



A Combined Weighting Based Large Scale Group Decision Making Framework for MOOC Group Recommendation

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Accepted: 12 January 2023 / Published online: 20 February 2023
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Abstract

Massive open online courses (MOOC) are free learning courses based on online platforms for higher education, which not only promote the open sharing of learning resources, but also lead to serious information overload. However, there are many courses on MOOCs, and it can be difficult for users to choose courses that match their individual or group preferences. Therefore, a combined weighting based large-scale group decision-making approach is proposed to implement MOOC group recommendations. First, based on the MOOC operation mode, we decompose the course content into three stages, namely pre-class, in-class, and post-class, and then the curriculum-arrangement-movement- performance evaluation framework is constructed. Second, the probabilistic linguistic criteria importance through intercriteria correlation method is employed to obtain the objective weighting of the criterion. Meanwhile, the word embedding model is utilized to vectorize online reviews, and the subjective weighting of the criteria are acquired by calculating the text similarity. The combined weighting then can be obtained by fusing the subjective and objective weighting. Based on this, the PL-MULTIMIIRA approach and Borda rule is employed to rank the alternatives for group recommendation, and an easy-to-use formula for group satisfaction is proposed to evaluate the effect of the proposed method. Furthermore, a case study is conducted to group recommendations for statistical MOOCs. Finally, the robustness and effectiveness of the proposed approach were verified through sensitivity analysis as well as comparative analysis.

Keywords MOOC · Group recommendation · Large scale group decision making · Online reviews · Combined weighting

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1 Introduction

MOOC are a free online teaching pattern, characterized by a large-scale, open, and flexible organization, with course content covering a wide range of subjects from natural sciences to humanities (Alturkistani et al. 2020). MOOC successfully unlocked an advanced knowledge exchange whose main goal is to make resources from prestigious universities freely available to everyone, anywhere, with any device (Tseng et al. 2022). The three largest MOOC platforms in the world emerged in 2012 and were originally founded by professors at American universities (Macleod et al. 2016). Each platform offers hundreds of courses, has attracted millions of students, and has been reported as a new thing that is changing universities by Times (2012). Among them, edX only provides courses from top universities, Coursera is positioned to provide a platform that is available to any university, and Udacity mainly focuses on science and technology courses, especially computer science.

The first MOOC emerged from the open educational resources movement, and the number of MOOC learners has exceeded 300 million by 2021 (Shah 2021). For example, Stanford offers free online college courses through their Office of the Vice Provost for Teaching and Learning (VPTL) in 1995; MIT announced program MITx in 2011, which offers massive open online courses in many disciplines. After the international MOOC storm, many renowned universities in China followed suite since 2012 (Doo et al. 2019; Wu 2021). For example, Peking University, Fudan University and Shanghai Jiao Tong University joined Coursera and edX MOOC platforms in 2013 respectively. Tsinghua University published MOOC platform “XuetangX” in 2013 (Li et al. 2021). In 2014, Shanghai Jiaotong University released “CNMOOC” and supported cross-campus learning and mutual recognition of credits in southwest China. By the end of 2021, more than 370 million registered students (MOE of China 2022) in China had studied online education platforms. MOOC have gradually matured and formalized, becoming one of the most popular online course development modes for higher education (Wu 2021). However, the emergence of diverse course resources has led to a serious information overload problem, which makes it tough for learners to choose the appropriate course because part of high-quality courses are concealed due to low clicks, while some low-quality courses are frequently recommended due to the high number of clicks. In addition, MOOC have been suffering from low course completion rates, ranging from 5 to 15% (Fidalgo-Blanco et al. 2016; Jordan 2015), which makes it difficult for learners to choose suitable MOOCs. Therefore, data analysis based on massive courses and recommending high-quality MOOCs to learners, thus solving the issues of painful class shopping and high trial-and-error costs, is an urgent task which remains to be solved in MOOC development.

Recommendation algorithms based on courses (online courses) mainly include: (1) content-based filtering approach (CBF). This approach mainly collects user and course attribute information, such as age, gender, text content, and number of clicks. Then algorithms such as TF-IDF are utilized to match user preferences




Stages	Contents				Criteria	Participants
Pre-Class	Course Framework	Course Outlines	Course Objectives	Faculty Team	Curriculum	
	Courseware Preparation	Record Video	Content Explanation	Assign Quiz	Arrangement	Teachers
In-Class	Online Learning	In-class Interaction	FAQ & Quiz	Knowledge Extensions	Movement	 Teachers & Students
Post-Class	Homework	Examination	Earning Credits	Course Completion	Performance	 Students

Fig. 1 MOOC operation pattern

with courses (Ghauth et al. 2010), thus implementing personalized recommendations for courses (Zhang et al. 2017); (2) collaborative filtering method (CF). The common practice is to model users based on association rules (Aher and Lobo 2013), KNN (Murad et al. 2020), social networks (Chen et al. 2022; Zhang et al. 2022; Zeng et al. 2022), etc., to depict user portraits (Jing and Tang 2017), and then identify users with the same preference based on distance or similarity calculation methods, thus completing course recommendations; (3) machine learning-based recommendations. In this category, researchers mainly use machine learning methods to extract preference information of users (Hu et al. 2022) or courses (Xu and Zhou 2020), and employ Bayesian neural networks (Li et al. 2020), RNN (Okubo et al. 2017) to characterize the courses, and make course recommendation; (4) Hybrid-based recommendation. The primary objective of the hybrid recommendation models is to predicting students' performance by combining the benefits of various recommendation methods and to recommend appropriate courses that match their interests by integrating personal information and course content (Esteban et al. 2019).

However, the following issues associated with recommendation methods and applications for courses (online courses) still exist:

1. Most existing methods recommend courses to individual users through personalized approaches. However, the audience of MOOC is dominated by college students, who mainly undertake learning activities as a group. Existing personalized course recommendation methods fail to satisfy the consistent preference demands of the group, resulting in inability to reach optimal group satisfaction in group decision making. Hence, group recommendations based on MOOC have emerged as an essential task.
2. In existing methods, the preference information of users is mainly represented by real numbers. However, the preference of each user is fuzzy and imprecise in real life because of cognitive bias, and they may be inconsistent and have different understanding towards the criteria when using MOOCs. Thus, users fail to deliver

- accurate evaluation information for each object. In addition, group preferences aggregated based on individual user preferences remain fuzzy and multidimensional, and real numbers fail to represent group preferences precisely. Thus, it is practical to conduct group recommendation research based on fuzzy information.
3. When multi-criterion recommendations are involved, methods such as AHP and entropy weighting are employed to estimate the criterion weights. However, these methods are either objective weights based on user preferences or subjective weights based on expert experience, and deviation exists in the recommendation results obtained by various weighting methods. Therefore, determining the appropriate weighting methods such that both subjective and objective information can be conveyed to achieve better recommendation results.
 4. Most existing studies calculate criterion weights based on the user preference matrix. However, this method can only reflect the preferences of a single user or a part of them, which is limited. In fact, online reviews contain the preference information expressed by global users after completing the experience, which can reflect the real feelings of global users more intuitively. Therefore, the weights obtained by analyzing online reviews are more reasonable and referential.

Therefore, this study proposes a combined weighting based large-scale group decision-making (LSGDM) method for MOOC group recommendations.

The contributions of this research are as follows: (1) A large-scale group decision-making (LSGDM) method under probabilistic linguistic environment for online reviews is proposed. (2) Based on the MOOC operation mode, we decompose the course content into three stages, namely pre-class, in-class, and post-class, and then the Curriculum-Arrangement-Movement-Performance (CAMP) evaluation framework is constructed. (3) A combined weighting method is proposed in which the online review-based criterion subjective weighting with the users' preference-based objective weighting is integrated. (4) An easy-to-use formula for group satisfaction is proposed to evaluate the performance of group recommendations.

The architecture of the remaining parts of this study is organized as follows: The methodology of MCDM and the evaluation framework of MOOC is presented in Sect. 2. Then, Sect. 3 introduces the framework and steps of the proposed combined weighting based LSGDM method for group recommendation. Section 4 elaborates on the recommendation method through a specific case study. Finally, the conclusions and future work are summarized in Sect. 5.

2 Preliminaries

2.1 MOOC Quality Evaluation Criterion

Through literature review, a basic understanding of the MOOC operation pattern was obtained, and the specific process is shown in Fig. 1. From where it can be seen that the MOOC operation pattern mainly includes three phases: namely pre-class, in-class and post-class. Among them, the pre-class stage indicates that

Table 1 MOOC "CAMP" quality evaluation framework

Criterion	Notation	Keyword	References
Curriculum	c_1	Introduction, organization, structure, framework, system, outline, objectives, teachers, design, style, ideology, format	Pawlowski (2007), Sung et al. (2011), Milligan and Littlejohn (2014)
Arrangement	c_2	Video, PPT, Word, document, book, case, material, content, lecture, knowledge, courseware	Nie et al. (2020), Tzeng et al. (2007), Margaryan et al. (2015)
Movement	c_3	Forum, group, discussion, test, Q&A, interaction, communication, extend	Lin (2010), Sung et al. (2011), Yousef et al. (2014), Nie et al. (2020)
Performance	c_4	Unit, quiz, midterm, final, assessment, questionnaire, feedback, performance, consolidation, quality	Lu et al. (2017), EADTU (2008), Jansen et al. (2020), Lee et al. (2019)

teachers release course resources through the online platform, so that students can preview the learning content and maximize the teaching effect. The in-class stage mainly focuses on students learning the knowledge of the lesson through the MOOC platform, discussing the questions detected in the pre-class phase, and displaying the learning results by completing class quizzes and online tests. The post-class stage mainly refers to the consolidation of the knowledge learned in the former two phases, while the teachers respond to the questions still encountered by students or release targeted learning tasks to make the MOOC learning pattern more accurate, comprehensive, and scientific.

Considering the three stages of MOOC, a “CAMP” MOOC quality evaluation framework (see Table 1) is proposed, which contains four criteria, namely Curriculum, Arrangement, Movement, and Performance. Among them, Curriculum refer to the basic structure including course introduction, course framework, course outline, course objectives, faculty team, etc. Arrangement is a major part of the MOOC, which indicates the arrangement of the content of the MOOC including course videos, course resources, textbooks, reference materials, etc. Movement is organized to enhance the interaction and communication between teachers and students through learning forums, group discussions and homework, as well as to improve students’ ability to implement independent learning and collaborative cooperation. Performance involves unit quizzes, midterm and final assessments, questionnaire feedback, etc., which is an assessment of the performance of the MOOC. Hence, the “CAMP” quality evaluation framework of MOOC is shown in Table 1.

2.2 Probabilistic Linguistic Term Sets

Decision makers typically utilize real numbers to evaluate online courses in MOOCs (Nie et al. 2020; Lu et al. 2017), but they fail to consider the fuzziness and unpredictability of user preferences. While the Probabilistic Linguistic Term Sets (PLTS) proposed by Pang et al. (2016) based on Linguistic Term Sets (LTS) can describe both hesitant and probabilistic components of uncertain information. In addition to expressing decision information in linguistic terms, decision makers can also reflect the preference degree through probability values, which can describe the real situation of decision makers more flexibly and appropriately than other fuzzy information (Zhang et al. 2018). Therefore, the concepts associated with the PLTS are introduced below.

Definition 1 Let s_t be a linguistic term, τ is positive integer, $S = \{s_t | t = -\tau, \dots, -1, 0, 1, \dots, \tau\}$ is a Linguistic Term Sets (LTS), which satisfies:

- (1) The S is ordered: $s_i > s_j$ if $i > j$;
- (2) Negation operator: $Neg(s_i) = s_j$, where $j = -i$;
- (3) Max operator: $\max\{s_i, s_j\} = s_i$, if $i \geq j$;

4) Min operator: $\max\{s_i, s_j\} = s_j$, if $i \leq j$;

Definition 2 (Pang et al. 2016): It is assumed that $S = \{s_t | t = -\tau, \dots, -1, 0, 1, \dots, \tau\}$ be a linguistic term set (LTS), then the definition of probabilistic linguistic term sets (PLTS) can be seen in Eq. (1):

$$L(p) = \left\{ L^{(k)}(p^{(k)}) | L^{(k)} \in S, r^{(k)} \in t, p^{(k)} \geq 0, k = 1, \dots, \#L(p), \sum_{k=1}^{\#L(p)} p^{(k)} \leq 1 \right\}, \tag{1}$$

where $L^{(k)}(p^{(k)})$ represents the linguistic term $L^{(k)}$ associated with the probability $p^{(k)}$, the number of distinct linguistic terms in $L(p)$ can be denoted as $\#L(p)$, $r^{(k)}$ is the subscript of linguistic terms. To be concise, $L^{(k)}(p^{(k)}) (k = 1, 2, \dots, \#L(p))$ is a probabilistic linguistic element (PLE).

Definition 3 (Pang et al. 2016): Suppose $L_1(p)$ and $L_2(p)$ be any two PLTSs: $L_1(p) = \{L_1^{(k_1)}(p_1^{(k_1)}) | k = 1, \dots, \#L_1(p_1)\}$ and $L_2(p) = \{L_2^{(k_2)}(p_2^{(k_2)}) | k = 1, \dots, \#L_2(p_2)\}$. The generalized form of the Euclidean distance between $L_1(p)$ and $L_2(p)$ is shown in Eq. (2):

$$d_{ned}(L_1(p), L_2(p)) = \left[\frac{1}{\#L_1(p)} \sum_{k=1}^{\#L_1(p)} \left[d(L_1^{(k_1)}(p_1^{(k_1)}), L_2^{(k_2)}(p_2^{(k_2)}))^2 \right] \right]^{\frac{1}{2}}, \tag{2}$$

where $d(L_1^{(k_1)}(p_1^{(k_1)}), L_2^{(k_2)}(p_2^{(k_2)})) = \left| p_1^{k_1} \times \frac{r_1^{(k_1)}}{\tau} - p_2^{k_2} \times \frac{r_2^{(k_2)}}{\tau} \right|$, the number of linguistic terms in $L_1(p)$ and $L_2(p)$ can be represented as $\#L_1(p)$ and $\#L_2(p)$, which satisfied $\#L_1(p) = \#L_2(p)$.

Definition 4 (Luo et al. 2020): To measure the similarity between two PLTSs, the correlation coefficient of PLTS is proposed. It is assumed that $L_1(p)$ and $L_2(p)$ be any two PLTSs: $L_1(p) = \{L_1^{(k_1)}(p_1^{(k_1)}) | k = 1, \dots, \#L_1(p_1)\}$ and $L_2(p) = \{L_2^{(k_2)}(p_2^{(k_2)}) | k = 1, \dots, \#L_2(p_2)\}$, $\#L_1(p) = \#L_2(p)$, then Eq. (3) is utilized to calculate the correlation coefficient between $L_1(p)$ and $L_2(p)$:

$$\kappa(L_1(p), L_2(p)) = \frac{\langle L_1(p), L_2(p) \rangle}{|L_1(p)||L_2(p)|} = \frac{\sum_{k=1}^{\#L_1(p)} (r_1^{(k)} p_1^{(k)}) (r_2^{(k)} p_2^{(k)})}{\sqrt{\sum_{k=1}^{\#L_1(p)} (r_1^{(k)} p_1^{(k)})^2} \sqrt{\sum_{k=1}^{\#L_1(p)} (r_2^{(k)} p_2^{(k)})^2}}. \tag{3}$$

Definition 5 (Pang et al. 2016): Assumed that $L(p) = \{L^{(k)}(p^{(k)}) | k = 1, \dots, \#L(p)\}$ be a PLTS, then Eqs. (4) and (5) are conducted to calculate the score function $s(L(p))$ and standard deviation $\sigma(L(p))$ of PLTS $L(p)$:

$$s(L(p)) = \frac{\sum_{k=1}^{\#L(p)} g(L^{(k)})p^{(k)}}{\sum_{k=1}^{\#L(p)} p^{(k)}}, \tag{4}$$

$$\sigma(L(p)) = \frac{\left(\sum_{k=1}^{\#L(p)} (g(L^{(k)})p^{(k)} - s(L(p)))^2 \right)^{1/2}}{\sum_{k=1}^{\#L(p)} p^{(k)}}, \tag{5}$$

where $g(L^{(k)}) = \frac{r^{(k)+\tau}{2\tau}$, $r^{(k)}$ is the subscript of linguistic term $L^{(k)}$.

After obtaining the probabilistic linguistic score function and standard deviation, the PLTSs can be compared. For example, given any two PLTSs $L_1(p)$ and $L_2(p)$:

- (1) if $s(L_1(p)) > s(L_2(p))$, then $L_1(p) > L_2(p)$, and vice versa;
- (2) if $s(L_1(p)) = s(L_2(p))$, then
 - i. if $\sigma(L_1(p)) > \sigma(L_2(p))$, then $L_1(p) > L_2(p)$, and vice versa;
 - ii. if $\sigma(L_1(p)) = \sigma(L_2(p))$, then $L_1(p) \sim L_2(p)$.

Definition 6 (Pang et al. 2016): Let $L_i(p) = \{s_{a,i}^l(p_i^l) | l = 1, 2, \dots, L_i\}$ ($i = 1, 2, \dots, n$) be n PLTSs, $w^T = (w_1, w_2, \dots, w_n)^T$ denotes the weighting vector, which satisfied $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$. Then Eq. (6) is employed to calculate the probabilistic linguistic weighted averaging (PLWA) operator:

$$\begin{aligned} PLWA(L_1(p), L_2(p), \dots, L_m(p)) &= w_1L_1(p) \oplus w_2L_2(p) \oplus \dots \oplus w_mL_m(p) \\ &= \cup_{r_1^n \in L_1(p)} \{w_1r_1^n p_1^n\} \oplus \cup_{r_2^n \in L_2(p)} \{w_2r_2^n p_2^n\} \oplus \dots \oplus \cup_{r_m^n \in L_m(p)} \{w_m r_m^n p_m^n\}, \end{aligned} \tag{6}$$

when $w^T = (1/n, 1/n, \dots, 1/n)^T$, the PLWA operator degenerates to the probabilistic linguistic averaging (PLA) operator.

2.3 PL-MULTIMOORA

The MULTIMOORA approach was first proposed by Brauers and Zavadskas (2010), which integrates the advantage of the additive utility function, multiplicative utility function as well as reference point method (Zhang et al. 2019; Zeng et al 2013). Li et al. (2020) extend the MULTIMOORA method in a probabilistic linguistic environment. Let $a_i (i = 1, 2, \dots, m)$ be the alternatives, $c_j (j = 1, 2, \dots, n)$ represent the criteria in the decision making progress, $L_{ij}(p)$ represent the decision maker’s probabilistic linguistic rating of alternative a_i on criteria c_j . The following subsections

describe probabilistic linguistic ratio system (PLRS), probabilistic linguistic reference point approach (PLRP) as well as probabilistic linguistic full multiplicative form (PLFMF) in the PL-MULTIMOORA approach:

2.3.1 Probabilistic Linguistic Ratio System (PLRS)

Let s_{ij} be the score of $L_{ij}(p)$. Then Eq. (7) is employed to obtain the standardized normalized probabilistic linguistic score matrix $D(s) = (s_{ij}^N)_{n \times m}$:

$$s_{ij}^N = \frac{s_{ij}}{\sqrt{\sum_{j=1}^m (s_{ij})^2}} (i = 1, 2, \dots, n), \tag{7}$$

Considering two types of criteria, which is benefit-based criteria as well as cost-based criteria. The Eq. (8) is utilized to calculate the utility value $U_1(a_i) (i = 1, 2, \dots, m)$ in the PLRS system.

$$U_1(a_i) = \sum_{j=1}^g \omega_j s_{ij}^N - \sum_{j=g+1}^n \omega_j s_{ij}^N, \tag{8}$$

where $c_j (j = 1, 2, \dots, g)$ and $c_j (j = g + 1, g + 2, \dots, n)$ represent the benefit criterion and the cost criterion respectively. ω_j denotes the weight of c_j . The larger the value of $U_1(a_i)$, the higher the ranking of a_i .

2.3.2 Probabilistic Linguistic Reference Point Approach (PLRP)

The PLRP model is defined based on the linear normalization of PLE, which is expressed in Eq. (9):

$$U_2(a_i) = \max_j \omega_j \frac{d(s_{ij^+}, s_{ij})}{d(s_{ij^-}, s_{ij^+})}, \tag{9}$$

where s_{ij^+} and s_{ij^-} denote the best and worst scores regarding to c_j , respectively. Therefore, the smaller the value of $U_2(a_i)$, the higher the ranking of alternative a_i .

2.3.3 Probabilistic Linguistic Full Multiplicative Form (PLFMF)

The PLRP guarantees that the performance of the chosen alternatives is not extremely poor under all criteria. According to Wu et al. (2018), the calculation process of PLFMF method is given by Eq. (10):

$$U_3(a_i) = \frac{\sqrt[g]{\prod_{j=1}^g \left(1 - \left(1 - s_{ij}^N\right)^{\omega_j}\right)}}{\sqrt[n-g]{\prod_{j=g+1}^n \left(1 - \left(1 - s_{ij}^N\right)^{\omega_j}\right)}}, \tag{10}$$

where $U_3(a_i)$ is the utility value of a_i . The final alternative preference is obtained by sorting the $U_3(a_i)$, the larger the $U_3(a_i)$, the higher the ranking of a_i .

2.3.4 Borda Rule

Referring to Wu et al. (2018), an improved Borda rule was utilized to assess the Borda score by integrating the utility value obtained in the PLRS, PLRP, and PLFMF methods, which can be seen in Eqs. (11) and (12):

$$U_y^N(a_i) = \frac{U_y(a_i)}{\sqrt{\sum_{i=1}^m (U_y(a_i))^2}}, y = 1, 2, 3, \tag{11}$$

$$IBS_i = U_1^N(a_i) \times \frac{m - r_1(a_i) + 1}{m(m+1)/2} - U_2^N(A_i) \times \frac{r_2(a_i)}{m(m+1)/2} + U_3^N(A_i) \times \frac{m - r_3(a_i) + 1}{m(m+1)/2}, \tag{12}$$

where IBS_i is the Borda score of alternative $a_i(i = 1, 2, \dots, m)$, $y = 1, 2, 3$ refers to the PLRS, PLRP, and PLFMF methods, $U_y(a_i)$ refers to the utility value obtained through the three methods, $U_y^N(a_i)$ is the corresponding normalized utility value, $r_y(a_i)$ is the ranking results of three methods.

2.4 Word Embedding

Word embedding is a vital part of natural language processing (NLP) that converts human-understood textual information into vectorial forms that can be understood by machines. Common word-embedding models include One-Hot, GloVe (Global Vectors for Word Representation), and Word2vec (Lauren et al. 2018; Rezaeinia et al. 2018). GloVe is a word embedding model based on the word co-occurrence matrix proposed by Pennington et al. (2014). Compared with other models, the GloVe model makes better use of global contextual information, speeds up the training iteration, shortens the training cycle, and provides better training results (Sakketou and Ampazis 2020). The objective function of the GloVe model is listed in Eq. (13):

$$J = \sum_{i,j}^N f(X_{ij})(v_i^T v_j + b_i + b_j - \log(X_{ij}))^2, \tag{13}$$

where v_i and v_j are the word vectors for word_{*i*} and word_{*j*}. b_i and b_j are the bias items of v_i and v_j , respectively. N is the size of the glossary; $f(X_{ij})$ is the weighting

function that dominates the frequency of co-occurrence word pairs; the higher the frequency, the greater the weight. Hence, the operation process of the GloVe model is:

Algorithm 1: GloVe model

INPUT: corpus D , sliding window ws .

OOUPUT: Word vector v^s .

BEGIN

- 1: For c_i in D :
- 2: let c_i be the centre, ws be the radius, D_i is the co-occurrence word set.
- 3: for D_i in D :
- 4: $f_i = \text{count}(c_i) + 1$, where f_j is the word frequency of c_i .
- 5: update co-occurrence matrix X based on c_i and f_i
- 6: For i in X :
- 7: Train GloVe model using Eq. (13).
- 8: update the parameters of the objective function.
- 9: word vector v^s is obtained until the model converges.
- 10: Return v^s :

END

2.5 PL-CRITIC

Criteria Importance through Intercriteria Correlation (CRITIC) is proposed to compute the objective weight of criterion (Diakoulaki et al. 1995), which involves calculating correlation coefficients and standard deviations of criteria and then determining the objective weights through both contrast strength and the conflicting nature of the indicators (Krishnan 2021). Wang et al. (2021) extended this approach to a probabilistic linguistic environment, which was calculated using Eqs. (14)–(17):

$$w_j = \frac{I_j}{\sum_{j=1}^n I_j}, \tag{14}$$

$$I_j = \sigma_j \sum_{t=1}^n (1 - \rho_{jt}), \tag{15}$$

$$\rho_{jt} = \frac{\sum_{i=1}^m \left(\sum_{k=1}^{\#L(p)} \left(r_{ij}^{(k)} p_{ij}^{(k)} - \bar{r}_j^{(k)} \bar{p}_j^{(k)} \right) \right) \left(\sum_{k=1}^{\#L(p)} \left(r_{it}^{(k)} p_{it}^{(k)} - \bar{r}_t^{(k)} \bar{p}_t^{(k)} \right) \right)}{\sqrt{\sum_{i=1}^m \left(\sum_{k=1}^{\#L(p)} \left(r_{ij}^{(k)} p_{ij}^{(k)} - \bar{r}_j^{(k)} \bar{p}_j^{(k)} \right) \right)^2 \sum_{i=1}^m \left(\sum_{k=1}^{\#L(p)} \left(r_{it}^{(k)} p_{it}^{(k)} - \bar{r}_t^{(k)} \bar{p}_t^{(k)} \right) \right)^2}}, \tag{16}$$

$$\sigma_j = \sqrt{\frac{1}{m} \sum_{i=1}^m \left(\sum_{k=1}^{\#L(p)} \left(r_{ij}^{(k)} p_{ij}^{(k)} - \bar{r}_j^{(k)} \bar{p}_j^{(k)} \right) \right)^2}, \quad (17)$$

where w_j is the objective weight of criteria and satisfies $w_j \in [0, 1]$, $\sum_{j=1}^n w_j = 1$. I_j is the amount of potential information possessed by criterion c_j , ρ_{ji} is the correlation coefficient between criterion c_j and c_i based on Eq. (3), σ_j is the standard deviation of the criterion c_j according to Eq. (5), $\bar{r}_j^{(k)} \bar{p}_j^{(k)} = \frac{\sum_{i=1}^m r_{ij}^{(k)} p_{ij}^{(k)}}{m} = \frac{\sum_{i=1}^m p_{ij}^{(k)}}{m}$.

3 The Combined Weighting Based LSGDM Model for Group Recommendation

3.1 The Framework of the Combined Weighting Based Group Recommendation Model

The LSGDM-based group recommendation model proposed in this paper consists of four modules: online review-based weighting process, clustering process, combined weighting process, ranking and recommendation process. The details are shown in Fig. 2.

- (1) Online review-based weighting process. The main contribution of this process is to crawl online reviews and extract text feature words based on NLP technology for text preprocessing. Then, the GloVe model is employed to vectorize the text feature words. Thus, the criterion weights can be obtained by calculating and normalizing the vector similarity between online reviews and criterion keywords.
- (2) Clustering process. This process aims to cluster user preferences using the K-means algorithm, so that users with the same preferences are gathered into the same sub-cluster, thus ensuring that the preferences of users within the subgroup are highly similar, while the preferences of users between subgroups differ.
- (3) Combined weighting process. The criterion weights obtained in this study were derived from two aspects: online review-based subjective weighting and user preference decision-making matrix-based objective weighting. The final criterion weights were obtained by fusing the two weights.
- (4) Ranking and recommendation processes. The alternatives were ranked using the PL-MULTIMOORA method, which consists of three parts: PLRS, PLRP, and PLFMF. Each part yields a utility value and ranking results for a set of alternatives. Furthermore, the Borda scores of the alternatives are calculated to determine the ultimate ranking in accordance with the Borda rule.

3.2 The Steps of the Combined Weighting Based Group Recommendation Model

It is assumed that alternatives set is represented as $A = \{a_1, a_2, \dots, a_m\}$, $E = \{e_1, e_2, \dots, e_t\}$ be the users set, criterion set can be denoted as $C = \{c_1, c_2, \dots, c_n\}$,

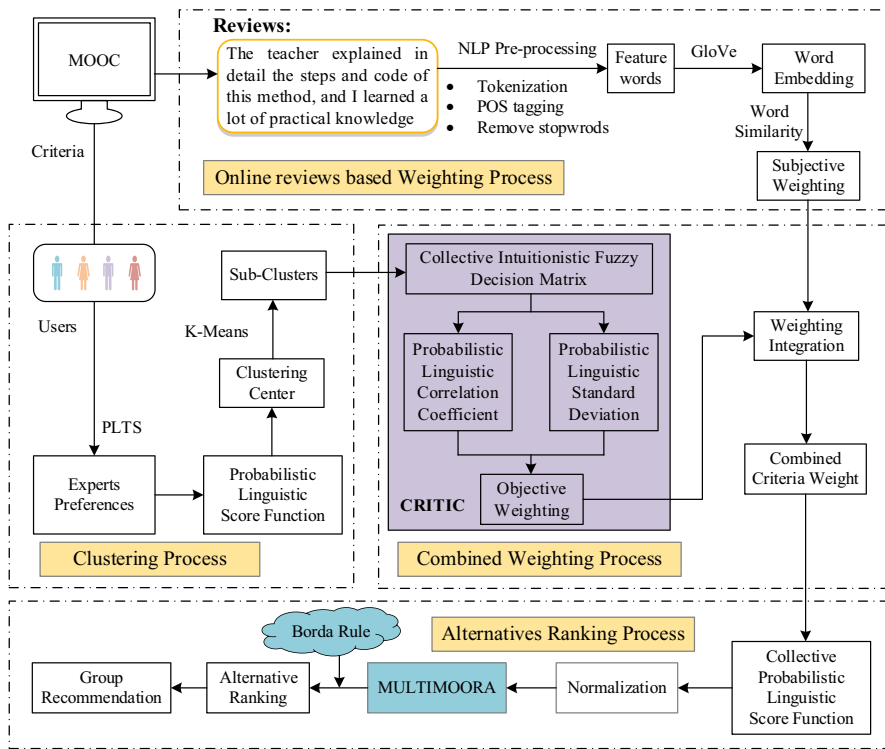


Fig. 2 Framework of the combined weighting based group recommendation model

user weight vector $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_t\}$ and criterion weight vector $\Omega = \{\omega_1, \omega_2, \dots, \omega_n\}$ remain unknown, but satisfy $\lambda_k \geq 0$ and $\sum_{k=1}^t \lambda_k = 1$, $\omega_j \geq 0$ and $\sum_{j=1}^n \omega_j = 1$. Then the probabilistic linguistic decision-making matrix R_{ij}^k of user e^k for the set of alternatives can be express using Eq. (18):

$$R_{ij}^k = \begin{bmatrix} L_{11}^k(p) & L_{12}^k(p) & \dots & L_{1n}^k(p) \\ L_{21}^k(p) & L_{22}^k(p) & \dots & L_{2n}^k(p) \\ \vdots & \vdots & \ddots & \vdots \\ L_{m1}^k(p) & L_{m2}^k(p) & \dots & L_{mn}^k(p) \end{bmatrix}, \tag{18}$$

where $L_{ij}^k(p)$ denotes the probabilistic linguistic rating of the user e^k for i th alternative with regard to criterion c_j . The pseudocode of the proposed combined weighting based LSGDM method for MOOC group recommendation is presented in Algorithm 2.

Algorithm 2: combined weighting based LSGDM method for MOOC group recommendation

INPUT: user decision matrix, alternatives set A , Criterion set C

OOUPUT: ranking and utility values of alternatives

BEGIN

- 1: Crawling iCourse using python to obtain the online reviews of students.
- 2: Pre-processing of the online reviews using NLP technology.
- 3: Building word vector v^s using GloVe model based on Algorithm 1.
- 4: Calculating text similarity based on v^s using Eq. (19).
- 5: Calculating Online reviews-based criterion weighting according to Eq. (20).
- 6: User preference clustering using K-Means algorithm.
- 7: Calculating user weighting using Eq. (21).
- 8: Constructing the collective decision matrix.
- 9: Calculating the combined weighting corresponding to C using Eq. (22).
- 10: Calculating the utility values using PL-MULTIMOORA and Borda rule.
- 11: Recommend the Top-N ranked alternatives in A to the group.
- 12: Calculating the group satisfaction.
- 13: Return ranking and Borda scores of alternatives, group satisfaction.

END

The proposed combined weighting based LSGDM method for MOOC group recommendation includes the following steps.

Step 1: Data acquisition and pre-processing. Based on Python web crawler technology, web data are parsed to obtain online reviews of users. Text feature words can then be accessed through NLP technology, including word segmentation, part-of-speech tagging, and stop-word removal.

Step 2: Building word vector. In accordance with Algorithm 1, the word co-occurrence matrix was obtained by setting a sliding window based on text feature words. The GloVe model is then utilized to train the text feature words to obtain the word vector according to Eq. (13).

Step 3: Calculate text similarity. After obtaining the word vector, the similarity of the word vector between the online reviews and criterion keyword words must be further calculated based on Eq. (19):

$$\cos(v_i, v_j) = \frac{v_i \times v_j}{\|v_i\| \times \|v_j\|}, \quad (19)$$

where v_i and v_j represent the word vectors of text feature words and $\cos(v_i, v_j)$ denotes the similarity of word vectors.

Step 4: Calculate the online reviews-based criterion weighting. The online review-based criterion weights q_j were obtained by normalizing the average similarity of the word vector, which was calculated using Eq. (20):

$$q_j = \frac{sim_j}{\sum_{j=1}^n sim_j}, \tag{20}$$

where $sim_j = \sum_{j=1}^n \cos(v_i, v_j)$ is the average similarity of word vectors for criterion c_j .

Step 5: User preference clustering. The probabilistic linguistic distances of each user’s rating regarding to alternative a_i are calculated in accordance with Eqs. (1)–(2). Subsequently, the K-Means algorithm was used to cluster the users’ preferences, and the clustering evaluation indexes, namely the Silhouette Coefficients (SC) index, Calinski-Harabaz (CH) Index, and Davies-Bouldin (DB) index, were calculated. The above process is repeated until all users are divided into g subclusters, denoted as $G^{(1)}, G^{(2)}, \dots, G^{(g)}$.

Step 6: Calculating the weights of users and subclusters. Based on ANOVA, the average standard deviation of each user’s probabilistic linguistic rating was calculated using Eq. (5), and the weight λ_k assigned to each user can be obtained by normalizing the average standard deviation as follows:

$$\lambda^k = \frac{\bar{\sigma}^k}{\sum_{k=1}^t \bar{\sigma}^k}, \tag{21}$$

where $\bar{\sigma}^k = \sum_{i=1}^m \sum_{j=1}^n \sigma_{ij}^k / (n \times m)$ denotes the average standard deviation of the probabilistic linguistic rating for each user. Then the user weights are summed to get the weights of subclusters $\lambda^{(r)} = \sum_{k \in r} \lambda^k$.

Step 7: Construct the collective probabilistic linguistic decision matrix. Based on the PLWA operator, the probabilistic linguistic decision matrix $R^{(r)}$ for the sub-cluster is obtained by integrating the user weights λ^k and user preference matrix R_{ij}^k .

$$R^{(r)} = \begin{bmatrix} L_{11}^{(r)}(p) & L_{12}^{(r)}(p) & \dots & L_{1n}^{(r)}(p) \\ L_{21}^{(r)}(p) & L_{22}^{(r)}(p) & \dots & L_{2n}^{(r)}(p) \\ \vdots & \vdots & \ddots & \vdots \\ L_{m1}^{(r)}(p) & L_{m2}^{(r)}(p) & \dots & L_{mn}^{(r)}(p) \end{bmatrix}.$$

Similarly, the collective probabilistic linguistic decision matrix R can be constructed by integrating the weights $\lambda^{(r)}$ and preference decision matrix $R^{(r)}$ of the sub-clusters.

$$R = \begin{bmatrix} L_{11}(p) & L_{12}(p) & \dots & L_{1n}(p) \\ L_{21}(p) & L_{22}(p) & \dots & L_{2n}(p) \\ \vdots & \vdots & \ddots & \vdots \\ L_{m1}(p) & L_{m2}(p) & \dots & L_{mn}(p) \end{bmatrix},$$

where $L_{ij}(p)$ is the probabilistic linguistic rating of alternative a_i under criterion c_j .

Step 8: Calculating combined weighting. In accordance with the collective probabilistic linguistic decision matrix, the objective weight of the criteria w_j can be obtained according to Eqs. (14)–(17). Further, since the online review-based

criterion weight q_j is obtained in step (4), the combined weight of the criterion ω_j can be calculated using Eq. (22):

$$\omega_j = \frac{w_j \times q_j}{\sum_{j=1}^n w_j \times q_j}. \quad (22)$$

Step 9: Ranking and Recommendation. Based on Eqs. (7)–(10), the PL-MULTI-MOORA method is employed to calculate the utility values of the alternatives, and the Borda rule is utilized to rank the alternatives based on Eqs. (11)–(12). Finally, the Top-N alternatives are recommended to the group.

Step 10: Calculate the group satisfaction. To evaluate the performance of group recommendation model, a distance-based satisfaction function is proposed based on (Zhu et al. 2018) to evaluate the performance of group recommendation which is shown in Eq. (23).

$$Sa = \min_r \left\{ 1 / \frac{1}{m} \sum_{i=1}^m \sqrt{\sum_{j=1}^n (\omega_j s_{ij}^{(r)} - \omega_j s_{ij})^2} \right\}, \quad (23)$$

where $s_{ij}^{(r)}$ is the score of the sub-cluster $G^{(r)}$, s_{ij} denotes the collective score, and ω_j represents the criterion weight. Sa refers to group satisfaction: the higher the Sa , the higher the satisfaction of the group.

A flowchart of the proposed LSGDM-based method for group recommendations is shown in Fig. 3.

4 Case Study

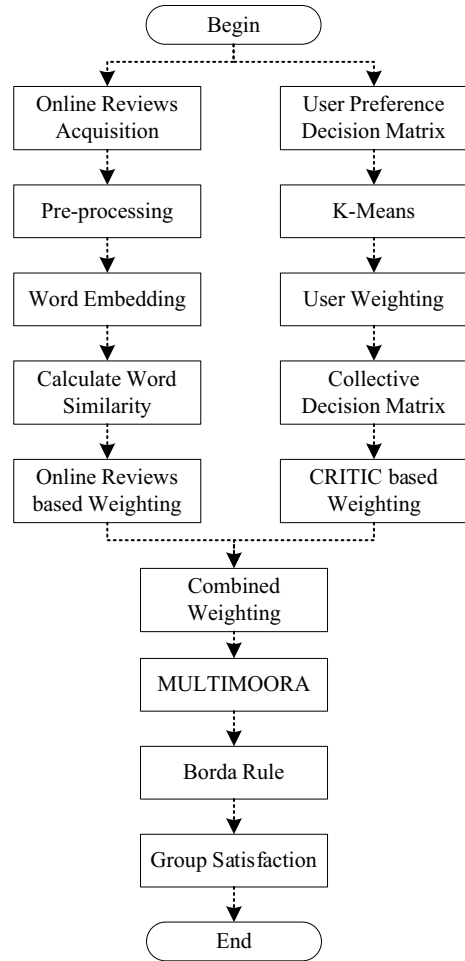
4.1 Practical Problem Description

The continued impact of COVID-19 has led to a shift from traditional offline teaching patterns to online teaching patterns. Thus, online learning has become a trend. iCourse (<https://www.icourse163.org/>) is an online learning and education platform jointly released by Higher Education Press of China and NetEase. The main purpose of iCourse is to undertake the mission of the Ministry of Education's National Quality Open Courses, offering high quality MOOC courses to the public (see Fig. 4).

For students majoring in statistics, statistics courses are generally conducted in class groups. However, more than 20 colleges and universities are releasing statistics courses on iCourses as of March 2022. Therefore, it is necessary to choose an appropriate statistics course among diverse MOOC.

In this context, a class containing 20 students decided to conduct collective learning of MOOC statistics and 8 statistics MOOCs with more than 1000 cumulative participants were selected on the iCourse platform (the selection process of 20 students and 8 statistics MOOCs are shown in Appendix 1): Henan University of Economics and Law (a_1), Zhejiang University of Finance and Economics (a_2), Central

Fig. 3 Flowchart of LSGDM-based group recommendation model



University of Finance and Economics (a_3), Nanjing University of Finance and Economics (a_4), Beijing Jiaotong University (a_5), Capital University of Economics and Business (a_6), East China Normal University (a_7), and Zhejiang Gongshang University (a_8). Furthermore, the statistical MOOCs released by these eight universities (abbreviated as eight alternatives) were evaluated using the proposed combined weighting based LSGDM approach for group recommendation.

4.2 The Combined Weighting Based LSGDM Model for Group Recommendation

Consider a typical group decision-making process, where 20 students in this class are required to provide individual preference information regarding the above 8 alternatives, and the group recommendation is completed by integrating the individual preference information. Owing to the cognitive bias of each student, it is not feasible for them to deliver precise preferences for each alternative. Hence, the LTS



Fig. 4 Statistics courses and user reviews on iCourse platform

$S = \{s_{-2} = \text{bad}, s_{-1} = \text{somewhat bad}, s_0 = \text{medium}, s_1 = \text{somewhat good}, s_2 = \text{good}\}$ is utilized to evaluate the alternatives. For student e_1 , the corresponding probabilistic linguistic decision matrix is:

$$R_{ij}^1 = \begin{bmatrix} \{s_3(0.136), s_4(0.47), s_5(0.394)\} & \{s_2(0.433), s_3(0.567)\} & \{s_1(1)\} & \{s_2(1)\} \\ \{s_2(0.099), s_3(0.901)\} & \{s_5(1)\} & \{s_2(0.435), s_3(0.307), s_4(0.258)\} & \{s_2(1)\} \\ \{s_1(0.266), s_2(0.285), s_3(0.449)\} & \{s_4(1)\} & \{s_3(0.105), s_4(0.333), s_5(0.562)\} & \{s_4(0.695), s_5(0.305)\} \\ \{s_3(0.034), s_4(0.428), s_5(0.538)\} & \{s_4(0.227), s_5(0.773)\} & \{s_2(0.031), s_3(0.089), s_4(0.881)\} & \{s_5(1)\} \\ \{s_4(0.911), s_5(0.089)\} & \{s_4(0.034), s_5(0.996)\} & \{s_2(0.825), s_3(0.175)\} & \{s_2(0.015), s_3(0.489), s_4(0.487)\} \\ \{s_1(0.244), s_2(0.464), s_3(0.292)\} & \{s_3(0.72), s_4(0.207), s_5(0.074)\} & \{s_1(1)\} & \{s_1(0.546), s_2(0.454)\} \\ \{s_3(0.883), s_4(0.117)\} & \{s_4(1)\} & \{s_3(1)\} & \{s_5(1)\} \\ \{s_3(0.619), s_4(0.268), s_5(0.114)\} & \{s_5(1)\} & \{s_3(0.589), s_4(0.045), s_5(0.365)\} & \{s_3(0.926), s_4(0.074)\} \end{bmatrix}$$

4.2.1 Online Reviews-Based Weighting

Based on the iCourse platform, python 3.6 software coupled with Selenium toolkit was employed to crawl the user online reviews for the above 8 MOOCs, and a total of 1311 online reviews were collected. Then, word segmentation, part-of-speech tagging, and stop-word removal were performed based on Jieba¹ tools, and 5361 text feature words were obtained, which are presented in Fig. 5 as the word cloud map.

The 5361 text feature words were fused with 40 attribute keywords to obtain the corpus of this study, which consists of 5401 text feature words. Furthermore, the vector dimension of the sliding window of the co-occurrence matrix ws was set to

¹ <https://github.com/fxsjy/jieba>.



Fig. 5 Word cloud map of online reviews for statistics MOOC

Table 2 The Top 10 closest terms to the keyword “授课”

Word	Similarity	Word	Similarity
讲课	0.7827	内容	0.6947
讲解	0.7289	知识点	0.6717
详细	0.7239	教材	0.6397
课程	0.7199	资料	0.5848
清晰	0.7084	学习	0.5714

Table 3 Average similarity and weighting of criterion

Index	c_1	c_2	c_3	c_4
Average similarity	0.4098	0.4503	0.3865	0.3849
weighting	0.2512	0.2760	0.2369	0.2359

100, and the GloVe model was utilized to vectorize the text feature words according to Eq. (11), and the text similarity of feature words between the user online reviews and criterion keywords was calculated based on Eq. (15). For example, the keyword “lecture” is transformed into a 100-dimensional vector after GloVe model training. Table 2 also presents the top ten feature words that are most similar to “授课” in the corpus. Among them, “授课” has the highest similarity with “讲课” (0.7827) and the lowest similarity with “学习” (0.5714).

Analogously, a set of Top-10 similar terms is obtained for each keyword, and the average similarity of each keyword is calculated and averaged under each criterion to obtain the average similarity of the criterion. Finally, the average similarity of the

Table 4 The average standard deviation of user ratings and weights

Experts	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9	e_{10}
Deviation	2.058	1.716	1.744	1.253	1.925	2.108	1.991	1.443	1.568	1.642
Weight	0.059	0.049	0.050	0.036	0.055	0.060	0.057	0.041	0.045	0.047
Experts	e_{11}	e_{12}	e_{13}	e_{14}	e_{15}	e_{16}	e_{17}	e_{18}	e_{19}	e_{20}
Deviation	1.850	1.888	1.812	1.664	1.476	1.703	2.026	1.846	1.609	1.823
Weight	0.053	0.054	0.052	0.047	0.042	0.048	0.058	0.053	0.046	0.052

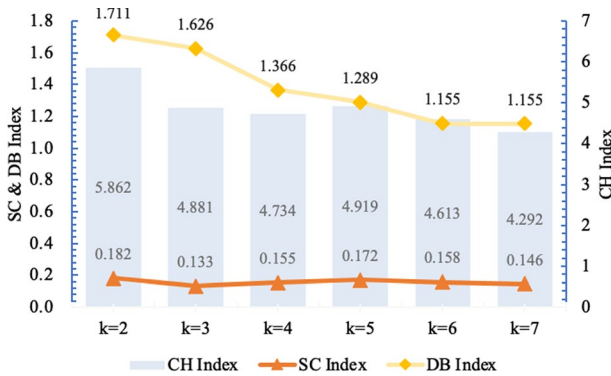


Fig. 6 Cluster evaluation index with varied number of clusters

criteria was normalized using Eq. (16) to obtain the online review-based criterion weights $q_j = (0.2512, 0.276, 0.2369, 0.2359)$, as listed in Table 3.

4.2.2 Experts Clustering

The average standard deviation of the probabilistic linguistic ratings for the 20 students was obtained using Eq. (5) and normalized based on Eq. (17) to obtain user weights, as listed in Table 4. From where it can be seen that among the 20 students, student e_6 scored the highest weight of 0.06, and student e_4 recorded the lowest weight of 0.036.

Further, the K-Means algorithm was employed to cluster the 20 users. Since this algorithm needs to set the number of clusters artificially, we calculate the clustering evaluation indexes when $k = 2, 3, \dots, 7$ respectively. As can be seen from Fig. 6, the CH index is 4.919 and the SC is 0.172 when $k = 5$, which is the largest value corresponding to varying number of cluster centers, indicating that the clustering performance is optimal in the situation. Therefore, the sub-clusters were divided into 5 categories.

The clustering results for the five subgroups are presented in Table 5. From where it can be observed that student e_1 and e_{18} are gathered into one category to form sub-cluster $G^{(1)}$ with a corresponding weight of 0.111; student e_4, e_8, e_9, e_{11} and e_{14} are clustered into one category namely $G^{(2)}$, with a corresponding weight of 0.217; student $e_2, e_5,$

Table 5 The members and weights of subcluster

Sub-cluster	Members	Weights
$G^{(1)}$	$\{e_1, e_{18}\}$	0.111
$G^{(2)}$	$\{e_4, e_8, e_9, e_{11}, e_{14}\}$	0.217
$G^{(3)}$	$\{e_2, e_5, e_{10}, e_{13}, e_{15}, e_{19}\}$	0.297
$G^{(4)}$	$\{e_7, e_{16}, e_{20}\}$	0.156
$G^{(5)}$	$\{e_3, e_6, e_{12}, e_{17}\}$	0.219

e_{10}, e_{13}, e_{15} and e_{19} are clustered together to form $G^{(3)}$ with a corresponding weight of 0.297; student e_7, e_{16} and e_{20} are clustered and formed $G^{(4)}$ with a corresponding weight of 0.156; student e_3, e_6, e_{12} and e_{17} are clustered into $G^{(5)}$ with a corresponding weight of 0.219.

Based on the clustering results, the probabilistic linguistic decision matrix of each user is aggregated using the PLWA operator, according to Eq. (6) to obtain the decision matrix $R^{(i)} (i = 1, 2, \dots, 5)$ of each sub-cluster and the collective decision matrix R , as shown in Appendix 2.

Furthermore, the score s_{ij} of the collective decision matrix can be obtained according to Eq. (4):

$$s_{ij} = \begin{bmatrix} 2.933 & 3.008 & 3.276 & 2.460 \\ 2.942 & 3.379 & 3.261 & 3.134 \\ 2.954 & 3.120 & 3.021 & 3.360 \\ 3.292 & 3.332 & 3.057 & 3.334 \\ 3.078 & 2.972 & 2.461 & 2.877 \\ 2.639 & 2.760 & 3.098 & 2.081 \\ 2.969 & 3.093 & 2.873 & 2.988 \\ 2.976 & 2.849 & 3.109 & 3.033 \end{bmatrix}.$$

4.2.3 Combined Weighting

In Sect. 2.4, the objective weight of the criterion is derived based on the PL-CRITIC method. Hence, on the basis of the collective probabilistic linguistic decision matrix, we compute the probabilistic linguistic correlation coefficient matrix of the criterion according to Eq. (18):

$$PLCC_{ij} = \begin{bmatrix} 1 & 0.618 & -0.274 & 0.466 \\ 0.618 & 1 & 0.194 & 0.558 \\ -0.274 & 0.194 & 1 & -0.065 \\ 0.466 & 0.558 & -0.065 & 1 \end{bmatrix}.$$

Similarly, the probabilistic linguistic standard deviation of criterion in the collective probabilistic linguistic decision matrix G can be obtained using Eq. (19):

$$PLSD_j = [0.238 \ 0.325 \ 0.227 \ 0.392].$$

Table 6 The results derived by the PL-MULTIMOORA method

Alternatives	PLRS		PLRP		PLFMF		Borda score	Final rank
	$u_1(a_i)$	Rank	$u_2(a_i)$	Rank	$u_3(a_i)$	Rank		
a_1	0.339	6	0.297	8	0.292	6	-0.067	8
a_2	0.372	2	0.111	3	0.300	2	0.126	2
a_3	0.366	3	0.107	2	0.292	5	0.093	3
a_4	0.381	1	0.072	1	0.308	1	0.166	1
a_5	0.331	8	0.266	7	0.293	4	-0.037	6
a_6	0.332	7	0.230	6	0.274	8	-0.042	7
a_7	0.348	5	0.132	4	0.293	3	0.067	4
a_8	0.351	4	0.197	5	0.286	7	0.019	5

Hence, the objective weight of the criterion is $w_j = (0.203, 0.207, 0.278, 0.311)$, based on Eq. (20).

The online review-based criterion weights are presented in Sect. 4.2.1, which is $q_j = (0.2512, 0.276, 0.2369, 0.2359)$. Therefore, the online review-based weights and CRITIC-based weights are fused, and the final combined weight of the criterion $\omega = (0.202, 0.209, 0.282, 0.308)$ is obtained according to Eq. (21).

4.2.4 Ranking and Recommendation

Based on the score matrix, the PL-MULTIMOOR method was employed to calculate the utility value of the collective probabilistic linguistic decision matrix according to Eqs. (22)–(25); the results are presented in Table 6. It can be concluded that alternative s_4 has the highest utility value of 0.381, while alternative s_5 has the lowest score of 0.331, so the ranking result of alternatives in the PLRS system is $a_4 > a_2 > a_3 > a_8 > a_7 > a_1 > a_6 > a_5$; Considering the PLRP system, the alternative a_4 exhibits the shortest distance from the positive ideal (0.072), while the alternative a_1 displays the longest distance from the positive ideal (0.297), so the ranking result of the alternative is $a_4 > a_3 > a_2 > a_7 > a_8 > a_6 > a_5 > a_1$; In the PLFMF system, alternative a_4 get the highest utility value (0.308), while alternative a_6 obtained the lowest score (0.274), so the ranking result of the alternatives is $a_4 > a_2 > a_7 > a_5 > a_3 > a_1 > a_8 > a_6$. Furthermore, Eq. (26) is utilized to access the Borda scores of the alternatives, and the specific results are listed in Table 6. Hence, the final ranking result of the alternatives was $a_4 > a_2 > a_3 > a_7 > a_8 > a_5 > a_6 > a_1$. Since a_4, a_2 , and a_3 ranked the highest, they were recommended to the group following the principle of Top-N recommendation.

4.3 Sensitivity Analysis

The sliding window of the co-occurrence matrix was artificially determined during construction of the GloVe model. Therefore, we carry out a sensitivity analysis to detect the effect of the sliding window size on the criterion weights, as well as the

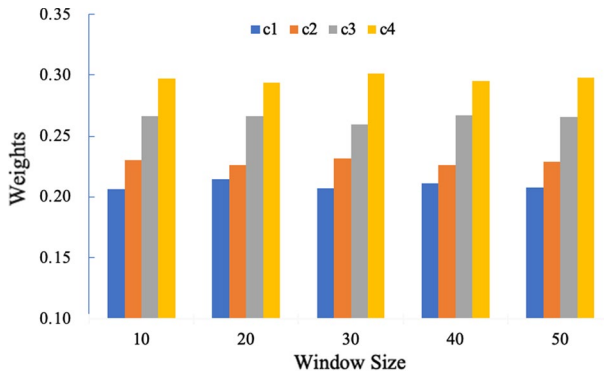


Fig. 7 Criterion weights for different sliding window size

Table 7 Borda scores and ranking of alternatives for different sliding window size

Alternatives	ws = 10		ws = 20		ws = 30		ws = 40		ws = 50	
	$u(a_i)$	Rank	$u(a_i)$	Rank	$u(a_i)$	Rank	$u(a_i)$	Rank	$u(a_i)$	Rank
a_1	-0.063	8	-0.063	8	-0.065	8	-0.063	8	-0.064	8
a_2	0.126	2	0.125	2	0.126	2	0.126	2	0.126	2
a_3	0.090	3	0.089	3	0.089	3	0.089	3	0.089	3
a_4	0.164	1	0.164	1	0.164	1	0.164	1	0.164	1
a_5	-0.037	6	-0.037	6	-0.034	6	-0.037	6	-0.037	6
a_6	-0.043	7	-0.042	7	-0.043	7	-0.042	7	-0.042	7
a_7	0.071	4	0.071	4	0.072	4	0.071	4	0.071	4
a_8	0.018	5	0.018	5	0.017	5	0.018	5	0.018	5

Borda scores and rankings. Figure 7 presents the normalized criterion weights when the sliding window ws is equal to 10, 20, 30, 40, and 50. It can be inferred that different sliding windows failed to generate a significant difference in the criterion weights. For example, the weights of criterion c_1 are 0.207, 0.215, 0.207, 0.211, and 0.208, respectively, which are not significantly different.

Table 7 presents the Borda scores and the final ranking results of each alternative under different sliding windows. It can be noted that there fails to exist significant difference in the Borda scores of the alternatives under different sliding windows, while the final ranking of the alternatives remains the same, which indicates that the size of the sliding window in the GloVe model does not affect the proposed LSGDM-based group recommendation model.

4.4 Comparative Analysis

To highlight the advantages of the proposed combined weighting based LSGDM method for group recommendation, a comparative analysis was performed using the following group recommendation models:

- Fuzzy VIKOR method proposed by Guo et al. (2018) (abbreviated as VIKOR). In this research, SVM method is conducted to model user preference, and then an improved VIKOR method is proposed to perform the group recommendation events. The pseudocode of the method is listed in Algorithm3.

Algorithm 3: Fuzzy VIKOR method proposed by Guo et al. (2018)

INPUT: candidate item set I_i

OOUPUT: recommendation result

BEGIN

- 1: generated the groups randomly.
- 2: compute preference distribution of groups towards each item I_i .
- 3: recover members' missing ratings towards items.
- 4: label distribution learning is implemented to model preference distribution.
- 5: calculate group profile concerning candidate items I_i .
- 6: rank the candidate items using a modified VIKOR method and fuzzy set theory.
- 7: finish Top-N group recommendation.

END

- FSSES-TOPSIS approach proposed by Rani and Kumar (2019) (abbreviated as TOPSIS). In this research, TOPSIS along with Fuzzy Soft Expert Set (FSSES) was applied to enable students to rank the faculty members based on their previous performance. The pseudocode of the method is listed in Algorithm4.

Algorithm 4: FSSES-TOPSIS method proposed by Rani and Kumar (2019)

INPUT: decision experts, alternatives, decision matrix of experts,

OOUPUT: ranking result of alternatives

BEGIN

- 1: Construct the agree-decision matrix D^+ and disagree-decision matrix D^- .
- 2: Compute the agree-normalized matrix R^+ and disagree-normalized matrix R^- .
- 3: Determine the weighted agree-normalized decision matrix V^+ and weighted disagree-normalized decision matrix V^- .
- 4: Compute PIS and NIS using V^+ and V^- matrices.
- 5: Find separation measurements S^+ and S^- using V^+ and V^- , respectively.
- 6: Compute relative closeness of alternatives.
- 7: Prioritize or rank alternatives.

END

- Fuzzy AHP approach proposed by Park et al. (2015) (abbreviated as AHP). The Bayesian network is utilized to characterize the preferences of users,

Table 8 Criteria weighting of different methods

Methods	c_1	c_2	c_3	c_4
Combined weighting based LSGDM	0.203	0.207	0.278	0.311
AHP	0.140	0.188	0.293	0.378
TOPSIS	0.189	0.233	0.267	0.311
VIKOR	0.192	0.223	0.273	0.313

while the evaluation and recommendation of the alternatives are performed using AHP model. The pseudocode of the method is listed in Algorithm 5.

Algorithm 5: Fuzzy AHP method proposed by Park et al. (2015)

INPUT: user profile

OUTPUT: recommendation results

BEGIN

- 1: collect context logs to handle uncertainty.
- 2: data pre-processing for context information.
- 3: model individual preferences using Bayesian networks.
- 4: learn network structure and parameters using K2 and MLE algorithm
- 5: conduct pairwise comparison matrix.
- 6: calculate weights of alternatives using AHP method.
- 7: calculate recommendation scores.

END

The similarity of the four methods is that the group preferences are generated based on individual preferences, and then the multi-attribute decision making method is applied to rank the alternatives to generate the final recommendations.

The difference is that: (1) In the Fuzzy VIKOR model, the SVM approach is employed to fit individual preferences, and objective weights are then applied to aggregate the indicators. However, the VIKOR method can only achieve better fits with large sample sizes; (2) The FSES-TOPSIS method assembles individual preferences into group preferences by fuzzy soft expert set and the indicators are integrated using objective weights. However, the TOPSIS approach requires decision makers to provide agree fuzzy value and disagree fuzzy value for the alternatives, which limits the input data for the model; (3) The fuzzy AHP model is used to integrate individual preferences. Although both subjective and objective weights of uses is considered in the AHP method, it is complicated to implement due to multiple interactions with decision users and the process is tedious.

Compared with the three models, the proposed combined weighting based group recommendation model incorporates both subjective and objective weights of individuals to generate group preferences based on clustering algorithm, which offers the superiority in terms of simplicity, convenient calculation and ease of implementation irrespective of sample size.

Table 9 Alternative ranking results and group satisfaction of different methods

Methods	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	Sa
Combined weighting based LSGDM	8	2	3	1	6	7	4	5	0.4326
AHP	7	2	4	1	5	8	3	6	0.3910
TOPSIS	8	2	3	1	7	6	4	5	0.4208
VIKOR	8	2	3	1	6	7	4	5	0.4271

Table 8 presents the weights obtained using various methods, from which it can be concluded that regardless of the methods employed, criteria c_4 always gain the highest weight, with the value greater than 0.3, which means that performance is the most important criteria in the “CAMP” evaluation system. The distinction between the four methods exists in the inconsistent weighting of the first three criteria. The proposed combined weighting based LSGDM method is relatively uniform in terms of weight assignment, and there is no extreme case of favoring one attribute over another, which is also an advantage of the combined weighting method.

Table 9 presents the alternative ranking results and group satisfaction obtained using different group recommendation methods. In terms of alternative ranking, among the recommendation results of the four models, the alternative ranking results of the model proposed in this paper are consistent with the VIKOR model and much closer to the TOPSIS model, while there are significant differences with the results of the AHP method. The main reason is that there are many subjective operations in the process of implementing the AHP model, which leads to major deviations in the results.

In terms of group satisfaction, it seems that the proposed LSGDM-based group recommendation model in this study yields the highest group satisfaction of 0.4326, while the group satisfaction of the AHP, TOPSIS model is 0.4208, and VIKOR models was 0.391, 0.4208, and 0.4271, respectively. This indicates that the proposed LSGDM-based group recommendation model exhibits a better performance.

5 Conclusion

The rise of MOOC has promoted the open sharing of learning resources and facilitated people’s learning but has also led to a serious information overload problem. People fail to select a suitable course from the massive courses to satisfy the demands of individuals or groups. Therefore, a combined weighting based LSGDM method for MOOC group recommendations is proposed in this study. First, in accordance with the MOOC operation mode, we decompose the course content into three stages, namely pre-class, in-class, and post-class, and then the “CAMP” evaluation framework is constructed. Second, the PL-CRITIC method is employed to obtain the objective weighting of the criterion. Meanwhile, the word embedding model is utilized to vectorize online reviews, and the subjective weighting of the criteria are acquired by calculating the text similarity. Then the combined weighting

Table 10 The personal information of 20 students

Students	School	Age	Grade
e_1	Shanghai Jiao Tong University, SJTU	18	Freshmen
e_2	Tsinghua University, THU	20	Sophomor
e_3	Peking University	24	Junior
e_4	Sichuan University	22	Junior
e_5	Tianjin University	21	Sophomor
e_6	Sun Yat-sen University	20	Freshmen
e_7	Xiamen University	22	Sophomor
e_8	Zhejiang University	21	Junior
e_9	Jinan University	17	Freshmen
e_{10}	Dongbei University of Finance and Economics	23	Junior
e_{11}	Xiamen University	18	Sophomor
e_{12}	Northeastern University	19	Freshmen
e_{13}	Zhejiang University	24	Senior
e_{14}	Chinese Academy of Sciences	25	Senior
e_{15}	Sun Yat-sen University	19	Freshmen
e_{16}	Renmin University of China	20	Sophomor
e_{17}	Xi'an Jiaotong University	20	Freshmen
e_{18}	University of Science and Technology of China	23	Junior
e_{19}	Fudan University	17	Freshmen
e_{20}	Sichuan University	21	Sophomor

of this study can be obtained by fusing the subjective and objective weighting. Further, the PL-MULTIMIIRA approach and Borda rule is employed to rank the alternatives for group recommendation. Based on this, an easy-to-use formula for group satisfaction was proposed to evaluate the effect of the group recommendation model. Finally, we conduct a case study by applying the LSGDM-based model to group recommendations for statistical MOOCs. Sensitivity and comparative analyses were carried out to verify the robustness and effectiveness of the proposed method.

The method proposed in this study is effectively applied to MOOC group recommendations, but shortcomings still exist. The calculation of online review-based weights requires construction of a text corpus. However, subjectivity exists in the construction of the text corpus, which may lead to a bias in the results. In future research, we will explore filling missing values in the recommendation model based on the distribution of the data.

Appendix 1

Students are the main users of statistical MOOC, therefore, we choose a group of 20 students to make recommendations. The process is as follows: more than 1000 college students from different universities participated in a student science and technology competition held in 2021. A total of 136 students signed up for the group

recommendation experiment on a voluntary basis. Among 136 students, 20 students were finally selected according to the distribution of colleges and universities, the participation of statistical MOOC and other factors. The personal information of 20 students is shown in Table 10.

In addition, the main work of this paper is to recommend statistical MOOC based on user comments. Consider the same person may perform multiple reviews (including that the same person may make multiple comments using different IDs), or too few comments may affect the robustness of recommendation result. Hence, after analyzing the relationship between the number of comments and the cumulative number of course participants, we chose 8 statistics MOOCs with the cumulative number of course participants exceeding 1000 as the candidate course.

Appendix 2

$R^{(1)}$	$\{s_1(0.53), s_1(0.25), s_1(0.22)\}$	$\{s_1(0.11), s_1(0.59), s_1(0.31)\}$	$\{s_1(0.54), s_1(0.46)\}$	$\{s_1(0.46), s_1(0.54)\}$
	$\{s_1(0.05), s_1(0.49), s_1(0.46), s_1(0.01)\}$	$\{s_1(0.08), s_1(0.17), s_1(0.75)\}$	$\{s_1(0.31), s_1(0.55), s_1(0.14)\}$	$\{s_1(0.54), s_1(0.46)\}$
	$\{s_1(0.14), s_1(0.15), s_1(0.71)\}$	$\{s_1(0.28), s_1(0.12), s_1(0.61)\}$	$\{s_1(0.39), s_1(0.21), s_1(0.04)\}$	$\{s_1(0.46), s_1(0.37), s_1(0.16)\}$
	$\{s_1(0.36), s_1(0.35), s_1(0.29)\}$	$\{s_1(0.58), s_1(0.42)\}$	$\{s_1(0.02), s_1(0.05), s_1(0.47), s_1(0.46)\}$	$\{s_1(1)\}$
$\{s_1(0.85), s_1(0.15)\}$	$\{s_1(0.13), s_1(0.33), s_1(0.52)\}$	$\{s_1(0.46), s_1(0.44), s_1(0.09)\}$	$\{s_1(0.01), s_1(0.64), s_1(0.35)\}$	
$\{s_1(0.13), s_1(0.59), s_1(0.28)\}$	$\{s_1(0.46), s_1(0.39), s_1(0.11), s_1(0.04)\}$	$\{s_1(1)\}$	$\{s_1(0.29), s_1(0.24), s_1(0.03), s_1(0.34), s_1(0.09)\}$	
$\{s_1(0.93), s_1(0.07)\}$	$\{s_1(0.46), s_1(0.54)\}$	$\{s_1(1)\}$	$\{s_1(0.07), s_1(0.19), s_1(0.2), s_1(0.54)\}$	
$\{s_1(0.46), s_1(0.33), s_1(0.14), s_1(0.06)\}$	$\{s_1(0.54), s_1(0.46)\}$	$\{s_1(0.03), s_1(0.75), s_1(0.02), s_1(0.20)\}$	$\{s_1(0.4), s_1(0.56), s_1(0.04)\}$	
$R^{(2)}$	$\{s_1(0.23), s_1(0.61), s_1(0.16)\}$	$\{s_1(0.15), s_1(0.01), s_1(0.19), s_1(0.18), s_1(0.45)\}$	$\{s_1(0.09), s_1(0.24), s_1(0.29), s_1(0.27), s_1(0.11)\}$	$\{s_1(0.38), s_1(0.39), s_1(0.4), s_1(0.07), s_1(0.12)\}$
	$\{s_1(0.37), s_1(0.5), s_1(0.1), s_1(0.03)\}$	$\{s_1(0.06), s_1(0.36), s_1(0.23), s_1(0.36)\}$	$\{s_1(0.12), s_1(0.16), s_1(0.43), s_1(0.29)\}$	$\{s_1(0.01), s_1(0.19), s_1(0.35), s_1(0.31), s_1(0.12)\}$
	$\{s_1(0.16), s_1(0.44), s_1(0.36), s_1(0.04)\}$	$\{s_1(0.02), s_1(0.3), s_1(0.23), s_1(0.22), s_1(0.23)\}$	$\{s_1(0.21), s_1(0.49), s_1(0.11), s_1(0.19)\}$	$\{s_1(0.21), s_1(0.08), s_1(0.12), s_1(0.06)\}$
	$\{s_1(0.38), s_1(0.06), s_1(0.19), s_1(0.38)\}$	$\{s_1(0.16), s_1(0.35), s_1(0.07), s_1(0.1), s_1(0.32)\}$	$\{s_1(0.57), s_1(0.23), s_1(0.2)\}$	$\{s_1(0.19), s_1(0.29), s_1(0.34), s_1(0.18)\}$
$\{s_1(0.07), s_1(0.44), s_1(0.15), s_1(0.2), s_1(0.14)\}$	$\{s_1(0.36), s_1(0.14), s_1(0.09), s_1(0.18), s_1(0.24)\}$	$\{s_1(0.19), s_1(0.51), s_1(0.29)\}$	$\{s_1(0.17), s_1(0.12), s_1(0.13), s_1(0.45), s_1(0.12)\}$	
$\{s_1(0.28), s_1(0.5), s_1(0.22)\}$	$\{s_1(0.31), s_1(0.08), s_1(0.22), s_1(0.16), s_1(0.23)\}$	$\{s_1(0.18), s_1(0.39), s_1(0.4), s_1(0.23)\}$	$\{s_1(0.21), s_1(0.06), s_1(0.22), s_1(0.39), s_1(0.12)\}$	
$\{s_1(0.19), s_1(0.68), s_1(0.13)\}$	$\{s_1(0.06), s_1(0.25), s_1(0.24), s_1(0.22), s_1(0.23)\}$	$\{s_1(0.16), s_1(0.41), s_1(0.2), s_1(0.23)\}$	$\{s_1(0.08), s_1(0.25), s_1(0.44), s_1(0.1), s_1(0.12)\}$	
$\{s_1(0.01), s_1(0.83), s_1(0.16)\}$	$\{s_1(0.19), s_1(0.29), s_1(0.15), s_1(0.01), s_1(0.36)\}$	$\{s_1(0.44), s_1(0.32), s_1(0.24)\}$	$\{s_1(0.2), s_1(0.43), s_1(0.08), s_1(0.19), s_1(0.12)\}$	
$R^{(3)}$	$\{s_1(0.37), s_1(0.19), s_1(0.32), s_1(0.24), s_1(0.08)\}$	$\{s_1(0.14), s_1(0.39), s_1(0.1), s_1(0.16)\}$	$\{s_1(0.48), s_1(0.11), s_1(0.04), s_1(0.36)\}$	$\{s_1(0.29), s_1(0.17), s_1(0.58)\}$
	$\{s_1(0.15), s_1(0.13), s_1(0.14), s_1(0.41), s_1(0.19)\}$	$\{s_1(0.04), s_1(0.19), s_1(0.08), s_1(0.4), s_1(0.21)\}$	$\{s_1(0.18), s_1(0.22), s_1(0.17), s_1(0.28), s_1(0.16)\}$	$\{s_1(0.18), s_1(0.27), s_1(0.35), s_1(0.02), s_1(0.18)\}$
	$\{s_1(0.47), s_1(0.33), s_1(0.18)\}$	$\{s_1(0.29), s_1(0.54), s_1(0.14), s_1(0.02)\}$	$\{s_1(0.41), s_1(0.22), s_1(0.17), s_1(0.11), s_1(0.08)\}$	$\{s_1(0.11), s_1(0.52), s_1(0.17), s_1(0.02), s_1(0.18)\}$
	$\{s_1(0.01), s_1(0.45), s_1(0.15), s_1(0.27), s_1(0.12)\}$	$\{s_1(0.11), s_1(0.12), s_1(0.14), s_1(0.45), s_1(0.2)\}$	$\{s_1(0.54), s_1(0.26), s_1(0.2)\}$	$\{s_1(0.04), s_1(0.35), s_1(0.07), s_1(0.34), s_1(0.2)\}$
$\{s_1(0.15), s_1(0.33), s_1(0.14), s_1(0.19), s_1(0.18)\}$	$\{s_1(0.12), s_1(0.25), s_1(0.06), s_1(0.02)\}$	$\{s_1(0.18), s_1(0.26), s_1(0.36), s_1(0.19)\}$	$\{s_1(0.28), s_1(0.21), s_1(0.28), s_1(0.18), s_1(0.05)\}$	
$\{s_1(0.32), s_1(0.36), s_1(0.2), s_1(0.11)\}$	$\{s_1(0.19), s_1(0.55), s_1(0.21), s_1(0.06)\}$	$\{s_1(0.11), s_1(0.47), s_1(0.41), s_1(0.01)\}$	$\{s_1(0.04), s_1(0.32), s_1(0.26), s_1(0.29), s_1(0.18)\}$	
$\{s_1(0.2), s_1(0.23), s_1(0.34), s_1(0.23)\}$	$\{s_1(0.02), s_1(0.23), s_1(0.31), s_1(0.26), s_1(0.18)\}$	$\{s_1(0.34), s_1(0.03), s_1(0.15), s_1(0.3), s_1(0.19)\}$	$\{s_1(0.16), s_1(0.15), s_1(0.21), s_1(0.09), s_1(0.19)\}$	
$\{s_1(0.15), s_1(0.21), s_1(0.22), s_1(0.26), s_1(0.17)\}$	$\{s_1(0.09), s_1(0.16), s_1(0.24), s_1(0.41), s_1(0.1)\}$	$\{s_1(0.11), s_1(0.05), s_1(0.16), s_1(0.44), s_1(0.24)\}$	$\{s_1(0.02), s_1(0.19), s_1(0.69), s_1(0.1)\}$	
$R^{(4)}$	$\{s_1(0.17), s_1(0.51), s_1(0.33)\}$	$\{s_1(0.23), s_1(0.06), s_1(0.47), s_1(0.23)\}$	$\{s_1(0.46), s_1(0.06), s_1(0.46)\}$	$\{s_1(0.51), s_1(0.28), s_1(0.61), s_1(0.01)\}$
	$\{s_1(0.24), s_1(0.54), s_1(0.42)\}$	$\{s_1(0.08), s_1(0.27), s_1(0.71)\}$	$\{s_1(0.80), s_1(0.04), s_1(0.45), s_1(0.15)\}$	$\{s_1(0.23), s_1(0.51), s_1(0.22), s_1(0.01)\}$
	$\{s_1(0.29), s_1(0.28), s_1(0.08), s_1(0.38)\}$	$\{s_1(0.13), s_1(0.1), s_1(0.12), s_1(0.68)\}$	$\{s_1(0.33), s_1(0.48), s_1(0.19)\}$	$\{s_1(0.33), s_1(0.27), s_1(0.27), s_1(0.11)\}$
	$\{s_1(0.27), s_1(0.02), s_1(0.71)\}$	$\{s_1(0.13), s_1(0.19), s_1(0.32)\}$	$\{s_1(0.13), s_1(0.25), s_1(0.67), s_1(0.02)\}$	$\{s_1(0.29), s_1(0.35), s_1(0.36)\}$
$\{s_1(0.05), s_1(0.1), s_1(0.07), s_1(0.22), s_1(0.35)\}$	$\{s_1(0.06), s_1(0.36)\}$	$\{s_1(0.07), s_1(0.06), s_1(0.31), s_1(0.1), s_1(0.06)\}$	$\{s_1(0.29), s_1(0.35), s_1(0.36)\}$	
$\{s_1(0.29), s_1(0.12), s_1(0.48)\}$	$\{s_1(0.12), s_1(0.04), s_1(0.22), s_1(0.09), s_1(0.54)\}$	$\{s_1(0.1), s_1(0.26), s_1(0.45), s_1(0.19)\}$	$\{s_1(0.01), s_1(0.56), s_1(0.01), s_1(0.38)\}$	
$\{s_1(0.36), s_1(0.51), s_1(0.06), s_1(0.67)\}$	$\{s_1(0.20), s_1(0.38), s_1(0.36)\}$	$\{s_1(0.06), s_1(0.05), s_1(0.37), s_1(0.00)\}$	$\{s_1(0.34), s_1(0.28), s_1(0.32), s_1(0.06)\}$	
$\{s_1(0.29), s_1(0.19), s_1(0.32), s_1(0.17), s_1(0.08)\}$	$\{s_1(0.29), s_1(0.54), s_1(0.18)\}$	$\{s_1(0.1), s_1(0.68), s_1(0.21)\}$	$\{s_1(0.82), s_1(0.07), s_1(0.38), s_1(0.05)\}$	
$R^{(5)}$	$\{s_1(0.02), s_1(0.55), s_1(0.06), s_1(0.34)\}$	$\{s_1(0.27), s_1(0.46), s_1(0.11), s_1(0.16)\}$	$\{s_1(0.02), s_1(0.22), s_1(0.36)\}$	$\{s_1(0.23), s_1(0.52), s_1(0.06), s_1(0.19)\}$
	$\{s_1(0.1), s_1(0.44), s_1(0.47)\}$	$\{s_1(0.1), s_1(0.31), s_1(0.19)\}$	$\{s_1(0.06), s_1(0.38), s_1(0.12), s_1(0.27), s_1(0.17)\}$	$\{s_1(0.17), s_1(0.41), s_1(0.03)\}$
	$\{s_1(0.17), s_1(0.13), s_1(0.08), s_1(0.42)\}$	$\{s_1(0.01), s_1(0.24), s_1(0.52), s_1(0.25)\}$	$\{s_1(0.09), s_1(0.05), s_1(0.21), s_1(0.03), s_1(0.06)\}$	$\{s_1(0.18), s_1(0.01), s_1(0.14), s_1(0.19), s_1(0.05)\}$
	$\{s_1(0.27), s_1(0.01), s_1(0.41), s_1(0.28)\}$	$\{s_1(0.4), s_1(0.06), s_1(0.51)\}$	$\{s_1(0.07), s_1(0.1), s_1(0.02), s_1(0.14)\}$	$\{s_1(0.04), s_1(0.17), s_1(0.48), s_1(0.12), s_1(0.01)\}$
$\{s_1(0.01), s_1(0.1), s_1(0.04), s_1(0.21)\}$	$\{s_1(0.06), s_1(0.04), s_1(0.48), s_1(0.08), s_1(0.26)\}$	$\{s_1(0.09), s_1(0.13), s_1(0.14), s_1(0.1), s_1(0.07)\}$	$\{s_1(0.6), s_1(0.17), s_1(0.34)\}$	
$\{s_1(0.20), s_1(0.33), s_1(0.38)\}$	$\{s_1(0.11), s_1(0.16), s_1(0.47), s_1(0.24), s_1(0.02)\}$	$\{s_1(0.29), s_1(0.52), s_1(0.01), s_1(0.38)\}$	$\{s_1(0.24), s_1(0.06), s_1(0.01), s_1(0.05)\}$	
$\{s_1(0.07), s_1(0.16), s_1(0.08), s_1(0.21), s_1(0.45)\}$	$\{s_1(0.28), s_1(0.27), s_1(0.41), s_1(0.06)\}$	$\{s_1(0.06), s_1(0.08), s_1(0.24), s_1(0.02)\}$	$\{s_1(0.14), s_1(0.29), s_1(0.49), s_1(0.08)\}$	
$\{s_1(0.13), s_1(0.33), s_1(0.34)\}$	$\{s_1(0.06), s_1(0.19), s_1(0.02), s_1(0.01)\}$	$\{s_1(0.14), s_1(0.46), s_1(0.19), s_1(0.15)\}$	$\{s_1(0.37), s_1(0.12), s_1(0.12), s_1(0.25), s_1(0.05)\}$	
$R^{(6)}$	$\{s_1(0.1), s_1(0.19), s_1(0.24), s_1(0.25), s_1(0.1)\}$	$\{s_1(0.09), s_1(0.34), s_1(0.23), s_1(0.19), s_1(0.17)\}$	$\{s_1(0.23), s_1(0.14), s_1(0.15), s_1(0.73), s_1(0.27)\}$	$\{s_1(0.21), s_1(0.73), s_1(0.03), s_1(0.06), s_1(0.07)\}$
	$\{s_1(0.19), s_1(0.24), s_1(0.26), s_1(0.21), s_1(0.1)\}$	$\{s_1(0.12), s_1(0.14), s_1(0.19), s_1(0.12), s_1(0.21)\}$	$\{s_1(0.07), s_1(0.27), s_1(0.14), s_1(0.12), s_1(0.11)\}$	$\{s_1(0.08), s_1(0.22), s_1(0.19), s_1(0.1), s_1(0.14)\}$
	$\{s_1(0.1), s_1(0.13), s_1(0.24), s_1(0.19), s_1(0.13)\}$	$\{s_1(0.03), s_1(0.25), s_1(0.36), s_1(0.11), s_1(0.06)\}$	$\{s_1(0.19), s_1(0.18), s_1(0.21), s_1(0.27), s_1(0.13)\}$	$\{s_1(0.07), s_1(0.27), s_1(0.14), s_1(0.12), s_1(0.11)\}$
	$\{s_1(0.09), s_1(0.29), s_1(0.22), s_1(0.23), s_1(0.21)\}$	$\{s_1(0.11), s_1(0.25), s_1(0.11), s_1(0.71), s_1(0.01)\}$	$\{s_1(0.17), s_1(0.12), s_1(0.13), s_1(0.29), s_1(0.11)\}$	$\{s_1(0.11), s_1(0.19), s_1(0.2), s_1(0.2), s_1(0.27)\}$
$\{s_1(0.13), s_1(0.24), s_1(0.19), s_1(0.08)\}$	$\{s_1(0.19), s_1(0.21), s_1(0.4), s_1(0.17), s_1(0.01)\}$	$\{s_1(0.23), s_1(0.23), s_1(0.13), s_1(0.19), s_1(0.02)\}$	$\{s_1(0.17), s_1(0.24), s_1(0.23), s_1(0.19), s_1(0.18)\}$	
$\{s_1(0.17), s_1(0.14), s_1(0.26), s_1(0.14), s_1(0.09)\}$	$\{s_1(0.23), s_1(0.21), s_1(0.1), s_1(0.06), s_1(0.84)\}$	$\{s_1(0.13), s_1(0.17), s_1(0.13), s_1(0.24), s_1(0.21)\}$	$\{s_1(0.09), s_1(0.24), s_1(0.23), s_1(0.13), s_1(0.11)\}$	
$\{s_1(0.1), s_1(0.21), s_1(0.22), s_1(0.18), s_1(0.17)\}$	$\{s_1(0.12), s_1(0.24), s_1(0.2), s_1(0.17), s_1(0.05)\}$	$\{s_1(0.1), s_1(0.21), s_1(0.1), s_1(0.24), s_1(0.06)\}$	$\{s_1(0.11), s_1(0.25), s_1(0.2), s_1(0.15), s_1(0.17)\}$	
$\{s_1(0.09), s_1(0.32), s_1(0.26), s_1(0.19), s_1(0.14)\}$	$\{s_1(0.21), s_1(0.19), s_1(0.25), s_1(0.24), s_1(0.11)\}$	$\{s_1(0.16), s_1(0.19), s_1(0.2), s_1(0.23), s_1(0.17)\}$	$\{s_1(0.1), s_1(0.29), s_1(0.19), s_1(0.35), s_1(0.08)\}$	

Acknowledgements This work was supported by the project of the National Social Science Fund of China (22ATJ003, 21ATJ010, 20 CTJ016).

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