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A maximum satisfaction-based feedback mechanism for non-cooperative behavior management with agreeableness personality traits detection in group decision making

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ABSTRACT

Non-cooperative behaviors will lead to consensus failure in group decision making problems. As a result, managing non-cooperative behavior is a significant challenge in group consensus reaching processes, which involves two main research questions:(1) How to define non-cooperative behavior? (2) How to design an appropriate model to manage non-cooperative behavior? Existing studies often overlook the psychological motivations behind non-cooperative behavior and achieve group consensus potentially at the expense of decision-makers' satisfaction. To address these issues, this study proposes a novel maximum satisfaction-based feedback mechanism for managing non-cooperative behavior with personality traits prediction. To address the first research question, a novel approach for identifying non-cooperative behavior is proposed by comparing the solution of the Minimum Adjustment Consensus Model (MACM) to the maximum acceptable adjustment. The latter is defined by the decision maker's Agreeableness trait within the Big Five personality traits framework, which is predicted by a CNN-BiLSTM model using the decision maker's online reviews. For addressing the second research question, a novel two-phases feedback mechanism is introduced to manage non-cooperative behaviors based on the satisfaction principle in decision-making. The first phase involves implementing adjustment rule for non-cooperative decision-makers. The second phase involves applying adjustment rule for cooperative decision-makers. Finally, this study presents a case study focusing on the selection of a new energy vehicle enterprise supplier to illustrate the effectiveness of the proposed model in real-world applications. Furthermore, sensitivity analysis and comparative assessments are conducted to demonstrate advantages over traditional methods. Results indicate that the proposed method enhances both satisfaction and consensus levels compared to conventional non-cooperative consensus-reaching mechanisms.

1. Introduction

Group decision making (GDM) is a process in which multiple decision makers(DMs) evaluate alternatives and reach a certain threshold of consensus through feedback mechanism [1]. To represent decision information, fuzzy linguistic models are widely utilized due to their ability to handle uncertainty [2], including 2-tuple linguistic model [3], hesitance linguistic term set [4], numerical scale-based fuzzy model [5–7]. In the consensus-reaching process (CRP), DMs' heterogeneity and bounded rationality have drawn attention to behavioral modeling [8–12], focusing on aspects like trust relationship [13–15], altruism preference [16], non-cooperative behavior [17–20]. The presence of non-cooperative behavior can lead to group consensus failure, and result in invalidated decision outcomes. However, there is no uniform definition of non-cooperative behavior in the existing studies, and the psychological motivations remain unexplored. In addition, the current feedback mechanism for non-cooperative behavior management lacks consideration for satisfaction, which is essential for fostering long-term cooperation. For instance, in the context of supplier selection, reaching a consensus at the expense of DM's satisfaction can negatively impact the stability of the supply chain. Therefore, this study aims to propose a novel feedback mechanism to effectively manage the non-cooperative behavior with the consideration of DMs' satisfaction

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and personality traits, addressing the following two research questions and challenges.

The first research challenge is to define and identify the non-cooperative behavior. In existing studies, non-cooperative behavior is often identified by DMs making only minor modifications [19–22] or deviating from the recommendations [23]. For instance, Shen et al. [17] categorized non-cooperative behaviors into three types based on the index of willingness to cooperate, determined by opinion similarity and trust levels. Liao et al. [18] defined cognitive and weight conflict based on the distance deviation and weight deviation between DMs' opinions and the collective, identifying non-cooperative behaviors by comparing these conflicts to subjective thresholds. However, each DM exhibits potential non-cooperative behavior, as the choice between cooperative and non-cooperative strategies is dynamic [24]. Non-cooperative behavior often emerges when decision outcomes or suggested adjustments are perceived as unacceptable. The shift is influenced by psychological factor. A body of literature explores the relationship between external behavior and personality traits [25–27]. Personality traits influence DMs' behavior, thereby impacting the decision-making process [28,29]. Jian et al. [29] posits that variations in personality traits affect investors' risk aversion, social interaction tendencies, and portfolio allocation, influencing investment decisions. Regarding cooperative and non-cooperative behavior, according to the Big Five personality traits theory, individuals with high Agreeableness degree are more willing to cooperate with others [30–32]. Consequently, defining non-cooperative behavior based on personality traits, thereby exploring the influence of personality traits on GDM process constitutes the first challenge of this study.

The second challenge is developing a feedback mechanism to manage non-cooperative behavior, which impacts the cost of consensus reaching [33]. Management approaches for non-cooperative behaviors in the existing literature mainly include weight penalty [34–37] and opinion adjustment [23,38]. The weight penalty method reduces non-cooperative DMs' weights or excludes them from the CRP. However, given the importance of fairness in decision-making processes for DMs, directly diminishing weights can significantly reduce satisfaction and may hinder consensus. The opinion adjustment approach faces challenges in determining appropriate parameters. Du et al. [38] determine adjustment parameters based on consensus level and trust, but they overlook DMs' acceptance of these parameters. What is more, the conventional feedback mechanism focused only on reaching consensus, while neglect DMs' satisfaction. The weight penalty approach sacrifices the weights and consensus levels of non-cooperative DMs, leading to dissatisfaction. Given the bounded rationality model, a satisfactory decision, rather than an optimized decision, is a more reasonable objective in group decision problems [39]. Existing studies that consider DMs' satisfaction levels measure it based on the level of consensus [40,41], subjectively provided by DMs [42] or behavioral characteristics [43]. However, these studies assume that the satisfaction changes linearly. The satisfaction level of DMs in decision-making is closely linked to their personality traits and perception of losses, which do not always follow a linear pattern. Some DMs are highly dissatisfied with minimal losses, while others accept significant losses to reach consensus. Therefore, managing non-cooperative behavior to maximize satisfaction and establishing an effective measure of satisfaction in the CRP is the second challenge of this study.

A review of the literature reveals that the shortcomings of the existing research of non-cooperative behavior management can be summarized as :

1. Instead of measuring the threshold at which cooperative behavior shifts to non-cooperative behavior for DMs, existing studies are dedicated to identifying non-cooperative DMs. The reason is that existing studies ignore the psychological motivation behind non-cooperative behavior. Different DMs have different shift thresholds according to their personality traits. Thus, a novel identification method for non-cooperative behavior based on personality traits needs to be considered.

2. Due to the bounded rationality of non-cooperative behavior in group decision-making, there is a significant drawback in the feedback mechanisms of existing research, which have ignored the satisfaction objective. Thus, novel feedback mechanisms for non-cooperative behavior management in GDM that ensure maximum satisfaction for all DMs need to be studied. To achieve this, the measurement of satisfaction level based on personality traits must be considered.

For the above issues, this paper proposes a maximum satisfaction feedback mechanism for non-cooperative behavior with Big Five personality traits. The main contributions are as follows:

1. A personality traits-based non-cooperative behavior identification method is proposed. By comparing the maximum acceptable adjustment based on personality traits with the minimum adjustment required to reach consensus, the threshold for triggering non-cooperative behavior in decision-makers can be more reasonably defined, revealing the psychological mechanism underlying non-cooperative behavior.

2. A novel maximum satisfaction-based feedback mechanism for managing non-cooperative behavior is constructed. To do that, a novel method for measuring satisfaction levels based on personality traits is investigated. what is more, a novel two-phase adjustment rule and a Maximum Satisfaction Level Model (MSLM) are introduced to manage non-cooperative behavior and prevent satisfaction loss. The proposed method prioritizes satisfaction as the objective of the CRP, aligning more closely with the bounded rationality and strategic characteristics of non-cooperative behavior in GDM. The results demonstrate that, compared with existing methods, the proposed approach can achieve both individual and global consensus among all DMs while ensuring minimal loss of group satisfaction.

The reminder of this paper is organized as follows: Section 2 provides some preliminaries about this study; Section 3 introduces the satisfaction-based feedback mechanism in detailed, which mainly involves Agreeableness trait prediction, non-cooperative DMs detection, maximum satisfaction-based feedback mechanism; to demonstrate the practicality of the proposed method, an illustrative case study is provided in Section 4; the discussions highlighting the method advantages and robustness provided in Section 5. Finally, Section 6 summarizes the paper with a conclusion.

2. Preliminary

This section will introduce basic concepts and knowledge related to the 2-tuple linguistic model and the consensus reaching process.

2.1. 2-Tuple linguistic representation model

In some decision-making situations, it is difficult for experts to use precise numerical values to evaluate the alternatives, while the fuzzy linguistic methods can provide effective results. The 2-tuple linguistic representation model was first proposed by Herrera [3] for compute with words. The definitions are as follows.

Definition 1 (*2-tuple linguistic representation model [3]*). Let $S = \{s_0, \dots, s_g\}$ be a linguistic term set, and $u \in [0, g]$ a value representing the result of a symbolic aggregation operation. Then the transformation function between u and 2-tuple linguistic model is defined as:

$$\begin{aligned} &\Delta : [0,g] \rightarrow S \times [-0.5, 0.5) \\ &\Delta(u) = (s_t, \alpha), with \begin{cases} s_t, t = round(u) \\ \alpha = u - t, \alpha \in [-0.5, 0.5) \end{cases} \end{aligned} \tag{1}$$

where (s_t, α) is the 2-tuple linguistic representation of u. Additionally, the inverse function of Δ is defined as $\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g]$ with $\Delta^{-1}(s_t, \alpha) = t + \alpha = u$.

In this study, let $S = \{s_0 = Extremely\ Poor, s_1 = Very\ Poor, s_2 = Poor, s_3 = Little\ Poor, s_4 = Medium, s_5 = Little\ Good, s_6 = Good, s_7 = Very\ Good, s_8 = Extremely\ Good\}$ be the linguistic term set for DMs to evaluate the alternatives.

2.2. Consensus reaching process

The CRP is a process in which inconsistent DMs reach a certain threshold level of consensus through a feedback mechanism in GDM, specifically involving consensus measurement and feedback adjustment process [44]. The GDM problem is described as follows: Let $X = \{x_1, \ldots, x_n\}$ be the set of alternatives; $D = \{d_1, \ldots, d_p\}$ be the set of DMs, d_k represents kth DM; $A = \{a_1, \ldots, a_m\}$ be the set of attributes; $L_k = (l_{ij,k})_{n\times m}$ be 2-tuple linguistic decision matrix (LDM) provided by d_k , where $l_{ij,k} = \{(s_t, \alpha), t = 1, \ldots, g\}$ represents the decision opinions of alternative i for attribute j; $\omega = \{\omega_1, \ldots, \omega_p\}$ be the set of weights of DMs, where satisfies $\omega_k > 0, k = (1, \ldots, p)$ and $\sum_{k=1}^{p} \omega_k = 1$.

Definition 2 (*Collective Decision Opinion*)**.** The collective LDM $L^c = (l^c_{ij})_{n\times m}$ using Weight Average(WA) operator is defined as:

$$\Delta^{-1}(l^c_{ij}) = \Delta^{-1}(\sum_{k=1}^{p} \omega_k \cdot \Delta^{-1}(l_{ij,k})) \tag{2}$$

Definition 3 (*Individual Consensus Level*)**.** Let $\overline{L}_k = (\bar{l}_{ij,k})_{n\times m}$ be the adjusted LDM of $d_k, k = (1, \ldots, p)$. The individual consensus level measures the distance between the DMs' decision opinions and collective decision opinions . It can be calculated by

$$ICL_k = 1 - \frac{1}{mn} \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{\left| \Delta^{-1}(\bar{l}_{ij,k}) - \Delta^{-1}(\bar{l}^c_{ij}) \right|}{g} \tag{3}$$

where $0 \le ICL_k \le 1$. It can reflect the consensus level of d_k. A higher ICL_k value indicates a higher consensus level of d_k.

Definition 4 (*Global Consensus Level*)**.** The Global Consensus level can reflect the overall consensus level of a group. It can be obtained by

$$GCL = \sum_{k=1}^{b} \omega_k \cdot ICL_k \tag{4}$$

where $0 \le GCL \le 1$, ω_k is the weight of d_k. The greater GCL, the higher consensus level of group.

3. Maximum satisfaction feedback mechanism with personality prediction

In real-world decision-making, it is inevitable that decision-makers will exhibit non-cooperative behavior. This section proposes a method to identify non-cooperative behavior with personality prediction and Two-phase satisfaction-based feedback mechanism to manage non-cooperative behavior. The Agreeableness degree of DMs is predicted to determine the maximum acceptable adjustment for each DM, which helps identify the non-cooperative DMs in Minimum Adjustment Consensus Model (MACM). The proposal of a novel adjustment rule and a maximum satisfaction level model fully considers the satisfaction of both cooperative and non-cooperative DMs in the CRP. The method is mainly divided into three parts: Data collection, Agreeableness prediction, Consensus Reaching Process (CRP) (shown in Fig. 1). The proposed two-stage consensus feedback mechanism facilitates the consensus reaching and reduces dissatisfaction.

Part 1. Data collection. The microblog online texts of DMs are crawled by Python using their IDs and translated into English.

Part 2. Agreeableness trait prediction. The Agreeableness degree of DMs is obtained by CNN-BiLSTM by feeding in their microblog texts. It determines the maximum acceptable adjustment for the DM, indicating the threshold at which the DM transitions from cooperative to non-cooperative behavior.

Part 3. Consensus Reaching Process. This part aims to obtain a decision outcome that satisfies all parties of GDM. The identification method for non-cooperative behavior with Agreeableness degree is investigated. A novel feedback mechanism based on maximum satisfaction level of DMs is proposed to manage non-cooperative behavior.

Table 1
The Big Five personality traits [30].

The Big Five personality traits	Facets
Extraversion	Talkative, social, assertive, active, gregarious
Neuroticism	Anxious, emotional, depressed, angry, worried, insecure
Agreeableness	Flexible, good-natured, trusting, cooperative,tolerant, forgiving, soft-hearted
Conscientiousness	Achievement-oriented, responsible, dependable,careful,thorough,organized
Openness	Intellectual, imaginative, curious,broad-minded, artistically sensitive

The point at which a decision-maker shifts from a cooperative to a non-cooperative stance is influenced by individual personality traits. This transition can be reasonably assessed by predicting the Agreeableness trait, which is the socialization dimension of the Big Five personality traits. Additionally, the proposed maximum satisfaction feedback mechanism considers the satisfaction and consensus levels of all DMs in the CRP, which ensures the stability and long-term cooperation of the group.

This section delineates the methods and procedures involved in the maximum satisfaction feedback mechanism with personality prediction for non-cooperative behavior management. The subsections describe the methods used in each part. The prediction steps of Agreeableness trait based on CNN-BiLSTM is expounded upon in Section 3.1. Section 3.2 introduces the method for identifying non-cooperative behavior with the minimum adjustment consensus model (MACM) and Agreeableness degree. Subsequently, Section 3.3 presents the two-phase maximum satisfaction feedback mechanism for the management of non-cooperative behavior, which involves a new adjustment rule and maximum satisfaction level model. Section 3.4 introduces the calculations of selecting process after the consensus has been reached. Finally, Section 3.5 outlines the detailed steps for the proposed method.

3.1. Agreeableness trait prediction

The Big Five personality traits theory is highly regarded as a comprehensive description of fundamental human traits, which categorizes personality into five dimensions: Openness, Agreeableness, Neuroticism, Conscientiousness, and Extraversion [30]. Each dimension comprises more specific facets, as presented in Table 1. In this study, the Agreeableness trait is used to determine the maximum adjustment amount for DMs, thereby identifying non-cooperative behavior and measuring the satisfaction level of DMs. Agreeableness is characterized by traits such as flexibility, good-naturedness, trust, cooperation, tolerance, forgiveness, and compassion. This dimension describes how cooperative and friendly an individual is in social interactions. People high in agreeableness prefer to cooperate and compromise with others, while those low in agreeableness are more likely to be competitive and self-centered.

As the Internet continues to evolve, an increasing number of individuals are engaging in online expression, including sharing opinions and reviews. This study aims to predict the probability of the DM's Agreeableness trait by analyzing their microblog texts collected from Weibo.com. The prediction value derived from online reviews is used to determine the upper bound of the adjustment coefficient, replacing the assumptions typically employed in existing studies. The prediction model is based on Convolutional Neural Networks (CNNs) and Bidirectional Long-Short Term Memory (BiLSTM) proposed by Rhea Mahajan et al. [45], which is trained utilizing the MyPersonality dataset. The dataset contains 9,917 Twitter online reviews from 250 users, each labeled with the Big Five personality traits. Deep learning methods provide relatively better accuracy by learning a large corpus with labels. Convolutional neural networks (CNNs) extract feature vectors by

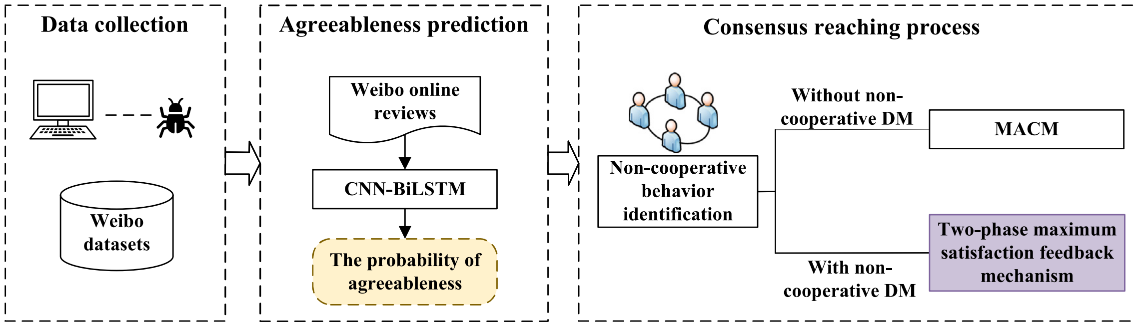

Fig. 1. The framework of proposed method.

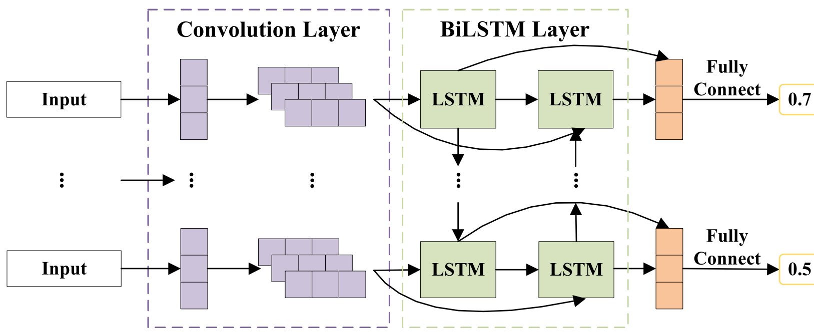

Fig. 2. CNN-BiLSTM.

Table 2
The parameters of the personality prediction model (CNN-BiLSTM).

Parameters	Value
Batch size	128
Convolution kernel size	3,5
Dropout	0.3
Learning rate	1e−4
Optimizer	Adam
Hidden activation	Sigmoid
epoch	50

sliding a convolution kernel across the input from top to bottom, allowing them to effectively capture shallow textual features through filters. However, CNNs are not sensitive to the order of words. In contrast, Bidirectional long-short term memory (BiLSTM) is particularly adept at capturing this information. The integration of CNNs and BiLSTMs enhances the overall capacity to capture comprehensive information within a sentence. The microblog texts of DMs are used as input, and the Agreeableness degree is obtained using the CNN-BiLSTM model, as shown in Fig. 2.

Using CNN-BiLSTM to predict personality traits mainly includes four processes: (1) Texts pre-processing, including abbreviation processing and case handling; (2) Texts vectorization. The text is converted into word vectors that can be recognized by computers; (3) Model training. The parameters of CNN-BiLSTM are shown in Table 2. Taking openness as an example, the accuracy is shown in Fig. 3; (4) Prediction. By feeding the DMs' microblog texts to the trained CNN-BiLSTM, The Agreeableness degree, denoted as $\varepsilon_k, (k = 1, \ldots, p)$ can be obtained.

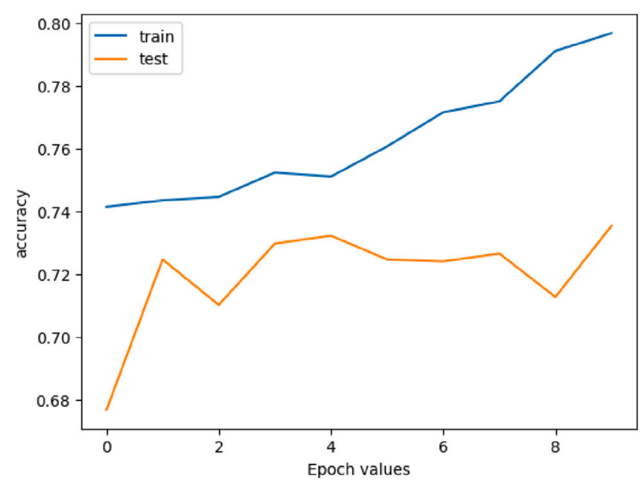

Fig. 3. The accuracy of prediction model.

3.2. Non-cooperative behavior detection

In the extant literature, a variety of methodologies for the identification of non-cooperative behavior have been proposed, with the specific approaches contingent upon the particular decision-making context. However, the non-cooperative behavior potentially exists in everyone, and is only manifested when the decision-making outcome is unacceptable. Whether an individual exhibits non-cooperative behavior is related to their personality traits. In this paper, the MACM model is initially employed to identify the minimum adjustment coefficient. If this coefficient exceeds the maximum acceptable level of the DM, as determined in Section 2, the DM is deemed to exhibit non-cooperative behavior. In such case, a two-phase maximum satisfaction feedback mechanism is employed in order to facilitate consensus. If the minimum adjustment coefficient obtained from MACM are acceptable, the opinions are adjusted accordingly for the DMs. The symbols used in the article and their meanings are shown in Table 3.

3.2.1. Minimum adjustment consensus model (MACM) with agreeableness degree

MACM demonstrates its advantages in many ways as an effective consensus feedback mechanism to prevent too much adjustment. In this paper, the minimum adjustment coefficient to reach a consensus is obtained by MACM, which is employed to identify the non-cooperative behavior. Let θ_k be the adjustment coefficient of $d_k, k=(1,\ldots,p)$; ε_k be the Agreeableness degree obtained from Section 3.1, which means the maximum acceptable adjustment of d_k; ω_k be the weight of d_k; $l_{ij,k}$ be the initial opinion provided by d_k; $\bar{l}_{ij,k}$ be the adjusted opinion for d_k; l^c_{ij} be the collective opinion . Thus, the MACM considering Agreeableness degree of DMs is denoted as follows

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{p}\frac{\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij,k})\right|}{g}$$
$$s.t.\begin{cases}\bar{l}_{ij,k}=\Delta((1-\theta_k)\cdot\Delta^{-1}(l_{ij,k})+\theta_k\cdot\Delta^{-1}(l^c_{ij})) & ((5)-1)\\ l^c_{ij}=\Delta(\sum_{k=1}^{p}\omega_k\cdot\Delta^{-1}(l_{ij,k})) & ((5)-2)\\ 1-\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij})\right|}{g}\geq\gamma & ((5)-3)\\ 0\leq\theta_k\leq\varepsilon_k & ((5)-4)\end{cases}\tag{5}$$

In Model (5), the decision variables are the adjustment coefficients of d_k, denoted as θ_k. Constraint(5-1) defines the adjustment rule for DMs; constraint(5-2) calculates the collective opinions; constraint(5-3) measures the consensus level; lastly, constraint (5-4) stipulates that the adjustment coefficient must not exceed the maximum acceptable adjustment threshold.

Proposition 1. *Model (5) can be transformed into a linear programming model.*

Proof. Let $\alpha_{ij,k}=\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij,k})\right|$, then we have $\alpha_{ij,k}\geq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij,k})$ and $\alpha_{ij,k}\leq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij,k})$. Similarly, let $\zeta_{ij,k}=\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij})\right|$, then we have $\zeta_{ij,k}\geq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij})$ and $\zeta_{ij,k}\leq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij})$. Thus, Model (5) can transform into the linear model as follows

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{p}\frac{\alpha_{ij,k}}{g}$$
$$s.t.\begin{cases}\alpha_{ij,k}\geq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij,k}) & ((6)-1)\\ \alpha_{ij,k}\leq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij,k}) & ((6)-2)\\ \bar{l}_{ij,k}=\Delta((1-\theta_k)\cdot\Delta^{-1}(l_{ij,k})+\theta_k\cdot\Delta^{-1}(l^c_{ij})) & ((6)-3)\\ l^c_{ij}=\Delta(\sum_{k=1}^{p}\omega_k\cdot\Delta^{-1}(l_{ij,k})) & ((6)-4)\\ 1-\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\zeta_{ij,k}}{g}\geq\gamma & ((6)-5)\\ \zeta_{ij,k}\geq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij}) & ((6)-6)\\ \zeta_{ij,k}\leq\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij}) & ((6)-7)\\ 0\leq\theta_k\leq\varepsilon_k & ((6)-8)\end{cases}\tag{6}$$

where constrains(6-1)(6-2) transform the objective function into linear functions; constrains(6-5), (6-6) and (6-7) ensure that $1-1/mn\sum_{i=1}^{n}\sum_{j=1}^{m}\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij})\right|/g\geq\gamma$. □

Proposition 2. $\theta_k=1-\frac{1-\gamma}{\frac{1}{mng}\sum_{i=1}^{n}\sum_{j=1}^{m}\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij})\right|}$ *is the minimum adjustment of* d_k *in Model (5).*

Proof. To simplify the proof, let $dis_k=\frac{1}{mng}\sum_{i=1}^{n}\sum_{j=1}^{m}\left|\Delta^{-1}(l_{ij,k})-\Delta^{-1}(l^c_{ij})\right|$. Notice that the constrain $1-\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l^c_{ij})\right|}{g}\geq\gamma$ and $\bar{l}_{ij,k}=\Delta((1-\theta_k)\cdot\Delta^{-1}(l_{ij,k})+\theta_k\cdot\Delta^{-1}(l^c_{ij}))$. There is

$$\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\left|(1-\theta_k)\cdot\Delta^{-1}(l_{ij,k})+\theta_k\cdot\Delta^{-1}(l^c_{ij})-\Delta^{-1}(l^c_{ij})\right|}{g}\leq1-\gamma$$
$$\to\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\left|\Delta^{-1}(l_{ij,k})-\Delta^{-1}(l^c_{ij})-\theta_k\cdot(\Delta^{-1}(l_{ij,k})-\Delta^{-1}(l^c_{ij}))\right|}{g}\leq1-\gamma$$

Table 3
The meaning of symbols.

Symbols	Meaning
$L_k=(l_{ij,k})_{n\times m}$	Initial LDM of d_k
$\overline{L}_k=(\bar{l}_{ij,k})_{n\times m}$	Adjusted LDM of d_k
$L^c=(l^c_{ij})_{n\times m}$	Collective LDM
$L_h=(l_{ij,h})_{n\times m}$	Initial LDM of cooperative DM d_h
$L_l=(l_{ij,l})_{n\times m}$	Initial LDM of non-cooperative DM d_l
$\overline{L}_h=(\bar{l}_{ij,h})_{n\times m}$	Adjusted LDM of cooperative DM d_h
$\overline{L}_l=(\bar{l}_{ij,l})_{n\times m}$	Adjusted LDM of non-cooperative DM d_l
$\overline{L}_l^{\,c}=(\bar{l}^c_{ij,l})_{n\times m}$	Collective LDM of non-cooperative DM
$\overline{L}^c_l=(\bar{l}^c_{ij,l})_{n\times m}$	Adjusted collective LDM
CS	Cooperative DMs set
NS	Non-cooperative DMs set
ω_k	Weight of d_k
ε_k	Agreeableness degree of d_k
γ	Consensus threshold

According to the triangle inequality theorem, there is

$$\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\left|\Delta^{-1}(l_{ij,k})-\Delta^{-1}(l^c_{ij})-\theta_k\cdot(\Delta^{-1}(l_{ij,k})-\Delta^{-1}(l^c_{ij}))\right|}{g}$$
$$\geq\frac{1}{mng}\sum_{i=1}^{n}\sum_{j=1}^{m}\left|\Delta^{-1}(l_{ij,k})-\Delta^{-1}(l^c_{ij})\right|$$
$$-\theta_k\cdot\frac{1}{mng}\sum_{i=1}^{n}\sum_{j=1}^{m}\left|\Delta^{-1}(l_{ij,k})-\Delta^{-1}(l^c_{ij})\right|$$
$$\Rightarrow dis_k-\theta_k\cdot dis_k\leq1-\gamma$$
$$\Rightarrow\theta_k\geq\frac{dis_k-1+\gamma}{dis_k}=1-\frac{1-\gamma}{dis_k}\quad\square$$

Note:

Given that the adjustment coefficient θ_k should not exceed the maximum acceptable adjustment ε_k of d_k, the solution of Model (5) can be classified into the following cases:

(1) When $\theta_k\leq\varepsilon_k$, the adjustment is accepted by d_k, the optimal solution is $\theta^*_k=1-(1-\gamma)/dis_k$.

(2) When $\theta_k>\varepsilon_k$, the adjustment needs to exceed the maximum acceptable adjustment of d_k in order to reach a consensus. In this cases, d_k will move from cooperation to non-cooperation.

3.2.2. Non-cooperative behavior identification

Each DM potentially exhibits some degree of non-cooperative behavior, which becomes evident only when the decision outcome is unacceptable. An individual's willingness to cooperate is reflected in their Agreeableness trait, with those exhibiting higher Agreeableness being more predisposed to cooperation. Therefore, this study identifies non-cooperative behavior by comparing Agreeableness degree(determined in section 3.1) and the minimum adjustment(obtained from MACM) to reach a consensus.

Definition 5. Given that a DM has a finite amount of acceptable adjustments, there may be instances where they cannot reach consensus even after making the maximum acceptable adjustment, thus being regarded as exhibiting non-cooperative behavior. The maximum acceptable adjustment is determined by Agreeableness degree, denoted as ε_k. The minimum adjustment required to reach consensus, denoted as θ^*_k, is obtained from 3.2.1. The non-cooperative behavior in group consensus reaching process can be defined as follows:

$$\theta^*_k>\varepsilon_k\tag{7}$$

which implies that although d_k has been adjusted to its maximum ε_k, the consensus level remains below the established consensus threshold. People with higher Agreeableness are less likely to be non-cooperative DM. The non-cooperative DMs form the sets $NS=\{l|\theta^*_l>\varepsilon_l\}$ and cooperative DMs form the sets $CS=\{h|h\in DS\cap h\notin NS\}$. If non-cooperative behavior exists, the MSLM in section 3.4 be employed for managing non-cooperative behavior.

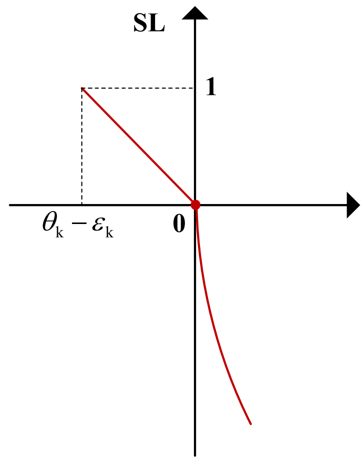

Fig. 4. The satisfaction function.

3.3. Maximum satisfaction-based feedback mechanism

This section proposes a satisfaction measure that considers personality traits and adjustment, and then proposes a maximum satisfaction level model (MSLM) which considers DMs' satisfaction level to enable non-cooperative DMs to reach consensus.

3.3.1. Satisfaction function with personality

Most of the satisfaction measures in the existing literature are related to the consensus level, but the acceptability of their adjustment amount, influenced by their personality, also affects satisfaction. Consequently, this study proposes a novel satisfaction measurement method, considering behavioral and psychological factors. Specifically, the maximum acceptable adjustment amount for each DM is determined based on their Agreeableness trait. The satisfaction function for decision-makers is divided into two segments (depicted in Fig. 4). For the first segment, which falls within the maximum acceptable adjustment range of the DM, the change in satisfaction should be gradual and show linear pattern. In contrast, for the second segment, where adjustments exceed the maximum acceptable threshold, change in satisfaction should be more pronounced.

Definition 6. Let θ_k be the adjust coefficient of d_k, and ε_k represents the Agreeableness degree which specifies the maximum acceptable adjustment for d_k. The satisfaction of d_k is defined as follows:

$$SLO_k = \begin{cases} -\frac{\theta_k-\varepsilon_k}{\varepsilon_k}, \theta_k - \varepsilon_k \le 0 \\ -\lambda(\frac{\theta_k-\varepsilon_k}{\varepsilon_k})^{\beta}, \theta_k - \varepsilon_k > 0 \end{cases} \quad (8)$$

where $SLO_k \in (-\infty, 1], \theta_k, \varepsilon_k \in [0, 1]$.

Note:

(1) When $\theta_k - \varepsilon_k \le 0$, it indicates that opinions are adjusted within the DM's acceptability range, and then the satisfaction level function changes linearly. A smaller Agreeableness degree indicates the DM is more sensitive to opinion adjustments, leading to a faster decrease in satisfaction.

(2) When $\theta_k - \varepsilon_k > 0$, it means that the adjustment beyond the DM's acceptable range, resulting in a dramatic change in their satisfaction level. β represents the altitude to loss and satisfies $0 < \beta < 1$. In this paper, β is related to the DM's Agreeableness degree. A lower Agreeableness degree (ε_k), implies higher sensitivity to changes in opinions and consequently lower satisfaction SLO_k, which can be represented as $\beta = \varepsilon_k$. Additionally, λ is loss aversion coefficient, set at $\lambda = 2.25$, which reflects the degree of aversion to losses for the DM. A larger coefficient indicates a higher level of loss aversion, leading to a greater decrease in satisfaction with adjustment opinion.

3.3.2. Two-phase maximum satisfaction feedback mechanism

The traditional feedback mechanism makes the experts who have not reached consensus move to the consensus center with optimization models. However, DMs with non-cooperative behaviors can lead to a failure of consensus. Chen et al. [46] pointed out that when there are stubborn DMs in a decision-making environment, where suggestive DMs adjust to align with stubborn DMs to reach consensus. Based on this, a more reasonable adjustment rule is proposed, focusing on adjusting to stubborn experts rather than the traditional consensus center, leading to a two-phase maximum satisfaction feedback mechanism. In phase 1, the non-cooperative DMs who have not met the consensus threshold adjust toward the consensus center, which is the fastest adjustment direction to reach consensus. However, due to the limitations of their maximum acceptable adjustment, consensus may still not be achieved. In such cases, phase 2 is implemented, where cooperative DMs adjust their opinions to non-cooperative DMs. The second rule shifts the adjustment center towards the non-cooperative DMs instead of consensus center, thereby facilitating consensus among them. This process considers the consensus levels of both non-cooperative and cooperative DMs, ensuring that each DM's consensus level meets the threshold through different adjustment rules. The detail of adjustment rule is shown in Fig. 5.

Phase 1:Non-cooperative DMs adjustment rule

For non-cooperative DMs, adjustments are made toward the consensus center up to their maximum acceptable adjustment. Let $l_{ij,l}$ be the initial opinion provided by $d_l, (l \in NS)$ which exhibits non-cooperative behavior. The adjustment rule for d_l can computed by

$$\bar{l}_{ij,l} = \Delta((1-\varepsilon_l)\cdot\Delta^{-1}(l_{ij,l}) + \varepsilon_l\cdot\Delta^{-1}(l^c_{ij})) \quad (9)$$

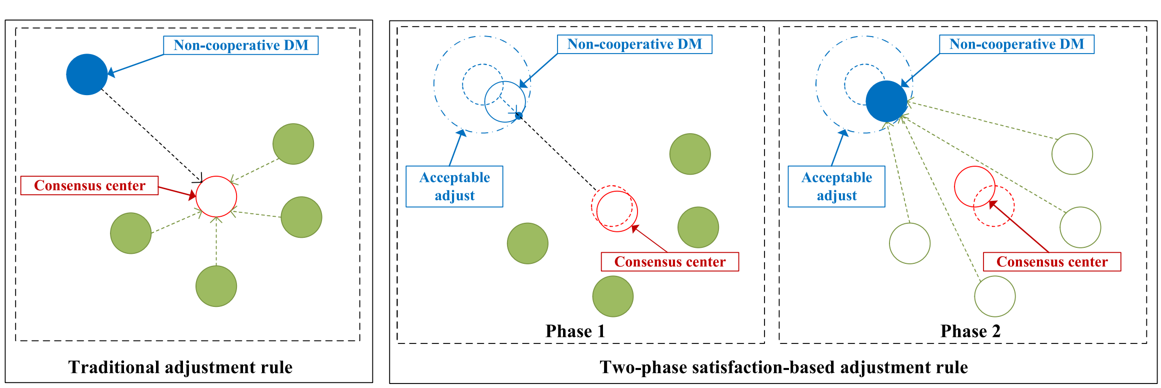

Fig. 5. Adjustment Rule.

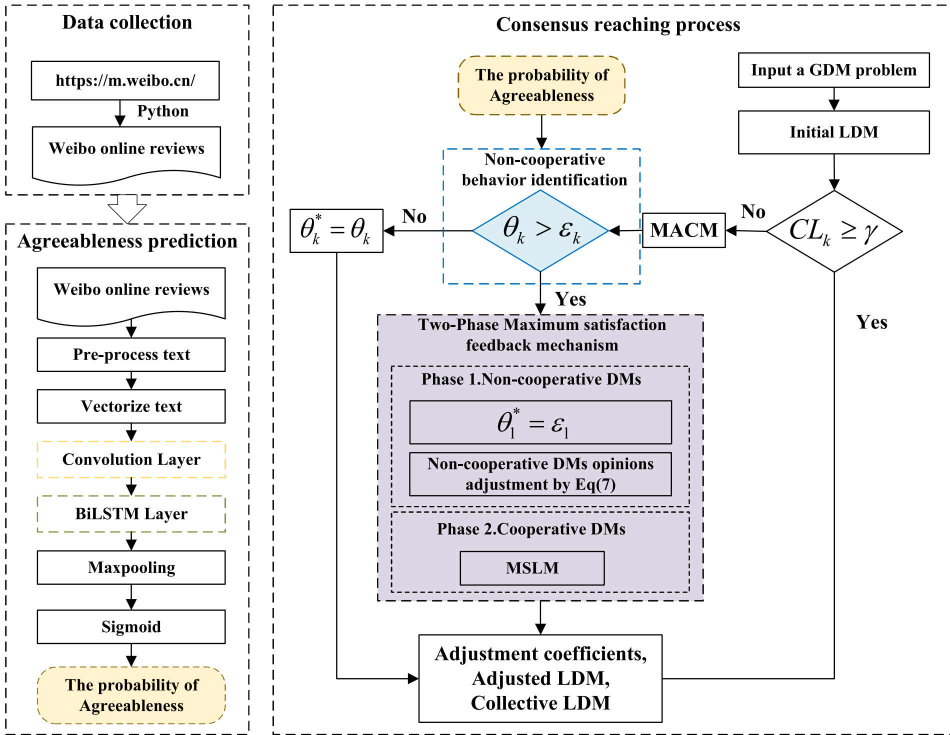

Fig. 6. The detailed framework of proposed method.

Since non-cooperative decision makers cannot reach consensus even when adjusted to the maximum adjustment, it becomes necessary for those who are cooperative to make the requisite adjustments.

Phase 2:Cooperative DMs adjustment rule

For cooperative DMs, adjusts his/her opinions in the direction of the non-cooperative DM instead of the consensus center. If there are more than one non-cooperative DM, adjustments are made toward the center of their opinions. Let θ_k be the adjustment coefficient and $l_{ij,h}$ be the initial opinion provided by $d_h, (h \in CS)$, where d_h is a cooperative DM. The adjustment rule for cooperative DMs is defined as follows

$$\bar{l}_{ij,h} = \Delta((1-\theta_h)\cdot\Delta^{-1}(l_{ij,h}) + \theta_h\cdot\Delta^{-1}(\bar{l}^c_{ij,l})) \tag{10}$$

Additionally, $\bar{l}^c_{ij,l}$ represents the collective opinion of non-cooperative DMs, and can be calculated by

$$\Delta^{-1}(\bar{l}^c_{ij,l}) = \Delta^{-1}(\frac{1}{q}\sum_{l=1}^{q}\Delta^{-1}(\bar{l}_{ij,l})) \tag{11}$$

The adjustment coefficient θ_k can be calculated by Maximum Satisfaction Level Model (MSLM) expressed as model (12).

$$\max \sum_{h=1}^{p-q} SLO_h = -\frac{\theta_h - \varepsilon_h}{\varepsilon_h}$$

$$s.t.\begin{cases}\bar{l}_{ij,h} = \Delta((1-\theta_h)\cdot\Delta^{-1}(l_{ij,h}) + \theta_h\cdot\Delta^{-1}(\bar{l}^c_{ij,l})) & ((12)-1)\\ \bar{l}^c_{ij,l} = \Delta(\frac{1}{q}\sum\limits_{l=1,l\in NS}^{q}\Delta^{-1}(\bar{l}_{ij,l})) & ((12)-2)\\ 1-\frac{1}{mn}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}\frac{\left|\Delta^{-1}(\bar{l}_{ij,l})-\Delta^{-1}(\bar{l}^c_{ij})\right|}{g}\geq\gamma & ((12)-3)\\ 1-\frac{1}{mn}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}\frac{\left|\Delta^{-1}(\bar{l}_{ij,h})-\Delta^{-1}(\bar{l}^c_{ij})\right|}{g}\geq\gamma & ((12)-4)\\ \bar{l}^c_{ij} = \Delta(\sum\limits_{h=1,h\in CS}^{p-q}\omega_h\cdot\Delta^{-1}(\bar{l}_{ij,h}) + \sum\limits_{l=1,l\in NS}^{q}\omega_l\cdot\Delta^{-1}(\bar{l}_{ij,l})) & ((12)-5)\\ 0\leq\theta_h\leq\varepsilon_h & ((12)-6)\end{cases} \tag{12}$$

Constraints (11-1) (11-2) represent the cooperative DMs' opinion adjustment rules; (11-3)-(11-5) denote the consensus level constraints, ensuring that both cooperative and non-cooperative experts are required to reach a certain threshold consensus level; and (11-6) specifies the bounds for the adjustment coefficient of cooperative DMs.

Proposition 3. *MSLM (12) can be transformed into a linear programming model.*

Proof. Same as **Proposition** 1, let $\mu_{ij,l} = \left|\Delta^{-1}(\bar{l}_{ij,l}) - \Delta^{-1}(\bar{l}^c_{ij})\right|$ and $v_{ij,h} = \left|\Delta^{-1}(\bar{l}_{ij,h}) - \Delta^{-1}(\bar{l}^c_{ij})\right|$. Thus, the MSLM (12) can be transformed into the linear programming model as follows

$$\max \sum_{h=1}^{p-q} SLO_h = -\frac{\theta_h - \varepsilon_h}{\varepsilon_h}$$

$$s.t.\begin{cases}\bar{l}_{ij,h} = \Delta((1-\theta_h)\cdot\Delta^{-1}(l_{ij,h}) + \theta_h\cdot\Delta^{-1}(\bar{l}^c_{ij,l})) & ((13)-1)\\ \bar{l}^c_{ij,l} = \Delta(\sum\limits_{l=1,l\in NS}^{q}\omega_l\cdot\Delta^{-1}(\bar{l}_{ij,l})) & ((13)-2)\\ 1-\frac{1}{mn}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}\frac{\mu_{ij,l}}{g}\geq\gamma & ((13)-3)\\ \mu_{ij,l}\geq\Delta^{-1}(\bar{l}_{ij,l})-\Delta^{-1}(\bar{l}^c_{ij}) & ((13)-4)\\ \mu_{ij,l}\leq\Delta^{-1}(\bar{l}_{ij,l})-\Delta^{-1}(\bar{l}^c_{ij}) & ((13)-5)\\ 1-\frac{1}{mn}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}\frac{v_{ij,h}}{g}\geq\gamma & ((13)-6)\\ v_{ij,h}\geq\Delta^{-1}(\bar{l}_{ij,h})-\Delta^{-1}(\bar{l}^c_{ij}) & ((13)-7)\\ v_{ij,h}\leq\Delta^{-1}(\bar{l}_{ij,h})-\Delta^{-1}(\bar{l}^c_{ij}) & ((13)-8)\\ \bar{l}^c_{ij} = \Delta(\sum\limits_{h=1,h\in CS}^{p-q}\omega_h\cdot\Delta^{-1}(\bar{l}_{ij,h}) + \sum\limits_{l=1,l\in NS}^{q}\omega_l\cdot\Delta^{-1}(\bar{l}_{ij,l})) & ((13)-9)\\ 0\leq\theta_h\leq\varepsilon_h & ((13)-10)\end{cases} \tag{13}$$

where constraints (13-3), (13-4) and (13-5) ensure that $1 - 1/mn\sum_{i=1}^{n}\sum_{j=1}^{m}\left|\Delta^{-1}(\bar{l}_{ij,l}) - \Delta^{-1}(\bar{l}^c_{ij})\right|/g \geq \gamma$ are equivalent with (11-3); constraints (13-6), (13-7) and (13-8) guarantee that $1 - 1/mn\sum_{i=1}^{n}\sum_{j=1}^{m}\left|\Delta^{-1}(\bar{l}_{ij,h}) - \Delta^{-1}(\bar{l}^c_{ij})\right|/g \geq \gamma$. So MSLM (12) can be converted into Model (13). □

Given that the maximum adjustment of cooperative DMs is limited, constraint(12-3) and (12-4) may conflict with constraint (12-6), resulting in MSLM (12) having no feasible domain. This study employs Model (14) to determine whether MSLM (12) has a feasible solution, which is shown as follows:

$$\min \sum_{h=1}^{p-q} \eta_h$$
$$s.t.\begin{cases} \bar{l}_{ij,h} = \Delta((1-\theta_h)\cdot \Delta^{-1}(l_{ij,h}) + \theta_h \cdot \Delta^{-1}(\bar{l}^{c}_{ij,l})) & ((14)-1)\\ \bar{l}^{c}_{ij,l} = \Delta(\frac{1}{q}\sum\limits_{l=1,l\in NS}^{q} \Delta^{-1}(\bar{l}_{ij,l})) & ((14)-2)\\ 1-\frac{1}{mn}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}\frac{\left|\Delta^{-1}(\bar{l}_{ij,l})-\Delta^{-1}(\bar{l}^{c}_{ij})\right|}{g} \geq \gamma & ((14)-3)\\ 1-\frac{1}{mn}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}\frac{\left|\Delta^{-1}(\bar{l}_{ij,h})-\Delta^{-1}(\bar{l}^{c}_{ij})\right|}{g} \geq \gamma & ((14)-4)\\ \bar{l}^{c}_{ij} = \Delta(\sum\limits_{h=1,h\in CS}^{p-q}\omega_h\cdot\Delta^{-1}(\bar{l}_{ij,h}) + \sum\limits_{l=1,l\in NS}^{q}\omega_l\cdot\Delta^{-1}(\bar{l}_{ij,l})) & ((14)-5)\\ 0\leq \theta_h \leq \varepsilon_h + \eta_h & ((14)-6)\\ \eta_h \geq 0 & ((14)-7) \end{cases} \tag{14}$$

Proposition 4. *If $\eta_h = 0, (h \in CS)$, MSLM (12) has a feasible solution.*

Proof. Let $\{\bar{l}^{*}_{ij,h}, \bar{l}^{c*}_{ij}, \theta^{*}_{k}\}$ be the solution of Model (14). When $\eta_h = 0$, constraint(14-6) satisfies $0 \leq \theta^{*}_{k} \leq \varepsilon_k$, indicating that constraint(12-6) is satisfied.$\{\bar{l}^{*}_{ij,h}, \bar{l}^{c*}_{ij}\}$ satisfies constraints (14-1)-(14-5) in Model (14). It follows that $\{\bar{l}^{*}_{ij,h}, \bar{l}^{c*}_{ij}\}$ also satisfies constraints (12-1)-(12-5) in MSLM (12). Therefore, MSLM (12) has a feasible solution. □

Note:

If $\eta_h > 0$, it indicates that cooperative DMs, even after making maximum adjustments, are unable to reach the established consensus threshold. In this case, a degree of satisfaction level can only be sacrificed to reach consensus.

Based on Section 3.2 and 3.3, the proposed maximum satisfaction-based feedback method for managing non-cooperative behavior is shown in Algorithm 1.

3.4. Selection process

When the consensus level of each expert reaches the threshold, the selection process is entered. By calculating the evaluation score (ES) of the alternatives, the ranking of the alternatives is obtained, and then the optimal alternative is selected. Let ϖ_j be the weight of attribute j, then the ES for each alternative x_i can be calculated by

$$ES(x_i) = \sum_{j=1}^{n} \varpi_j \cdot \Delta^{-1}(\bar{l}^{c}_{ij}) \tag{15}$$

where $\varpi_j \in [0,1], j = (1,\ldots,n)$ and $\sum_{j=1}^{n}\varpi_j = 1$. The greater $ES(x_i)$, the higher ranking of x_i.

3.5. The detailed step of maximum satisfaction-based feedback mechanism

This subsection outlines the flow for the proposed maximum satisfaction-based feedback mechanism for managing non-cooperative behavior with personality prediction (depicted in Fig. 6). The mechanism mainly involves the following parts and steps:

Part 1: Data Collection

Step 1. Use Python to crawl microblog texts in Weibo.com of each DMs based on their IDs and then translate into English.

Algorithm 1: Consensus reaching process

Input: Initial LDM $L_k = (L_{ij,k})_{n\times m}, (k = 1,2,...,p)$, DMs' Agreeableness degree ε_k, Consensus threshold γ, DMs' weight ω_k

Output: Adjustment coefficient, Adjusted LDM , Collective LDM

begin
- **Consensus measure**;
- Using Eq. (2) and (3) to compute collective LDM and Individual consensus level ICL_k;
- **if** $ICL_k > \gamma$ **then**
  - Consensus has reached and output the collective LDM ;
- **else**
  - Move to the next process;
- **end**
- **Non-cooperative behavior identification**;
- **step 1.** Substitute $l_{ij,k}$, ω_k, γ into Model (5) ;
- **step 2. if** $\theta_k{}^{*} < \varepsilon_k$ **then**
  - Adjustment is within acceptable range. Then use Model (5) to get adjustment coefficient, adjusted LDM and collective LDM .
- **else**
  - Move to the next process;
- **end**
- **Non-cooperative behavior management**;
- **begin**
  - **step 1.** Use Eq (9) to get adjusted LDM $\bar{l}_{ij,l}$ of non-cooperative DMs.;
  - **step 2.** Calculate the collective LDM $\bar{l}^{c}_{ij,l}$ of NS by Eq (11).;
  - **step 3.** Substitute $l_{ij,h}$, $\bar{l}_{ij,l}$, $\bar{l}^{c}_{ij,l}$, ω_k, γ into MSLM (12) to obtain the adjustment coefficient θ_h, adjusted opinions and collective opinions .
- **end**
- Output adjustment coefficient, adjusted LDM and collective LDM .

end

Part 2: Agreeableness trait prediction

Step 2. Train prediction model with the parameters in [45].

Step 3. Pre-process texts, including abbreviation and case processing.

Step 4. Vectorize texts. Microblog texts of DMs will be transformed into word vectors.

Step 5. Input the processed texts into the trained model in Section 3.1 to obtain DMs' Agreeableness degree $\varepsilon_k, (k = 1,2,\ldots,b)$.

Part 3: Consensus Reaching Process

Step 6. Utilize the initial LDM provided by DMs and Eq (2) to obtain the collective LDM $L^c = (l^c_{ij})_{n\times m}$, and then use Eq (3) to measure the Individual Consensus Level ICL_k of d_k.

Step 7. Use Model (5) to get the minimum adjustment coefficient θ_k of d_k.

Step 8. Use Eq (7) to identify non-cooperative behavior. If it presents, move to Step 9; if not, θ_k in Step 7 is the adjustment coefficient of d_k. The adjusted LDM and collective LDM are also obtained in Step 7.

Step 9. Calculate the adjusted LDM $\bar{L}_l = (\bar{l}_{ij,l})_{n\times m}$ and the collective LDM $\bar{L}^{c}_{l} = (\bar{l}^{c}_{ij,l})_{n\times m}$ of non-cooperative DMs by Eq (9) and Eq (11).

Step 10. Substitute γ, λ, ε_k, ω_k, $l_{ij,h}$, $\bar{l}_{ij,1}$ into MSLM (12) to obtain adjust coefficient θ_h and adjusted collective LDM $\bar{L}^{c} = (\bar{l}^{c}_{ij})_{n\times m}$.

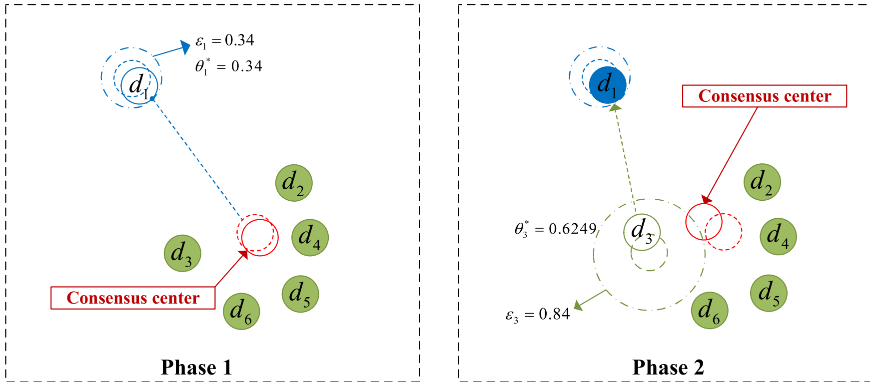

Fig. 7. The two-phase adjustment.

4. An illustrative example about new energy vehicle supplier selection

4.1. Background description

With the rapid development of human society, environmental and survival problems have become more and more significant, and the balance and stability of the global ecosystem are seriously threatened by the excessive emission of greenhouse gases. Responding to this challenge, the United Nations has established several conventions aimed at protecting the environment. China proposed the carbon peaking and carbon neutrality goals to achieve green, low-carbon energy development and address climate change. To achieve the goal of sustainable development, industries are actively promoting a low-carbon transition.

The new energy vehicle industry plays a pivotal role in addressing the challenges posed by conventional vehicle emissions and resource depletion. The rapid development of new energy vehicles not only provides people with environmentally friendly, convenient, economical and comfortable means of transportation, but also makes great contributions to controlling environmental pollution, combating climate change and promoting strategic energy transformation, which has become the focus of attention in the process of global economic development and strategic energy transformation.

Choosing high-quality and stable suppliers can realize the company's goal of reducing costs and increasing efficiency. Therefore, the selection of suppliers for new energy vehicle enterprises is very important for their operation and long-term development. The example of supplier selection for a top ten Chinese new energy vehicle company is taken to show the effectiveness of the method proposed in this paper. The senior managers of six management departments-production (d_1), purchasing (d_2), sales (d_3), management (d_4), operations (d_5), and finance (d_6)-provide their evaluation for suppliers noted as $X = \{x_1, x_2, x_3, x_4\}$. The DMs use the 2-tuple linguistic term set $S = \{s_0, \dots, s_8\}$ to provide their opinions, considering the following attributes: benefits (a_1), corporate credit level (a_2), green technology facilities (a_3), transportation efficiency (a_4), and quality of supply (a_5). These attributes are evaluated to inform the final selection of a supplier.

4.2. Numerical study

Part 1: Data collection.

Step 1. Crawl DMs' online Weibo(https://m.weibo.cn/) microblog texts and translate into English.

Part 2: Agreeableness trait prediction

Step 2. Utilize the model from Section 3.1 with DMs' online reviews to derive their Agreeableness degree as $\varepsilon_k = (0.34, 0.71, 0.84, 0.24, 0.52, 0.61)^T$.

Part 3: consensus reaching process

Step 3. Initial LDM provided by DMs for attribute a_j of alternative x_i are as follows:

$$L_1 = \begin{pmatrix} s_5 & s_0 & s_1 & s_6 & s_8 \\ s_4 & s_2 & s_4 & s_5 & s_7 \\ s_8 & s_1 & s_2 & s_8 & s_3 \\ s_1 & s_2 & s_1 & s_0 & s_3 \end{pmatrix}, L_2 = \begin{pmatrix} s_4 & s_4 & s_8 & s_3 & s_4 \\ s_3 & s_0 & s_6 & s_4 & s_2 \\ s_2 & s_6 & s_5 & s_4 & s_2 \\ s_4 & s_5 & s_3 & s_7 & s_5 \end{pmatrix},$$

$$L_3 = \begin{pmatrix} s_3 & s_4 & s_5 & s_3 & s_3 \\ s_3 & s_3 & s_4 & s_4 & s_1 \\ s_4 & s_6 & s_5 & s_4 & s_5 \\ s_5 & s_7 & s_5 & s_8 & s_4 \end{pmatrix}$$

$$L_4 = \begin{pmatrix} s_4 & s_7 & s_5 & s_2 & s_3 \\ s_2 & s_3 & s_5 & s_2 & s_3 \\ s_0 & s_5 & s_5 & s_3 & s_4 \\ s_4 & s_3 & s_8 & s_2 & s_5 \end{pmatrix}, L_5 = \begin{pmatrix} s_2 & s_6 & s_5 & s_1 & s_1 \\ s_5 & s_4 & s_0 & s_3 & s_1 \\ s_3 & s_7 & s_4 & s_6 & s_5 \\ s_5 & s_6 & s_5 & s_3 & s_4 \end{pmatrix},$$

$$L_6 = \begin{pmatrix} s_5 & s_1 & s_6 & s_3 & s_5 \\ s_4 & s_3 & s_5 & s_3 & s_6 \\ s_4 & s_8 & s_7 & s_3 & s_4 \\ s_3 & s_5 & s_7 & s_4 & s_2 \end{pmatrix}$$

Step 4. Consensus measure. Let consensus threshold $\gamma = 0.8$; weights of DMs $\omega_1 = \omega_2 = \omega_3 = \omega_4 = \omega_5 = \omega_6 = 1/6$; The collective LDM $L^c = (l_{ij}^c)_{n\times m}$ can be calculated by Eq (2).

$$L^c = \begin{pmatrix} (s_4,-0.17) & (s_4,-0.33) & (s_5,0) & (s_3,0) & (s_4,0) \\ (s_4,-0.5) & (s_3,-0.5) & (s_4,0) & (s_4,-0.5) & (s_3,0.33) \\ (s_4,-0.5) & (s_6,-0.5) & (s_5,-0.33) & (s_5,-0.33) & (s_4,-0.17) \\ (s_4,-0.33) & (s_5,-0.33) & (s_5,-0.17) & (s_4,0) & (s_4,-0.17) \end{pmatrix}$$

And then the individual consensus level ICL_k of d_k and the global consensus level GCL can be obtained by Eq (3) and Eq (4):

$ICL_1 = 0.676, ICL_2 = 0.864, ICL_3 = 0.893, ICL_4 = 0.845, ICL_5 = 0.824, ICL_6 = 0.855,$

$GCL = 0.826.$

$ICL_1 = 0.676 < \gamma = 0.8$, so Model (5) is used to reach a consensus.

Step 5. Identify non-cooperative DM. Substituting m, n, $L_k = (l_{ij,k})_{n\times m}$, λ, ω_k into Model (5) yields Model (16).

$$\min \quad \sum_{i=1}^{4}\sum_{j=1}^{5}\sum_{k=1}^{6}\frac{\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij,k})\right|}{8}$$

$$s.t.\begin{cases}\bar{l}_{ij,k}=\Delta((1-\theta_k)\cdot\Delta^{-1}(l_{ij,k})+\theta_k\cdot\Delta^{-1}(l_{ij}^{c}))\\ l_{ij}^{c}=\Delta(\sum_{k=1}^{6}\omega_k\cdot\Delta^{-1}(l_{ij,k}))\\ 1-\frac{1}{20}\sum_{i=1}^{4}\sum_{j=1}^{5}\frac{\left|\Delta^{-1}(\bar{l}_{ij,k})-\Delta^{-1}(l_{ij}^{c})\right|}{8}\geq 0.8\\ 0\leq\theta_1\leq 0.34\\ 0\leq\theta_2\leq 0.71\\ 0\leq\theta_3\leq 0.84\\ 0\leq\theta_4\leq 0.24\\ 0\leq\theta_5\leq 0.52\\ 0\leq\theta_6\leq 0.61\end{cases}\tag{16}$$

The minimum adjustment coefficient to reach a consensus threshold is obtained:

$\theta_1 = 0.3826 > \varepsilon_1 = 0.34, \theta_2 = 0 < \varepsilon_2 = 0.71, \theta_3 = 0 < \varepsilon_3 = 0.84,$

$\theta_4 = 0 < \varepsilon_4 = 0.24, \theta_5 = 0 < \varepsilon_5 = 0.52, \theta_6 = 0 < \varepsilon_6 = 0.61.$

According to Eq. (9), d_1 is non-cooperative DM, who needs to adjust more than the maximum adjustment to reach consensus.

Step 6. Non-cooperative DM adjusts opinions. Using Eq (7), d_1 adjusts opinion to maximum acceptable adjustment. The adjusted LDM $\overline{L}_l = (\bar{l}_{ij,l})_{n\times m}$ of d_1 is

$$\overline{L}_1=\begin{pmatrix}(s_5,-0.40)&(s_1,0.25)&(s_2,0.36)&(s_5,-0.02)&(s_7,-0.36)\\(s_4,-0.17)&(s_2,0.17)&(s_4,0)&(s_4,0.49)&(s_6,-0.25)\\(s_6,0.47)&(s_3,-0.47)&(s_3,-0.09)&(s_7,-0.13)&(s_3,0.28)\\(s_2,-0.09)&(s_3,-0.09)&(s_2,0.3)&(s_1,0.36)&(s_3,0.28)\end{pmatrix}$$

Step 7. Substituting $m, n, \varepsilon_k, \gamma, \omega_k, l_{ij,h}, \bar{l}_{ij,1}$ into MSLM (12) transforms into Model (17).

$$\max \quad \sum_{h=2}^{6} SLO_h=-\frac{\theta_h-\varepsilon_h}{\varepsilon_h}$$

$$s.t.\begin{cases}\bar{l}_{ij,h}=\Delta((1-\theta_h)\cdot\Delta^{-1}(l_{ij,h})+\theta_h\cdot\Delta^{-1}(\bar{l}_{ij,l}))\\ 1-\frac{1}{20}\sum_{i=1}^{4}\sum_{j=1}^{5}\frac{\left|\Delta^{-1}(\bar{l}_{ij,l})-\Delta^{-1}(\bar{l}_{ij}^{c})\right|}{8}\geq 0.8\\ 1-\frac{1}{20}\sum_{i=1}^{4}\sum_{j=1}^{5}\frac{\left|\Delta^{-1}(\bar{l}_{ij,h})-\Delta^{-1}(\bar{l}_{ij}^{c})\right|}{8}\geq 0.8\\ \bar{l}_{ij}^{c}=\Delta(\sum_{h=2}^{6}\frac{1}{6}\cdot\Delta^{-1}(\bar{l}_{ij,h})+\frac{1}{6}\cdot\Delta^{-1}(\bar{l}_{ij,l}))\\ 0\leq\theta_2\leq 0.71\\ 0\leq\theta_3\leq 0.84\\ 0\leq\theta_4\leq 0.24\\ 0\leq\theta_5\leq 0.52\\ 0\leq\theta_6\leq 0.61\end{cases}\tag{17}$$

By solving MSLM (17), the adjustment coefficient $\theta_3 = 0.6249$ is obtained. And the adjusted LDM and collective LDM are as follows

$$\overline{L}_2=\begin{pmatrix}s_4&s_4&s_8&s_3&s_4\\s_3&s_0&s_6&s_4&s_2\\s_2&s_6&s_5&s_4&s_2\\s_4&s_5&s_3&s_7&s_5\end{pmatrix},$$

$$\overline{L}_3=\begin{pmatrix}(s_4,0)&(s_2,0.28)&(s_3,0.35)&(s_4,0.24)&(s_5,0.27)\\(s_4,-0.48)&(s_2,0.48)&(s_4,0)&(s_4,0.31)&(s_4,-0.03)\\(s_5,-0.46)&(s_4,-0.17)&(s_4,-0.31)&(s_6,-0.21)&(s_4,-0.07)\\(s_3,0.07)&(s_4,0.44)&(s_3,0.31)&(s_4,-0.15)&(s_4,-0.45)\end{pmatrix}$$

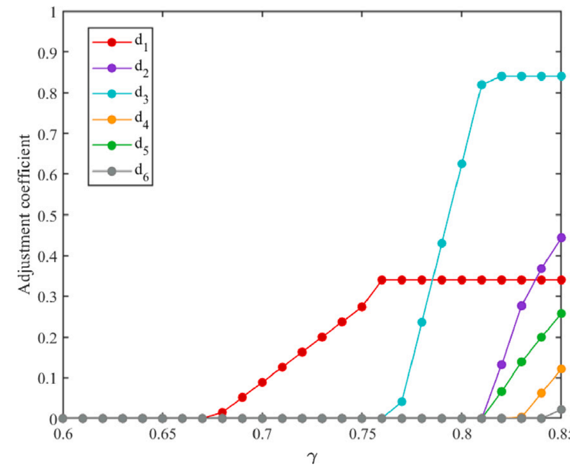

Fig. 8. The individual consensus level of different γ.

$$\overline{L}_4=\begin{pmatrix}s_4&s_7&s_5&s_2&s_3\\s_2&s_3&s_5&s_2&s_3\\s_0&s_5&s_5&s_3&s_4\\s_4&s_3&s_8&s_2&s_5\end{pmatrix},\overline{L}_5=\begin{pmatrix}s_2&s_6&s_5&s_1&s_1\\s_5&s_4&s_0&s_3&s_1\\s_3&s_7&s_4&s_6&s_5\\s_5&s_6&s_5&s_3&s_4\end{pmatrix},$$

$$\overline{L}_6=\begin{pmatrix}s_5&s_1&s_6&s_3&s_5\\s_4&s_3&s_5&s_3&s_6\\s_4&s_8&s_7&s_3&s_4\\s_3&s_5&s_7&s_4&s_2\end{pmatrix}$$

$$\overline{L}^{c}=\begin{pmatrix}(s_4,-0.07)&(s_4,-0.41)&(s_5,-0.05)&(s_3,0.04)&(s_4,0.15)\\(s_4,-0.44)&(s_2,0.44)&(s_4,0)&(s_3,0.47)&(s_4,-0.38)\\(s_4,-0.5)&(s_5,0.39)&(s_5,-0.4)&(s_5,-0.22)&(s_4,-0.3)\\(s_4,-0.5)&(s_4,0.39)&(s_5,-0.23)&(s_4,-0.46)&(s_4,-0.19)\end{pmatrix}$$

We can obtain the individual consensus level and global consensus level of d_k by Eq (3) and Eq (4):

$ICL_1 = 0.800, ICL_2 = 0.854, ICL_3 = 0.907, ICL_4 = 0.843, ICL_5 = 0.819, ICL_6 = 0.852,$

$GCL = 0.846.$

The two-phased adjustment is shown in Fig. 7.

Step 8. Selection process. Using $\overline{L}^{c} = (\bar{l}_{ij}^{c})_{n\times m}$ and Eq (15), the ES_i of alternative x_i is obtained. $ES_1 = 3.93, ES_2 = 3.42, ES_3 = 4.39, ES_4 = 4.00$. So the ranking of alternatives is $x_3 > x_4 > x_1 > x_2$.

5. Disscussion

In this section, a sensitivity analysis of the parameters in the satisfaction-based feedback mechanism is conducted to investigate their impact on the CRP. Additionally, a detailed comparison with existing studies on non-cooperative behavior is provided.

5.1. Sensitive analysis

The experiment compares the changes in adjustment coefficient(see Fig. 8), satisfaction level (see Fig. 9) and consensus level (see Fig. 10) of each DM under different consensus thresholds (γ) in the two-stage consensus feedback mechanism. As illustrated in Fig. 8, as the consensus threshold increases, a greater number of DMs are required to adjust their opinions, which also results in a decline in their satisfaction level. For example, when $\gamma = 0.8$, Only d_1 and d_3 need to adjust their opinions. However, when $\gamma = 0.85$, it requires that all DMs adjust their opinions in order to reach consensus.

From Fig. 9, it can be seen that when the consensus threshold γ between 0.8 and 0.85, d_1 is less satisfied due to reaching the maximum

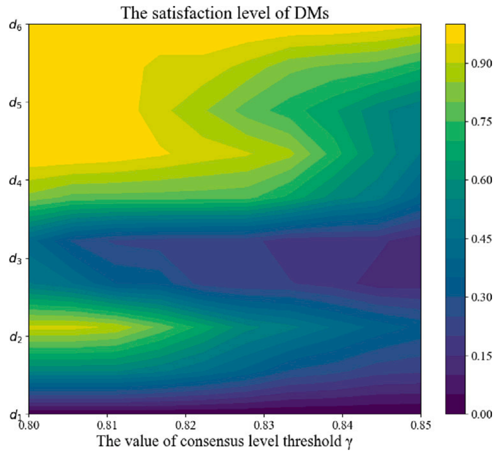

Fig. 9. Influence of γ on DMs' adjust coefficient.

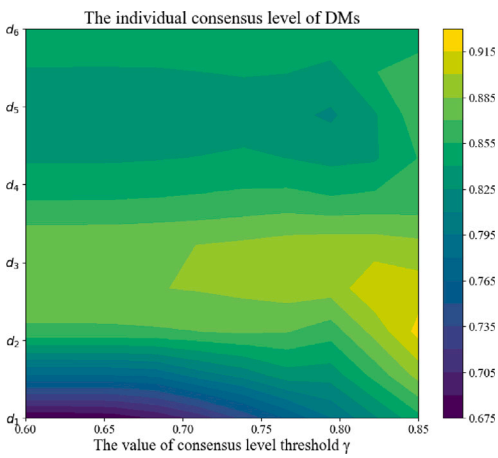

Fig. 10. Influence of γ on DMs' satisfaction level.

amount of adjustment. For the remaining DMs, as the consensus threshold increases and the number of adjustments rises, the satisfaction decreases gradually. However, the satisfaction level of each DM remains above zero. Fig. 10 illustrates that as γ increases, the individual consensus level of non-cooperative DM (d_1) keeps rising and the overall consensus level of cooperative DMs remains unchanged or increase.

5.2. Comparative analysis

This section compares the feedback method in this paper with the recent studies on non-cooperative behavior management and traditional feedback mechanisms.Non-cooperative management primarily involves weight penalty and opinion adjustment to reach consensus. Adjusting opinions within the acceptable range of decision makers minimizes satisfaction loss. However, adjusting an expert's weight can lead to significant dissatisfaction. For comparison, this section proposes the satisfaction level of the adjusted weight as defined in Section 3.3.1. Let ω_k be the initial weight of d_k, and $\omega_k{}'$ be the adjusted weight. The satisfaction level of weight SLW_k can be calculated as follows:

$$SLW_k = -\lambda(-\frac{\omega_k{}' - \omega_k}{\omega_k})^{\beta} \tag{18}$$

where $SLW_k \in (-\infty, 0]$, λ and β has same meaning as Section 3.3.1.

Both opinion adjustments and weighting adjustments reduce lower expert satisfaction, and the comprehensive satisfaction function is calculated as follows

$$CSL_k = SLO_k + SLW_k \tag{19}$$

(1) Comparison of variables in resent feedback mechanism for non-cooperative behavior

There are numerous methods for identifying non-cooperative behavior, as the decision maker's subjective maximum adjustable amount is indeterminable. This paper employs the Agreeableness traits to accurately identify non-cooperative DMs. The management of non-cooperative behavior mainly includes weight penalty and opinion adjustment. Weight penalty reduce decision maker satisfaction, while this study employs a satisfaction-oriented feedback mechanism to reach consensus with less satisfaction loss. Therefore about the following three issues are compared (see Table 4):

Q1: Identification of non-cooperative behavior.
Q2: Management of non-cooperative behavior.
Q3: Concerns about DMs' satisfaction level.

(2) Comparison of the satisfaction level and consensus level with existing studies

Some numerical comparisons with different non-cooperative behavior management methods are made to illustrate the efficient of our approach (see Fig. 11):

Method 1: The satisfaction-based feedback mechanism proposed in this paper.
Method 2: The weight penalty method proposed by Liu et al. [37].
Method 3: The adjustment and weight penalty method proposed by Du et al. [38].

(1) For Method 2, this article achieves consensus by decreasing the weight of non-cooperating DMs and increasing the weight of cooperating DMs. This approach will cause the consensus center move towards the cooperative DMs, thereby increasing the global consensus level. However, it fails to consider the consensus levels of non-cooperative DMs, resulting in a significant loss of their satisfaction. We use Eq (18) to calculate the non-cooperative DM's satisfaction level. While the two-phase satisfaction-based feedback mechanism proposed in this paper reaches consensus with less loss of satisfaction. In addition, the condition for weight penalty to reach consensus is that the global consensus level reaches a threshold, whereas consensus is supposed to make all experts reach a certain consensus threshold. Thus, we find the weight penalty method has a lower individual consensus level from Fig. 11. This study proposes a new adjustment rule, allowing non-cooperative DMs to adjust to the consensus center and cooperative DMs to adjust to non-cooperative DMs, moving the consensus center toward non-cooperative DMs and considering the consensus level of each DM.

(2) For method 3, since both opinion adjustment and weight adjustment are used, satisfaction is calculated using Eq (19). The adjustment coefficient for non-cooperative DMs is directly derived from distance deviation, without considering the maximum acceptable adjustment for DMs. Additionally, a weight penalty is applied, resulting in a lower overall satisfaction level.

(3) Comparison of different feedback mechanism for adjustment direction

There are numerous efficient feedback mechanisms designed to help decision-makers reach consensus, such as MACM [9] and MCCM [10]. Each of these mechanisms aims to align decision-makers toward the consensus center(see Fig. 5). However, in situations with stubborn decision-makers, this central alignment approach may result in a failure to achieve consensus. In such cases, adjusting the direction towards the positions of stubborn experts, rather than the center, is a more reasonable approach.

6. Conclusion

Oriented to the principle of satisfaction, this study proposes a maximum satisfaction level model (MSLM) for the management of non-cooperative behavior , defined based on the Big Five personality traits.

Table 4
Comparisons of the proposed mechanism and other literatures.

Article	Q1	Q2	Q3
Guo et al. [21]	Subjective adjustment threshold	Weight penalty	×
Liu et al. [37]	Subjective adjustment threshold	Weight penalty	×
Liao et al. [18]	Opinions and weight deviation	Exit-delegation	×
Du et al. [38]	Subjective coefficient and punishment coefficient	Opinion and weight penalty	×
This paper	Personality trait orientation	Opinion adjustment	✓

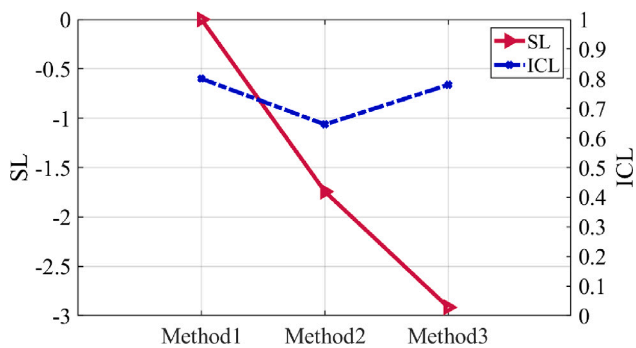

Fig. 11. The non-cooperative DMs' SL and ICL for different management method.

The mainly innovations and conclusion are as follows:

(1) An identification method for non-cooperative behavior based on personality traits is proposed. To do this, the Agreeableness trait of DMs is predicted using a CNN-BiLSTM based on their reviews from social platforms. This predicted value is used to determine the maximum acceptable adjustment for each DM, which replaces the assumptions commonly employed in existing studies. By integrating this value with the minimum adjustment derived from the MACM, the occurrence of non-cooperative behavior can be effectively identified.

(2) A novel management method for non-cooperative behavior considering maximum satisfaction level of DMs is proposed. Specifically, a satisfaction measure method based on the Agreeableness trait and adjustment is proposed for the first time in this study. Based on this, a satisfaction-oriented two-phase feedback mechanism for managing non-cooperative behavior is proposed. This includes novel two-phase adjustment rules for non-cooperative and cooperative DMs, where cooperative DMs adjust towards non-cooperative DMs rather than the consensus center, with adjustment parameters determined through the proposed MSLM model.

(3) The novel energy vehicle supplier selection case validates the practicality and advantages of the proposed framework. It is observed that the method improves both the satisfaction level and consensus level of DMs in comparison to traditional methods.

The identification and management of non-cooperative behaviors can significantly enhance cooperation and satisfaction in the group decision-making process, providing insights into addressing real-world problems such as inter-departmental conflicts in product development and resident-government disputes in infrastructure planning. However, there are some limitations to this study. (1) This study employs 2-tuple linguistic representation model to express DMs' decision information under uncertainty. In future work, advanced fuzzy linguistic modeling techniques [47,48] and Personality Individual Semantics(PIS) [6] will be used to better represent opinions and enhance the handling of uncertainty. (2) This study only utilizes online comments from the Weibo platform for predicting the personality traits of DMs. Future research could improve the accuracy of personality traits prediction by integrating diverse heterogeneous data sources, such as audio and video, alongside data from multiple platforms.

CRediT authorship contribution statement

Yujia Liu: Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Yuwei Song:** Writing – review & editing, Validation, Methodology, Formal analysis. **Jian Wu:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Changyong Liang:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis. **Francisco Javier Cabrerizo:** Writing – review & editing, Supervision, Funding acquisition, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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