Classification-Based Consensus Decision-Making for Portfolio Selection Considering Overconfidence

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Abstract. Constructing a rational stock portfolio selection model is critical for enhancing investment returns. Given the negative impact of fund team members' overconfidence on portfolio selection, we propose a classification-based consensus decision-making method and a minimum adjustment classification-based consensus model that consider overconfidence. By identifying overconfident members and providing adjustment recommendations, we aim to achieve group consensus on stock classifications. The case study and analysis indicate that overconfidence affects stock classifications, and identifying overconfident members effectively improves group classification-based consensus level. The research findings provide a theoretical basis for fund teams to identify overconfident members, and offer methodological guidance for fund companies to facilitate consensus-reaching in portfolio selection.

Keywords: Portfolio, Fund team, Classification-based consensus, Overconfidence, Stock pool

1 Introduction

Rational stock selection is fundamental to constructing an optimal portfolio. The team-based investment model has attracted considerable attention in the fund industry, as it can significantly mitigate extreme performance fluctuations arising from extreme investment styles and high sector concentration. However, given market volatility, cognitive limitations and external pressures, fund team members are not entirely rational, making it necessary to consider mental factors in portfolio selection (Tu et al., 2025). Fund team members often possess considerable social resources, high autonomy, and elevated professional status, which make them overestimate their decision-making capabilities and thus exhibit overconfidence, negatively affecting fund performance (Wang et al., 2025). According to the theory of transfer groups, this negative impact is significantly greater than in single-manager model. Therefore, neglecting overconfidence may induce decision-making errors, ultimately resulting in an irrational portfolio.

© The Author(s) 2026
V. Erokhin et al. (eds.), *Proceedings of the 6th International Conference on Internet Finance and Digital Economy (ICIFDE 2026)*, Advances in Economics, Business and Management Research 412,
https://doi.org/10.2991/978-94-6239-830-6_22

Scholars have argued that stock portfolio selection is essentially a classification-based decision-making problem (Emamat et al., 2023). However, few studies explore fund team's portfolio decision-making of from the perspective of classification-based consensus. The classic return-risk model typically optimizes portfolio under fixed capital constraints (Dias et al., 2025). In fact, fund team members negotiate to select stocks from a candidate pool and reach a consensus on stock classifications (Li et al., 2024). Importantly, this process does not require a complete ranking of all alternative stocks. The final decision is reached once a consensus on classifications is achieved. Thus, it can be regarded as a classification-based consensus decision-making problem, for which the classification-based consensus model provides an appropriate and effective solution.

Classification-based consensus decision-making extends traditional consensus decision-making by categorizing alternatives into ordered or unordered classifications and has attracted considerable research interest. Existing models have been developed from various perspectives such as minimum information loss, minimum offense, and minimum cost, which have been applied to classify alternatives into predefined classifications across diverse fields (Zhang et al., 2024; Hao et al., 2026). However, in the context of fund teams, the number of stocks in each classification is unknown, whereas existing methods presuppose known numbers, making them difficult to address portfolio selection problems faced by fund teams. Therefore, it is necessary to explore a new method that can adaptively handle unknown number of stocks in each classification.

Overconfidence has long been a focus of attention in portfolio selection research, yet research on the its impact on fund team' portfolio decision-making remains scarce. Managerial overconfidence can impair corporate investment efficiency, while investors' overconfidence may induce over-investment, destroy corporate value, or lead to failed mergers and acquisitions and stock price crashes (Hwang et al., 2020). Some scholars have explored overconfidence in consensus reaching process (CRP) (Liu et al., 2019; Hao et al., 2023), but none have incorporated it into classification-based CRP (CCRP). Whether overconfidence affects CCRP and alters portfolio results remains to be further explored. Furthermore, existing studies identify overconfidence solely from decision-makers' (DMs') initial self-assessments, ignoring interpersonal trust, which has grown through social media and fosters varying trust level within social networks. Therefore, the identification of overconfidence should consider both self-assessment and mutual trust among fund team members.

Although significant progress has been made in existing research, there are still the following shortcomings. First, most portfolio studies rely on traditional financial theories that examine individual decisions, such as the mean-variance model, with little attention to team decision-making and stock classifications. Second, most classification-based consensus models assume known numbers of alternatives in each classification, which does not align with fund teams' practice. Third, while overconfidence negatively affects fund performance, existing research has not incorporated it into CCRP to investigate its impact on portfolio. Moreover, existing overconfidence identification ignores trust relationship.

To address these limitations, this study explores the classification-based consensus decision-making that considers overconfidence in portfolio selection by fund team. The

main contributions are as follows. First, we incorporate overconfidence into CCRP, and explore its impact on portfolio decision-making. Our results indicate that identifying overconfidence can enhance group classification-based consensus and improve the efficiency of portfolio decision-making. Second, to address unknown number of stocks in each classification, we introduce a preference-approval structure that categorizes stocks and aligns with practical fund team's portfolio decision-making. Third, we propose a novel method for identifying overconfident members and develop a minimum adjustment classification-based consensus model. This model adjusts overconfident members' opinions or self-confidence levels to facilitate consensus on stock classifications.

2 Preliminaries

To facilitate the subsequent research, we first review relevant theoretical concepts, including the fuzzy preference relations with self-confidence, the preference-approval structure, and the minimum adjustment consensus model.

2.1 Fuzzy Preference Relations with Self-Confidence

Let the set of DMs be $DM = \{dm_1, dm_2, \ldots, dm_m\}$ and the set of alternatives be $X = \{x_1, x_2, \ldots, x_n\}$. The fuzzy preference relation is then defined as follows:

Definition 1 (Orlovsky, 1978) Let $R^k = \left(r_{ij}^k\right)_{n\times n}$ denote the fuzzy preference relation of DM dm^k, where r_{ij}^k represents the degree of preference of dm^k for alternative x_i relative to x_j, and satisfies $r_{ij}^k + r_{ji}^k = 1$, $r_{ii}^k = 0.5$.

Let the linguistic term set $S^{SL} = \{s_i \mid i = 0,1,\ldots,g\}$ be used to characterize DMs' self-confidence level in fuzzy preference values, where s_i is a linguistic term. We assume that DMs use a set of seven-granularity linguistic term set $S^{SL} = \{s_0, s_1, s_2, \ldots, s_6\}$ to express their self-confidence level.

2.2 Preference-Approval Structure

The preference-approval structure is a preference representation model proposed by Brams et al. (2009), which has played a positive role in CRP (Dong et al., 2021). It comprehensively considers both ranking and classification, extending ordinal models by adding two classification labels, acceptable and unacceptable, to the ranking framework.

Definition 2 (Erdamar et al., 2014) For a given preference-approval structure (P_R, I_A), let $P_R = (P_R(x_1), \ldots, P_R(x_n))$ denote the ranking information, and $I_A = (I_A(x_1), \ldots, I_A(x_n))$ denote the approval information. They are defined as follows:

$$P_R(x_i) = n - \#\{x_j \mid x_j < x_i\} - \frac{1}{2}\#\{x_j \in X \setminus x_i \mid x_j \sim x_i\} \tag{1}$$

$$I_A(x_i)=\begin{cases}1, & x_i \text{ is approved}\\ 0, & x_i \text{ is not approved}\end{cases} \tag{2}$$

where # denotes the number of elements in the set.

To obtain a collective preference-approval structure, Dong et al. (2021) proposed a preference-approval structure axiomatic distance-based aggregation model (PAS-ADAM). The specific expression is as follows:

$$\begin{aligned}&\min \sum_{k=1}^{m}\sum_{i=1}^{n}\left(\alpha\left|P_{R_k}(x_i)-P_R(x_i)\right|+(1-\alpha)\left|I_{A_k}(x_i)-I_A(x_i)\right|\right)\\ &s.t.\begin{cases}P_R(x_i)\neq P_R(x_j), i\neq j\\ P_R(x_i)=1,2,...,n\\ I_A(x_i)=0 \text{ or } 1\end{cases}\end{aligned} \tag{3}$$

where α is the weight of the ranking information.

2.3 Minimum Adjustment Consensus Model

The minimum adjustment consensus model aims to minimize the extent to which DMs' opinions are adjusted, thereby achieving the largest efficiency in the CRP (Dong et al., 2010). Let $DM=\{d_1,d_2,\ldots,d_m\}(m>2)$ denote the set of DMs. $o=\{o^1,o^2,...,o^m\}$ and $\overline{o}=\{\overline{o}^1,\overline{o}^2,...,\overline{o}^m\}$ are the sets of DMs' initial and adjusted preferences, respectively. During the CRP, the magnitude of preference adjustment for all DMs should be as small as possible, that is, the distance between o and $\overline{o}$ should be minimized. Let $\overline{o}^c$ denote the adjusted collective preference, and $F_\lambda(\overline{o}^1,\overline{o}^2,...,\overline{o}^m)=\sum_{k=1}^{m}\lambda_k\overline{o}^k$ be the aggregation function for obtaining the adjusted collective preferences, where λ_k denotes the weight of DM d_m. ε is a given threshold, and when $\left|\overline{o}^k-\overline{o}^c\right|<\varepsilon$, $k=1,2,...,m$, it means that all DMs have reached consensus. The minimum adjustment consensus model is defined as:

$$\begin{aligned}&\min \sum_{k=1}^{m} d(o^k,\overline{o}^k)\\ &s.t.\begin{cases}\overline{o}^c=F_\lambda(\overline{o}^1,\overline{o}^2,...,\overline{o}^m)\\ \left|\overline{o}^k-\overline{o}^c\right|<\varepsilon, k=1,2,...,m\end{cases}\end{aligned} \tag{4}$$

3 Classification-Based Consensus Model for Portfolio Selection Considering Overconfidence

Based on the characteristics of fund team's portfolio decision-making, this study constructs a classification-based consensus model for portfolio selection that considers

overconfidence. The model includes the CCRP that considers overconfidence of fund team members, and identification of overconfident members and feedback adjustment.

3.1 Problem Description

This study explores the problem of portfolio decision-making that considers overconfidence from the perspective of classification-based consensus, with the aim of identifying high-quality stocks for the portfolio. We assume that the fund team consists of an investment director, several investment analysts and fund managers, denoted as $DM = \{dm_1, dm_2, \ldots, dm_m\} (m > 2)$. The weight vector of the fund team members is $\lambda = (\lambda_1, \lambda_2, ..., \lambda_m)^T (m > 2)$, where $0 \le \lambda_k \le 1$, $k = 1, 2, \ldots, m$, and $\sum_{k=1}^{m} \lambda_k = 1$. The set of stocks is denoted as $X = \{x_1, x_2, \ldots, x_n\} (n \ge 2)$, the set of stock attributes as $C = \{c_1, c_2, \ldots c_q\} (q \ge 2)$, and the weight vector for stock attributes as $\omega = (\omega_1, \omega_2, \ldots, \omega_q)^T$, where $0 \le \omega_t \le 1$, $t = 1, 2, ..., q$ and $\sum_{t=1}^{q} \omega_t = 1$. Fund team members use fuzzy preference relations with self-confidence to express their opinions, denoted as $RS^{k,t} = (R^{k,t}, S^{k,t})$, representing the preference and self-confidence of dm^k under attribute c_t . The process primarily comprises the determination of team members' weights, a CCRP that considers overconfidence, and a feedback adjustment process.

3.2 Determination of Fund Team Members' Weights

According to Tan et al. (2022), TID^k and NID^k denote the trust in-degree strength and the node in-degree strength, respectively. The trust in-degree strength represents the total trust value assigned to dm^k by other members within the trust network, while the node in-degree strength represents the total strength of the node at dm^k within the trust network. Both can be calculated using the trust propagation operator. Therefore, the comprehensive relative in-degree is defined as:

$$ID^k = TID^k \times NID^k \tag{5}$$

To ensure members' weights satisfy the normalization condition, the following improvements are made:

$$\lambda^k = \frac{ID^k}{\sum_{k=1}^{m} ID^k} \tag{6}$$

where λ^k denotes the weight of member dm^k , and satisfies $0 \le \lambda^k < 1$, $\sum_{k=1}^{m} \lambda^k = 1$.

3.3 CCRP Considering Overconfidence

Based on the initial fuzzy preference matrices with self-confidence, the individual self-confidence-based classification-based consensus level (SC-CCL) and preference-based

classification-based consensus level (P-CCL) are calculated respectively, and both are comprehensively considered to obtain group classification-based consensus level (GCCL). When GCCL does not meet a given threshold, the identification of overconfident members and feedback adjustment are required to facilitate the members in reaching a consensus on stock classifications.

Calculation of Individual P-CCL. Let $R^{k,t}=\left(r_{ij}^{k,t}\right)_{n\times n}$ denote the preference matrix of dm^k under attribute c_t. Then, the preference matrix of dm^k is represented as:

$$R^k=\sum_{t=1}^{q}\omega_t R^{k,t} \tag{7}$$

where ω_t is the weight of stock attribute.

Based on the initial preference of members, the rankings of each member for the stocks are calculated using the weighted average operator, which is represented as:

$$\widetilde{R^k}(x_i)=\frac{1}{n}\sum_{j=1}^{n}r_{ij}^k, i=1,2,...,n \tag{8}$$

Obviously, the larger the value of $\widetilde{R^k}(x_i)$, the more pronounced the fund team members' preference for stock x_i. Therefore, if $\widetilde{R^k}(x_i)>\widetilde{R^k}(x_j)$, member dm^k will consider stock x_i to be superior to stock x_j. Then each member's ranking of the stocks is obtained. Subsequently, members determine classification points based on their rankings, and their complete preference-approval structures are obtained. The collective preference-approval structure is then obtained by the PAS-ADAM model.

Based on the individual and collective preference-approval structure, the individual P-CCL for member dm^k is calculated as follows:

$$P-CCL^k=1-(\alpha\frac{1}{n(n-1)}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}d(P_{R_k},P_{R_c})+(1-\alpha)\frac{1}{n}\sum_{i=1}^{n}d(I_{A_k},I_{A_c})) \tag{9}$$

where $d(P_{R_k},P_{R_c})=\left|\mathrm{sgn}(P_{R_k}(x_i)-P_{R_k}(x_j))-\mathrm{sgn}(P_{R_c}(x_i)-P_{R_c}(x_j))\right|$, $d(I_{A_k},I_{A_c})=\left|I_{A_k}(x_i)-I_{A_k}(x_i)\right|$, and $\mathrm{sgn}(x)=\begin{cases}1,x>0\\0,x<0\end{cases}$. α denotes the weight of preference in the preference-approval structure.

Group Classification-Based Consensus Measurement. The individual SC-CCL is derived from self-confidence values in fuzzy preference relations with self-confidence. By referring to the individual preference matrix, the individual self-confidence matrix $S^k=(s_{ij}^k)_{n\times n}$ can be obtained. According to Liu et al. (2019), individual SC-CCL for member dm^k is calculated as:

$$SC-CCL^k=1-\frac{2}{n(n-1)}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}d(S^k,S^c) \tag{10}$$

where $d(S^k, S^c) = \frac{\left|\Delta^{-1}(s_{ij}^k) - \Delta^{-1}(s_{ij}^c)\right|}{g}$ and $s_{ij}^c = \sum_{k=1}^{m} \lambda^k s_{ij}^k$.

Considering both individual P-CCL and SC-CCL, the GCCL is calculated as follows:

$$GCCL = \sum_{k=1}^{m} \lambda^k (\rho\left(P - CCL^k\right) + (1-\rho)\left(SC - CCL^k\right)) \tag{11}$$

where ρ denotes the weight of individual P-CCL, and $0 \le \rho \le 1$.

If the GCCL is larger than or equal to the classification-based consensus threshold δ, the temporary collective preference-approval structure becomes the final decision result. Otherwise, the feedback adjustment will be initiated.

3.4 Identification of Overconfident Members and Feedback Adjustment

If GCCL$< \delta$, overconfident members are identified by comparing their trust level with their self-confidence level. Based on the type of overconfidence exhibited by fund team members, a feedback adjustment model is constructed to adjust members' preference-approval structures or self-confidence matrices.

Self-Confidence Level and Trust Level of Fund Team Members. According to the above, individual self-confidence matrix for dm^k is $S^k = (s_{ij}^k)_{n\times n}$. Let $S = (s_g)_{n\times n}$ be the maximum self-confidence matrix, and $s_{ij}^k, s_g \in S^{SL}$. Then, the self-confidence level for dm^k is $SCL(dm^k)$, which is shown as:

$$SCL(dm^k) = 1 - \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} d(S^k, S) \tag{12}$$

where $d(S^k, S) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{\left|\Delta^{-1}(s_{ij}^k) - \Delta^{-1}(s_g)\right|}{g}$.

In previous studies on DMs' overconfidence, the identification of overconfidence relied solely on the self-confidence matrix provided by DMs. In reality, trust relationships exist among fund team members. Being highly trusted by other members may also lead to overconfidence. Based on this, this study calculates the trust level of member dm^k based on their trust in-degree as follows:

$$TL^k = TID'^k \tag{13}$$

where TID'^k is the normalized result of the trust in-degree. Since the maximum value that TID^k can reach is m-1, we set $TID'^k = \frac{TID^k}{m-1}$.

Identification and Adjustment of Overconfidence. If the GCCL is not accepted, the difference between the trust level and self-confidence level of each member is calculated. The member with the largest absolute difference is identified as the overconfident member. Subsequently, the member's individual P-CCL and SC-CCL are compared with the collective P-CCL and SC-CCL, respectively, to determine the type of overconfidence. The adjustment rules are as follows:

(1) **Overconfidence I:** $P-CCL^k \geq \varepsilon$, $SC-CCL^k < \vartheta$. This scenario indicates that the fund team member, due to over-reliance on experience, has an excessively high individual self-confidence level that deviates from the collective self-confidence level. Based on this, a feedback adjustment model is constructed to adjust the individual self-confidence matrix:

$$\begin{aligned} &\min d(s_{ij}^k, s'^k_{ij}) \\ &s.t.\begin{cases} \sum_{k=1}^{m} \lambda^k (\rho\left(P-CCL^k\right)+(1-\rho)\left(SC-CCL'^k\right)) \geq \delta & \text{(14-1)} \\ s'^c_{ij} = F_\pi(s'^1_{ij}, s'^2_{ij}, ..., s'^m_{ij}) & \text{(14-2)} \end{cases} \end{aligned} \tag{14}$$

where the objective function is the distance between the self-confidence matrix of dm^k before and after adjustment. Constraint (14-1) indicates that the GCCL has reached the threshold. Constraint (14-2) indicates the adjusted collective self-confidence value. ε and ϑ represent the collective P-CCL and SC-CCL, respectively. $\varepsilon = \sum_{k=1}^{m} \lambda^k \left(P-CCL^k\right)$, and $\vartheta = \sum_{k=1}^{m} \lambda^k \left(SC-CCL^k\right)$.

(2) **Overconfidence II:** $P-CCL^k < \varepsilon$, $SC-CCL^k > \vartheta$. This scenario indicates that, due to limitations in own knowledge, fund team member is unable to consider issues comprehensively. It results in a significant deviation between individual and collective preferences. Based on this, a feedback adjustment model is constructed to adjust the individual preference-approval structure:

$$\begin{aligned} &\min d((P_k, A_k), (P'_k, A'_k)) \\ &s.t.\begin{cases} \sum_{k=1}^{m} \lambda^k (\rho\left(P-CCL'^k\right)+(1-\rho)\left(SC-CCL'^k\right)) \geq \delta & \text{(15-1)} \\ (P'_c, A'_c) = F_\pi((P'_1, A'_1), ..., (P'_m, A'_m)) & \text{(15-2)} \end{cases} \end{aligned} \tag{15}$$

where the objective function is the distance between the preference-approval structures of dm^k before and after adjustment. Constraint (15-1) indicates that the GCCL reaches a threshold. Constraint (15-2) represents the adjusted collective preference-approval structure.

(3) **Overconfidence III:** $P-CCL^k < \varepsilon$, $SC-CCL^k < \vartheta$. This situation arises when fund team members are unaware of knowledge limitations and continue to rely on experience, causing both their preferences and self-confidence level to deviate from the group. Based on this, a feedback adjustment model is constructed to simultaneously adjust individual self-confidence matrix and preference-approval structure as follows:

$$\min d((P_k, A_k),(P'_k, A'_k)) + d(s_{ij}^k, s'^k_{ij})$$
$$s.t.\begin{cases} \sum_{k=1}^{m} \lambda^k (\rho(P - CCL^k) + (1-\rho)(SC - CCL^k)) \geq \delta & \text{(16-1)} \\ s'^c_{ij} = F_\pi(s'^1_{ij}, s'^2_{ij}, ..., s'^m_{ij}) & \text{(16-2)} \\ (P'_c, A'_c) = F_\pi((P'_1, A'_1), ..., (P'_m, A'_m)) & \text{(16-3)} \end{cases} \tag{16}$$

where the objective function represents the distance between the preference-approval structures and self-confidence matrices of dm^k before and after adjustment. Constraint (16-1) represents that the GCCL reaches the threshold. Constraints (16-2) and (16-3) represent the adjusted collective self-confidence value and preference-approval structure, respectively.

By adjusting the initial opinions through the feedback adjustment, a preference-approval structure that meets the classification-based consensus threshold can be obtained, thereby determining the final stock classifications.

4 Case Study

In this study, we use a fund team's investment research meeting as a case study to validate the feasibility of the proposed classification-based consensus model.

4.1 Background Description

Assuming the fund team consists of a general manager, an investment director, an investment analyst and two fund managers, they hold an investment meeting to determine the portfolio of key food and beverage holdings for a consumer sector fund. The five stocks are Tsingtao Brewery (600600), Yili (600887), Shanxi Fenjiu (600809), Yanghe (002304), and Yanjin Puzi (002847), denoted as x_1, x_2, x_3, x_4, x_5. Fund team members expressed their preference for the five stocks based on two attributes: return on equity (c_1) and debt-to-asset ratio (c_2), with equal weight assigned to two attributes. Fund team members express their initial opinions, and subsequently employ a preference-approval structure to classify stocks into two ordered classifications: "Buy" and "Do not buy". The relevant parameters are set as follows:

(1) The weight of "preference" and "approval" in the preference-approval structure are equal, that is, $\alpha = 0.5$.

(2) The SC-CCL and P-CCL of members are equally important, that is $\rho = 0.5$.

(3) The GCCL for the fund team is $\delta = 0.85$.

4.2 Classification-Based Consensus Decision-Making Process Considering Overconfidence

Based on the attribute information of stocks, the initial fuzzy preference relations with self-confidence provided by members are shown in Appendix A. The strength of

relationship between fund team members is shown below, where "-" indicates no direct relationship between the two members: $A = \begin{pmatrix} 1 & - & 0.5 & - & - \\ 0.8 & 1 & - & - & 0.4 \\ 0.7 & - & 1 & 0.6 & 0.6 \\ 0.9 & 0.5 & - & 1 & - \\ 0.9 & - & 0.3 & - & 1 \end{pmatrix}$.

Firstly, the weights of the fund team members are calculated. Using Eq.(5), the comprehensive relative in-degree ID^k of members are obtained. Finally, the weights of members are obtained by Eq. (6): $\lambda^1 = 0.46$, $\lambda^2 = 0.1$, $\lambda^3 = 0.15$, $\lambda^4 = 0.13$, $\lambda^5 = 0.16$. Secondly, the classification-based consensus results considering overconfidence are calculated. The CCRP is primarily divided into two parts: the temporary classifications of stocks and the measurement of GCCL. The results are shown below.

Based on the initial preference of members, the preference-approval structures are obtained using Eqs. (7) and (8) as follows: $PA^1 = x_2x_4x_3 \mid x_5x_1$, $PA^2 = x_3x_2 \mid x_4x_5x_1$, $PA^3 = x_5x_2 \mid x_3x_1x_4$, $PA^4 = x_1x_5 \mid x_4x_2x_3$, $PA^5 = x_3x_5x_1x_2 \mid x_4$. Based on the classification results, it can be seen that member dm^2, dm^3, dm^4 choose to buy two stocks, while dm^1 and dm^5 choose to buy three and four stocks, respectively.

Then, using Eq. (11), the $GCCL = 0.79$ is obtained, which has not reached the threshold. Therefore, the feedback adjustment is initiated. Using the proposed method, dm^1 is identified as an overconfident member, meeting the criteria for overconfidence II. The adjustment of dm^1's initial opinion is performed using Eq. (15). By solving the model, the modified collective preference-approval structure is obtained: $PA^c = x_2x_3x_5 \mid x_4x_1$.

The GCCL reaches the threshold. Then, based on the collective preference-approval structure, Shanxi Fenjiu (600809), Yili (600887), and Yanjin Puzi (002847) are selected into the final portfolio.

5 Model Discussion

To demonstrate the feasibility and validity of the proposed model, relevant literature is selected for comparison, and a sensitivity analysis of key parameters is conducted to explore the impact of overconfidence on portfolio selection.

5.1 Comparative Analysis

To highlight the differences between this study and the relevant literature, as well as the contributions, the proposed model is compared with several relevant literature, which is shown in Table 1. It can be found that there are few studies exploring the mechanism of the impact of overconfidence on fund team's portfolio decision-making. Furthermore, none of the existing studies have investigated the classification-based consensus decision-making considering overconfidence by optimization models, which provides research motivation for this study.

Table 1. Comparison of this study with other relevant literature.

Literature	Self-confidence	Overconfidence	Classification-based consensus	Mathematical optimization models	Application scenarios
This study	✓	✓	✓	✓	Portfolio selection by fund team
Liu et al., 2019	✓	✓	×	×	No specific scenario
Zhang et al., 2024	×	×	✓	✓	Corporate resource allocation
Hao et al., 2026	×	×	✓	×	Portfolio selection by fund team
Liu et al., 2019	✓	×	×	×	No specific scenario

5.2 Sensitivity Analysis

This section explores the impact of overconfidence on GCCL and classifications, and analyzes changes in the weight of SC-CCL, different allocation methods for members' weights, and the impact of not considering overconfidence on GCCL and classifications.

The Impact of Weight of SC-CCL on GCCL. It is assumed that the weights of P-CCL and SC-CCL are equal in this study. To explore the impact of weight of SC-CCL on GCCL, an analysis is conducted using values in the range [0,1] with a step size of 0.1 as the weight of SC-CCL.

As can be seen from Figure 1, GCCL increases as the weight of SC-CCL increases. Increasing the importance of SC-CCL can improve GCCL, and GCCL gradually approaches the threshold as the weight of SC-CCL increases.

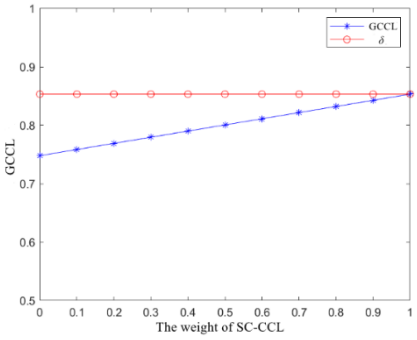


Fig. 1. The impact of the weight of SC-CCL on GCCL.

The Impact of Member Weight Allocation Methods on GCCL. In this study, fund team members' weights are determined based on trust relationships. To explore the

impact of different weight allocation methods on GCCL, an analysis is conducted under different weights of SC-CCL within the range [0,1], with a step size of 0.1.

As can be seen from Figures. 2 and 3, although the weight allocation method based on trust relationship sometimes yields a slightly lower initial GCCL, the maximum GCCL after feedback adjustment is always higher than the maximum achievable with equal allocation. It means that the weight allocation method based on trust relationship improves GCCL compared to the traditional equal allocation method.

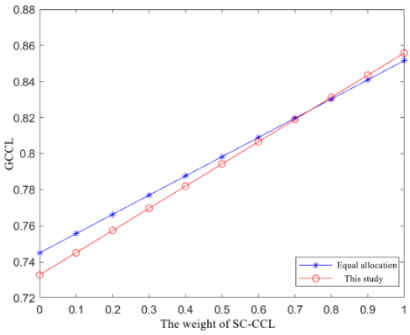


Fig. 2. The impact of different weight allocation methods on initial GCCL.

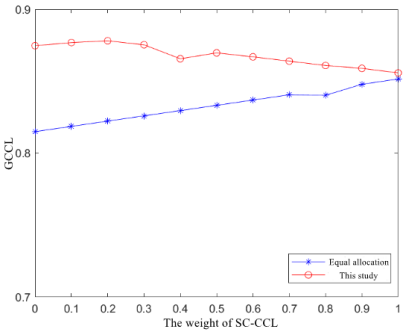


Fig. 3. The impact of different weight allocation methods on maximum GCCL.

The Impact of Weight of SC-CCL on Stock Classifications. In this study, we assume that the weights of P-CCL and SC-CCL are equal to calculate the final stock classifications. To investigate the impact of the weight of SC-CCL on classification results, values in the range [0,1] are selected as the weights of SC-CCL with a step size of 0.1. The results are shown in Table 2.

As can be seen from Table 2, with the exception of the classifications when the weight of SC-CCL is set to 0.8, the classifications for all other weights are consistent with those of the proposed case study, with only minor differences in the ranking. Changes in the weight have virtually no effect on stock classifications.

Table 2. The impact of the weight of SC-CCL on stock classifications.

Weight of SC-CCL	Stock classifications
0.1, 0.4, 0.5, 0.9	$(5,1,2,4,3\|0,1,1,0,1)$, $x_2x_3x_5 \mid x_4x_1$
0, 0.2, 0.3	$(4,1,2,5,3\|0,1,1,0,1)$, $x_2x_3x_5 \mid x_1x_4$
0.7	$(4,2,3,5,1\|0,1,1,0,1)$, $x_5x_2x_3 \mid x_1x_4$
0.8	$(5,2,1,4,3\|0,1,1,0,0)$, $x_3x_2 \mid x_5x_4x_1$

Without Considering Overconfidence of Fund Team Members. Based on the context of the portfolio selection by fund team, this study investigates classification-based consensus decision-making that considers overconfidence. To examine the impact of

overconfidence on the consensus results of fund teams, the classification-based consensus results obtained without considering overconfidence are compared with those in this study, as shown in Table 3.

Table 3. Comparison of GCCL and stock classifications under different scenarios.

Overconfidence	GCCL	Stock classifications
Considered	0.80	(5,2,4,3,1|0,0,0,0,1), $x_5 \mid x_2x_4x_3x_1$
Not considered	0.85	(5,1,2,4,3|0,1,1,0,1), $x_2x_3x_5 \mid x_4x_1$

As can be seen from Table 3, identifying overconfident members enables the team to achieve a higher consensus level, and overconfidence has a significant impact on rankings and classifications. When the threshold of GCCL is reached, only one stock is selected when team members' overconfidence is not considered. The analysis indicates that overconfidence hinders consensus reaching and leads to inefficient decision-making. Consequently, classification-based consensus decision-making that considers overconfidence better align with practical requirements.

6 Conclusions

This study constructs a classification-based consensus model for portfolio selection that considers overconfidence. First, the members' weights are calculated by trust propagation operator based on the fund team's portfolio decision-making environment and trust relationship, avoiding inappropriate allocation. Second, the GCCL is measured based on SC-CCL and P-CCL, and a preference-approval structure is introduced regarding the characteristics of fund team's portfolio decision-making. A minimum adjustment classification-based consensus model is then constructed to facilitate consensus on stock classifications.

Results show that identifying overconfident members improve the GCCL. Overconfidence significantly affects stock classifications, while the weight of SC-CCL has no impact on final stock selection. Thus, identifying overconfident members facilitates group consensus reaching. When overconfidence is ignored and the threshold of GCCL is too high, decision-making efficiency may decline, or consensus may even fail. Individual investors should consider fund team members' self-confidence level when selecting stocks. Fund teams should promptly identify overconfident members to enhance the efficiency of portfolio decision-making. Regulators should strengthen risk education and supervise the rationality and compliance of fund companies' decision-making, especially regarding overconfidence's negative impact.

Future research could explore portfolio decision-making models for fund teams that consider dynamic trust relationship. Furthermore, the influence of other psychological behaviors of fund team members, such as conformity and mental account, on portfolio decision-making is also worthy of exploration.

Acknowledgments

This work was supported by the Social Science Foundation of Jiangsu Province under Grant 23GLB030.

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Appendix A: Initial Fuzzy Preference Relations with Self-Confidence

$$R^{1,1}, S^{1,1} = \begin{pmatrix} (0.5,s_6) & (0.6,s_1) & (0.1,s_4) & (0.3,s_3) & (0.1,s_1) \\ & (0.5,s_6) & (0.9,s_3) & (0.3,s_2) & (0.7,s_2) \\ & & (0.5,s_6) & (0.7,s_5) & (0.4,s_5) \\ & & & (0.5,s_6) & (0.8,s_5) \\ & & & & (0.5,s_6) \end{pmatrix}, R^{2,1}, S^{2,1} = \begin{pmatrix} (0.5,s_6) & (0.1,s_4) & (0.7,s_1) & (0.4,s_2) & (0.2,s_4) \\ & (0.5,s_6) & (0.6,s_4) & (0.4,s_3) & (0.4,s_2) \\ & & (0.5,s_6) & (0.8,s_6) & (0.8,s_1) \\ & & & (0.5,s_6) & (0.8,s_2) \\ & & & & (0.5,s_6) \end{pmatrix}$$

$$R^{3,1}, S^{3,1} = \begin{pmatrix} (0.5,s_6) & (0.7,s_5) & (0.1,s_1) & (0.4,s_2) & (0.6,s_4) \\ & (0.5,s_6) & (0.6,s_4) & (0.4,s_3) & (0.4,s_2) \\ & & (0.5,s_6) & (0.9,s_6) & (0.2,s_1) \\ & & & (0.5,s_6) & (0.4,s_2) \\ & & & & (0.5,s_6) \end{pmatrix}, R^{4,1}, S^{4,1} = \begin{pmatrix} (0.5,s_6) & (0.7,s_4) & (0.6,s_3) & (0.9,s_6) & (0.8,s_5) \\ & (0.5,s_6) & (0.7,s_4) & (0.6,s_3) & (0.4,s_2) \\ & & (0.5,s_6) & (0.3,s_2) & (0.1,s_1) \\ & & & (0.5,s_6) & (0.3,s_1) \\ & & & & (0.5,s_6) \end{pmatrix}$$

$$R^{5,1}, S^{5,1} = \begin{pmatrix} (0.5,s_6) & (0.7,s_5) & (0.2,s_1) & (0.6,s_4) & (0.3,s_1) \\ & (0.5,s_6) & (0.7,s_5) & (0.2,s_1) & (0.8,s_5) \\ & & (0.5,s_6) & (0.7,s_4) & (0.2,s_1) \\ & & & (0.5,s_6) & (0.3,s_1) \\ & & & & (0.5,s_6) \end{pmatrix}, R^{1,2}, S^{1,2} = \begin{pmatrix} (0.5,s_6) & (0.1,s_1) & (0.6,s_1) & (0.2,s_5) & (0.2,s_2) \\ & (0.5,s_6) & (0.6,s_2) & (0.3,s_5) & (0.9,s_3) \\ & & (0.5,s_6) & (0.9,s_1) & (0.7,s_5) \\ & & & (0.5,s_6) & (0.6,s_2) \\ & & & & (0.5,s_6) \end{pmatrix}$$

$$R^{2,2}, S^{2,2} = \begin{pmatrix} (0.5,s_6) & (0.3,s_1) & (0.1,s_6) & (0.9,s_6) & (0.4,s_6) \\ & (0.5,s_6) & (0.4,s_5) & (0.9,s_5) & (0.6,s_1) \\ & & (0.5,s_6) & (0.1,s_5) & (0.9,s_1) \\ & & & (0.5,s_6) & (0.4,s_2) \\ & & & & (0.5,s_6) \end{pmatrix}, R^{3,2}, S^{3,2} = \begin{pmatrix} (0.5,s_6) & (0.3,s_1) & (0.9,s_5) & (0.9,s_6) & (0.1,s_1) \\ & (0.5,s_6) & (0.7,s_5) & (0.9,s_5) & (0.4,s_2) \\ & & (0.5,s_6) & (0.8,s_5) & (0.3,s_1) \\ & & & (0.5,s_6) & (0.2,s_1) \\ & & & & (0.5,s_6) \end{pmatrix}$$

$$R^{4,2}, S^{4,2} = \begin{pmatrix} (0.5,s_6) & (0.6,s_3) & (0.7,s_4) & (0.3,s_6) & (0.8,s_5) \\ & (0.5,s_6) & (0.3,s_2) & (0.2,s_3) & (0.7,s_4) \\ & & (0.5,s_6) & (0.7,s_4) & (0.1,s_1) \\ & & & (0.5,s_6) & (0.6,s_4) \\ & & & & (0.5,s_6) \end{pmatrix}, R^{5,2}, S^{5,2} = \begin{pmatrix} (0.5,s_6) & (0.6,s_4) & (0.7,s_4) & (0.4,s_3) & (0.4,s_3) \\ & (0.5,s_6) & (0.2,s_1) & (0.7,s_4) & (0.8,s_5) \\ & & (0.5,s_6) & (0.8,s_5) & (0.8,s_5) \\ & & & (0.5,s_6) & (0.3,s_1) \\ & & & & (0.5,s_6) \end{pmatrix}$$

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