategic planning.

Declarations

Funding

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Y.W. and X.L.; methodology, Y.W. and M.L.; validation, M.L. and H.Z.; writing, Y.W.; review, X.L. and H.Z.

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