Collaborative Grouping and Interactive Relationship Construction of College Students Based on Group Preference

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Abstract—Collaborative learning allows learners to gain more learning resources, learning experiences, and even learning habits from other group learners, thus improving themselves and achieving better learning outcomes. The existing studies only fully consider the differences in learners' learning preferences, while ignoring the preference of each group and the balance between groups, which is not conducive to the overall improvement of learners' achievements in each group. To this end, this article focuses on studying collaborative grouping and interactive relationship construction of college students based on group preference. A collaborative learning grouping algorithm based on group preference is proposed, considering the differences in learners' learning preferences and the preference of learning groups in a balanced way, and the problems in collaborative grouping of college students are described. A group preference-based collaborative learning grouping algorithm is designed, the main ideas and implementation process of the algorithm are expounded, experiments are designed to compare the intra-group difference degree of different grouping algorithms, and the algorithm's evaluation method is introduced. The experimental results verify the effectiveness of the proposed algorithm.

Keywords—group preference, collaborative grouping, interactive relationship construction

1 Introduction

As an important learning mechanism in online learning systems, collaborative learning, mainly in teams and groups, can effectively improve the learning efficiency of learners, enabling group learners to achieve shared learning goals as soon as possible [1–4]. Compared with traditional learning methods, collaborative learning has many advantages such as stimulating learners' interest in learning, enhancing learners' learning initiative, facilitating teachers to keep track of learners' learning status, and assisting in adjusting teaching ideas [5–9]. The main body and center of collaborative learning is the learners, and when there is more interaction between learners in a collaborative group, learners can gain more learning resources, learning experiences and even learning habits from group learners, thus improving themselves and achieving better learning results [10–18]. Therefore, how to divide collaborative learning groups and how to construct effective interactive relationships has become an issue with theoretical research and application values when it comes to college students' participation in online collaborative learning activities.

Many online learning environments are characterized by students' high diversity in socio-demographic attributes and task-related attributes. Voltmer et al. [19] investigates the relationship between multi-attributional diversity and CSCL process and outcome. The cohort consists of 1,525 distance education freshmen randomly assigned to 343 groups for a 9-week CSCL task. The pathway analysis at the group level shows that demographic diversity is negatively associated with structural integration of groups in a society with higher multi-attribution in the absence of explicit management. Cooperative learning, as a new learning strategy, can greatly improve the quality of classroom teaching and improve the efficiency of students' group leader-led cooperation and learning. Traditional student grouping models used for collaborative learning take less account of the complementary knowledge structures and learning interests of students, and for this reason, Wang and Wang [20] investigates student grouping methods for large-scale online collaborative learning. The student knowledge state identification problem is described and characterized, and a student knowledge state diagnosis model based on gated recurrent neural networks is constructed, which simulates the cooperative learning process. Creating an online collaborative learning scenario that considers both students' knowledge state and interests is considered as an NP problem, and then, an enhanced particle swarm optimization algorithm is used to achieve student grouping for large-scale online collaborative learning. Joslyn and Hyne [21] carries out collaborative action research to explore the implementation of transformative learning and teaching methods in designed human-centered environments to understand how students make sense of engineering environments that involve unique socio-technical factors. The findings suggest that introducing students to these contexts allows them to use alternative perspectives that can challenge dominant engineering thinking and promote openness of engineering to the society, leading to a deeper understanding of the overall nature of engineering.

In most computer-supported collaborative learning activities, teachers monitor and/or review the data generated by students and groups as they complete learning tasks in order to provide guidance and feedback. Without the appropriate technical means to support the process of collecting and selecting student-generated responses, these duties may impose a high cognitive load on teachers, especially if students generate qualitative or textual content requiring real-time review. Alvarez et al. [22] proposes a solution based on enhanced EthicApp's teacher interface and automated content analysis features, including dashboards that automatically display the most relevant contributions of students and cluster visualizations that allow the identification of groups of students with similar responses to tasks. Pan et al. [23] proposes an enhanced solution that supports instructional decisions for each student without increasing the cost of the equipment, realizing a context-aware LFD student client that presents dynamic viewing areas for each student via face tracking and supports anti-cheat tests. By synchronizing each student's tracking data with the local area network (LAN) middleware, the AR teacher client can differentiate between students in order to assign test progress to each corresponding student in real time and provide targeted instructions. Ten university veterinary/anatomy faculty members participated in a remote expert review study to provide professional feedback. Based on the questionnaire results, they found the designed collaborative learning tools to be helpful for both faculty and students.

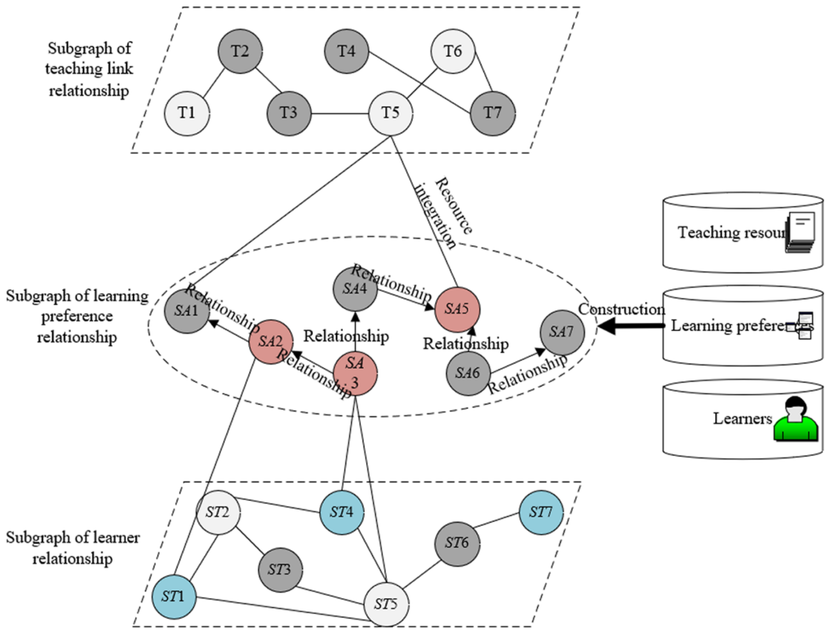

Fig. 1. Collaborative grouping model of college students

As can be seen from the available references, scholars at home and abroad have conducted a lot of research on grouping with the purpose of improving the efficiency of collaborative learning. However, most studies only fully consider the difference in learners' learning preferences, while ignoring the preference of each group and the balance between groups, which is not conducive to the overall improvement of learners' achievements in each group. Therefore, in order to make up for the shortcomings of existing algorithms, this article conducts a study on collaborative grouping and interactive relationship construction of college students based on group preference, taking the English online learning scenario as an example. In the second chapter, a collaborative learning grouping algorithm based on group preference is proposed, considering the differences in learners' learning preferences and the preference of learning groups in a balanced way, and the problems in collaborative grouping of college students are described. In the third chapter, a group preference-based collaborative learning grouping algorithm is designed, the main ideas and implementation process of the algorithm are expounded. In the fourth chapter, experiments are designed to compare the intra-group difference degree of different grouping algorithms, and the algorithm evaluation method is introduced. The experimental results verify the effectiveness of the proposed algorithm.

2 Description of problems in collaborative grouping of college students

Figure 1 illustrates the structure of the collaborative grouping model for college students. This article first clarifies the concepts and details of the three layers of the model: the teaching session layer, the layer of learners' learning preference, and the learner layer. Secondly, it describes in detail the process of collaborative grouping and the construction of interactive relationships represented by the layer of learners' learning preference. In order to better solve the problems in collaborative grouping of college students, this article proposes a group preference-based collaborative learning grouping algorithm, taking into account the differences in learners' learning preferences and preferences of learning groups in a balanced way. In order to maximize the learning efficiency of collaborative groups, this article sets the goals of maximizing heterogeneity of learning preferences within groups and homogeneity of learning preferences between groups for the collaborative learning grouping algorithm. Assuming that any group is represented by l, learners i and j are represented by i and j, respectively, the degree of difference in learning preference between i and j is represented by SA_{ij}, and the number of learners included in the l-th group is represented by $g(l)$. In this article, the following formal expressions for the collaborative learning grouping problem are given as follows:

$$Max\, \underset{\forall l}{Min} \sum_{i=1}^{g(l)} \sum_{j=1}^{g(l)} SA_{ij} \tag{1}$$

$$\begin{aligned} & Min\left(\left| \underset{\forall l}{Max}\left(\sum_{i=1}^{g(l)}\sum_{j=1}^{g(l)} SA_{ij}\right) - \underset{\forall l}{Min}\left(\sum_{i=1}^{g(l)}\sum_{j=1}^{g(l)} SA_{ij}\right)\right|\right) \\ & s.t. \quad (1)\, 0 < g(l) \le \left[M/L\right] \\ & \qquad (2) \sum_{l=1}^{L} g(l) = M \end{aligned} \tag{2}$$

Assuming the normalized attribute feature vectors of learners i and j are represented by y_i and y_j, respectively, $i, j \in \{1, 2, \ldots, M\}$, $i \neq j$. Let $y_i = (y_i^{(1)}, yi^{(2)}, \ldots, y_i^{(M)})$, $y_j = (y_j^{(1)}, y_j^{(2)}, \ldots, y_j^{(M)})$, the transposition of the vectors $(y_i–y_j)$ is represented by $(y_i–y_j)^T$, and the covariance matrix between various attribute eigenvectors is represented by R. SA_{ij} can be defined as in the following formula:

$$SA_{ij} = \sqrt{(y_i - y_j)\cdot R \cdot (y_i - y_j)^T} \tag{3}$$

Assuming that the normalized vectors of the i'-th and j'-th attribute features in all learners are represented by $v_{i'}$ and $v_{j'}$, respectively, and the covariance between the vectors $\lambda_{i'}$ and $\lambda_{j'}$ is represented by $cov(\lambda_{i'}, \lambda_{j'})$, let $\lambda_{i'} = (y_{1i'}, + y_{2i'} + \dots + y_{Mi'})/M$, $\lambda_{j'} = (y_{1j'}, + y_{2j'} + \dots + y_{Mj'})/M$. The following formula shows the expression for any learner $R_{i'j'}$ in R:

$$R_{i'j'} = cov\,(v_{i'}, v_{j'})/(n-1) \tag{4}$$

Assuming that the expectation is represented by UH and the normalized mean values of i'-th and j'-th attribute features of all learners are represented by $\lambda_{i'}$ and $\lambda_{j'}$, respectively, that is $\lambda_{i'} = (y_{1i'}, + y_{2i'} + \dots + y_{Mi'})/M$, $\lambda_{j'} = (y_{1j'}, + y_{2j'} + \dots + y_{Mj'})/M$, where $i', j' \in \{1,2, \dots, N\}$, then the covariance $cov(\lambda_{i'}, \lambda_{j'})$ can be calculated as follows:

$$cov\,(v_{i'}, v_{j'}) = UH\left[(v_{i'} - v_{i'})(v_{j'} - v_{j'})\right] \tag{5}$$

In particular, the degree of difference between learner i and his own learning preference is 0, i.e., $SA_{ii} = 0$.

Constraint 1 in Formula 2 requires that $g(l)$ is always less than the maximum number of learners accommodated in the l-th group, and that $g(l)$ must be greater than zero to ensure that there are learners in each group. Assuming that the total number of learners to be grouped is represented by M and the number of groups is represented by L, $g(l)$ can be calculated by the following formula):

$$g\,(l) = \begin{cases} 1 + M/L, \text{If L is not exactly divided by } M, \text{ and } l \le M - (M/L) \\ M/L, \text{ Otherwise} \end{cases} \tag{6}$$

It can be seen from Formula 6 that in order to obtain $g(l)$, L needs to be determined first. In other words, the group preference-based collaborative learning grouping studied in this article does not conform to the traditional even grouping, and it is necessary to determine whether the group learners are evenly distributed according to the specific grouping situation after L is determined.

To sum up, this article gives a detailed description of collaborative grouping base on the group preference. Given the number of learners to be grouped M and the number of attribute features of learners N, let the attribute features be represented by $u_i = (x_i^{(1)}, xi^{(2)}, \dots, x_i^{(N)})$, and finite numbers of positive integers are represented by N and M. Determine the value of L according to the demand, and determine $g(l)$ based on the above formula. The M learners are divided into L groups to ensure that each learner belongs to a learning group and satisfies $0 < g(l) < = [M/L]$. Figure 2 shows network diagram of the collaborative grouping and interactive relationship of college students. Learners within a group are susceptible to the influence of other learners in their group, and when that influence reaches a certain level, it may change the learner's study habits or learning tendencies. In Figure 2, the red nodes represent collaborative learning groups, and the blue and purple nodes represent learners with different learning preferences. The result of grouping requires maximizing the difference degree of learning preference within groups and minimizing the difference of learning preference between groups, that is, realizing the objective functions of Formula 1 and Formula 2.

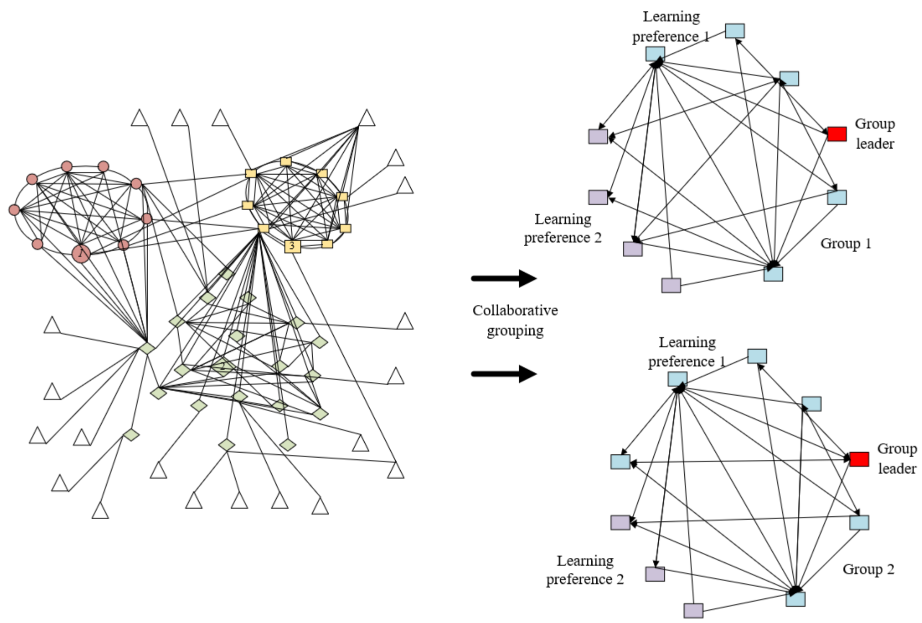

Fig. 2. Network diagram of collaborative grouping and interactive relationship of college students

3 Design of collaborative grouping algorithm for college students based on group preference

The design of collaborative learning grouping algorithm based on group preference is designed below, whose main idea is detailed as follows: The learners in the class are divided into learning groups of two, calculate the degree of difference in learning preferences among all learning groups, and perform an incremental ranking based on the calculated values, and then divide all learning groups based on the ranking results.

If the number of learners in a group is 0, the learners in the unassigned learning group will be assigned to the group. If the number of learners in all groups is greater than 0, the degree of difference between the group preference of the unassigned learning group and the group preference of the group without enough learners is calculated and the learners in the unassigned learning group are assigned to the group with the largest degree of difference in the group preference, until all the learners are grouped.

Figure 3 shows the grouping algorithm flow of collaborative learning based on group preference. The steps of the algorithm are described in detail below:

STEP1: Collect N important attribute features of M learners to be grouped $u_i = (x_i^{(1)}, x_i^{(2)}, \ldots, x_i^{(N)})$;

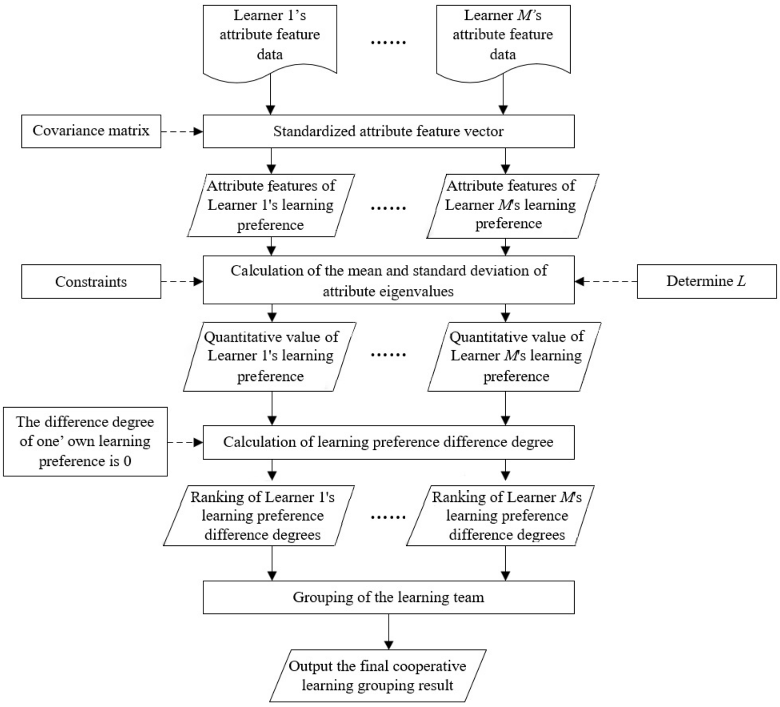

Fig. 3. Flow of collaborative learning grouping algorithm based on group preference

STEP2: Based on the actual demand for lectures and classroom activities, the M learners to be grouped are divided into L groups, and then the number of learners in each group is calculated according to Formula 6.

STEP3: Normalizing N attribute features of learners based on the following formula assuming that the n-th attribute feature value of any learner i is represented by x_{in}, and the mean value of the n-th attribute feature value of all learners is represented by λ_n, that is, $\lambda_n = (x_{1n} + x_{2n} + \ldots + x_{Mn})/M$. The standard deviation of the eigenvalue of the n-th attribute of all learners is expressed by ε_n and satisfies $\varepsilon_n = [1/M\sum^{M}_{i=1}(x_{in}\text{-}\lambda_n)]^{1/2}$, where $n\in \{1, 2, \ldots, M\}, i\in \{1,2, \ldots, M\}$ and normalized x_{in} is y_{in}:

$$y_{in} = \frac{x_{in} - \lambda_n}{\varepsilon_n} \tag{7}$$

STEP4: Calculate the difference degrees of all learners on their learning preferences and sort them incrementally. It should be noted that learner i has a difference degree of 0 with its own learning preference, i.e., $SA_{ii} = 0$

STEP5: Use the Allocation function to group each learning team and output the final collaborative learning grouping result.

The Allocation function used in STEP5 is the key function of the proposed collaborative learning grouping algorithm based on group preference, which describes the specific grouping process of learning groups. If all the learners in the learning teams (I, J)

are grouped, the next learning team will be processed. If there are learners in learning teams (*i, j*) who have not been grouped, then first determine whether there is a group with zero learners, and if so, assign them to that group, and if not, determine the groups that can admit learners. The degrees of difference in learning preferences between the ungrouped learners and the groups can admit learners is then calculated based on the following formula:

$$SA(i,l') = \underset{r\in R(l')}{Min}(SA_{ir}) \tag{8}$$

Finally, the ungrouped learners are assigned to the group with the greatest degree of difference in their learning preferences.

4 Verification of collaborative grouping algorithm

In order to verify the effectiveness of group preference-based collaborative learning grouping algorithms, this article designs experiments on the intra-group difference degree of different grouping algorithms. The algorithm is executed respectively each time the number of learners to be grouped is determined, or the computer randomly generates the data or the grouping data of real learners in collaborative learning.

In order to highlight the advantages of this algorithm in attaching importance to the group preference and improving the overall learning effect led by the group leader, this article summarizes the minimum difference degree index of learners' learning preference within a group and gives the calculation formula of the minimum difference degree of learning preference within a group:

$$MinLPD = \underset{l\in(1,2,\ldots,L)}{Max}\ \underset{i,j\in R(l)}{Min}(SA_{ij}) \tag{9}$$

Assuming that the number of groupings is represented by L, the learner set contained in the l-th grouping is represented by $R(l)$, and the degree of difference in learning preference between learners i and j is represented by SA_{ij}.

In order to validate the positive effect of group preference-based collaborative learning grouping algorithm on learners' achievements, this article evaluates the algorithm based on variance analysis, that is, the inter-group variance and intra-group variance to measure learners' achievements. Assuming that inter-group differences in learners' achievements are represented by inter-group variance NR_y, intra-group differences by intra-group variance NR_q, the intra-group and inter-group sum of squares by RR_y and RR_Q, respectively, and the intra-group and inter-group freedom are represented by cg_y and cg_q, respectively, then

$$NR_y = \frac{RR_y}{cg_y} \tag{10}$$

$$NR_q = \frac{RR_q}{cg_q} \tag{11}$$

After figuring out NR_y and NR_q, the two are compared to obtain the corresponding G values:

$$G = \frac{NR_y}{NR_Q} \tag{12}$$

Assuming that the number of groups is denoted by h, the number of people in group i is denoted by m_i, the mean of group i's achievement is denoted by A_i^*, and the overall mean of the sample is denoted by A^*. RR_y can be calculated by the following formula:

$$RR_y = \sum_{i=1}^{h} m_i (A_i^* - A^*)^2 \tag{13}$$

Similarly, assuming that the achievement of the j-th learner in group i is represented by A_{ij}, RR can be calculated by the following formula:

$$RR_q = \sum_{i=1}^{h} \sum_{j=1}^{m_i} (A_{ij} - A_i^*)^2 \tag{14}$$

Assuming that the number of groups is represented by L, cg_y can be calculated as follows:

$$cg_y = L - 1 \tag{15}$$

cg_q can be calculated as follows:

$$cg_q = \sum_{i=1}^{L} (m_i - 1) \tag{16}$$

5 Experimental results and analysis

Firstly, the number of learners to be grouped and the data generated randomly by computer are preprocessed. Then the SPSS software is used to process the preprocessed data and performs the repeated measurement of variance and freedom degrees. The independent variables are learner identity (in-group, out-group), group goals (maximization of heterogeneity of intra-group learning preferences, maximization of homogeneity of inter-group learning preferences), and evaluation context (initial grouping, collaboration matching, collaboration success, and collaboration failure), the dependent variable is learner's achievement evaluation rating, and the covariate is learners' identity score.

The descriptive results of learner's achievement evaluation for learners with maximization of heterogeneity of intra-group learning preferences and maximization of homogeneity of inter-group learning preferences at four different collaborative grouping stages in an English online teaching context are given in Table 1.

Table 1. Experimental results [$M \pm SD$] for different group goals in different collaborative grouping stages

Contexts	Within the Group		Between Groups	
	Maximization of Heterogeneity of Intra-Group Learning Preferences	Maximization of Homogeneity of Inter-Group Learning Preferences	Maximization of Heterogeneity of Intra-Group Learning Preferences	Maximization of Homogeneity of Inter-Group Learning Preferences
Initial grouping	3.62(1.27)	4.27(1.21)	3.15(1.74)	3.57(1.37)
Collaboration matching	3.14(1.62)	3.62(1.79)	3.28(1.59)	4.16(1.23)
Collaboration success	3.59(1.08)	3.48(1.95)	4.13(1.02)	4.05(1.15)
Collaboration failure	3.07(1.45)	3.52(1.38)	4.36(1.95)	3.28(1.8)

A three-factor mixed experimental design analysis of 2 (learner identity) × 2 (group goal) × 4 (evaluation context) is performed on learner achievement evaluation and learner identity scores. SPSS analysis shows that only the interaction between group goal and evaluation context is significant among the three factors. The results of simple effect analysis show that under the group goal of maximization of heterogeneity of intra-group learning preferences, learners' achievement evaluation is different in four evaluation contexts. The results of multiple comparisons show that learners' identity scores in the collaboration matching stage are significantly higher than those in the initial grouping stage, and the margin of learner identity score in collaboration success stage is significantly higher than that in collaboration matching stage. On the whole, with the successful matching of learners' learning preferences to collective learning group, learners' evaluation scores of themselves and other members of the group gradually increase under the group goal of maximization of heterogeneity of intra-group learning preferences. As a covariate, learner identity has a significant effect on learner identity, group goal, learner achievement evaluation, and learner identity score.

In order to analyze the experimental results more accurately, the learners' data are divided into two parts, namely "initial grouping-collaboration matching-collaboration success" and "initial grouping-collaboration matching-collaboration failure", according to the different learning effects in different collaborative grouping stages, in an effort to investigate interaction between the two factors respectively. First, the successful case of collaborative grouping is analyzed, in which the evaluation context has three levels and it is found that the interaction between three factors is significant. The results of simple effects analysis show that under the group goal of maximization of homogeneity of inter-group learning preferences, learners' evaluation scores differ significantly among the three contexts when evaluating other members of the group, and learners' identity scores are significantly lower in the collaboration success stage than in the initial grouping stage. Although under the group goal of maximization of heterogeneity of intra-group learning preferences, there is no significant difference in learners' identity scores in the three contexts when evaluating other members of the group, but the lowest identity scores are obtained during initial grouping. The identity scores after collaboration matching of learning preference improve and are the highest after collaboration success, as can be seen in Figure 4.

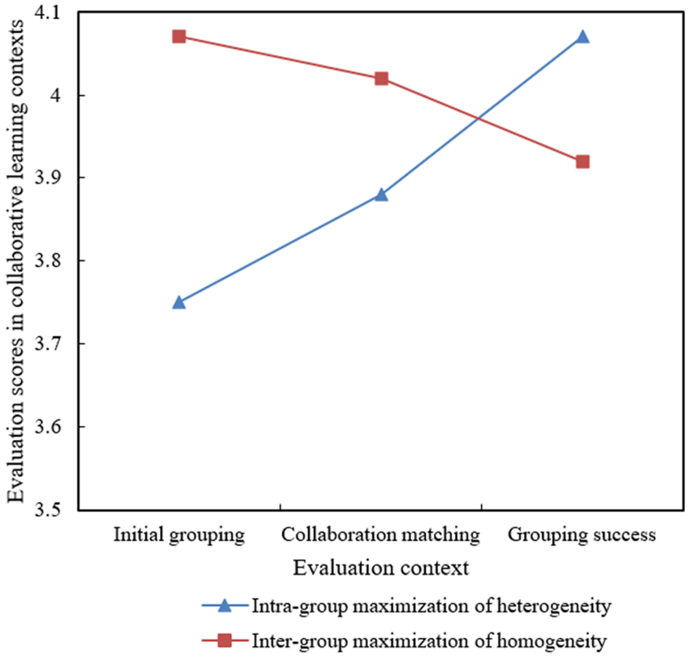

Fig. 4. Comparison of evaluation scores for different grouping goals at different collaborative grouping stages

The interaction between group goal and evaluation context is significant. The results of the simple effects analysis show that under the group goal of maximization of heterogeneity of intra-group learning preferences, learners' identity scores differ across the three contexts. The results of multiple comparisons show that the marginal identity scores of the collaboration success stage are significantly higher than that of the initial grouping stage, and the identity scores of the collaboration success stage are also significantly higher than that of the collaboration matching stage. On the whole, under the group goal of maximization of heterogeneity of intra-group learning preferences, the learners' evaluation scores of other members in the group also show a gradual increase from initial grouping to collaborative matching to collaborative success.

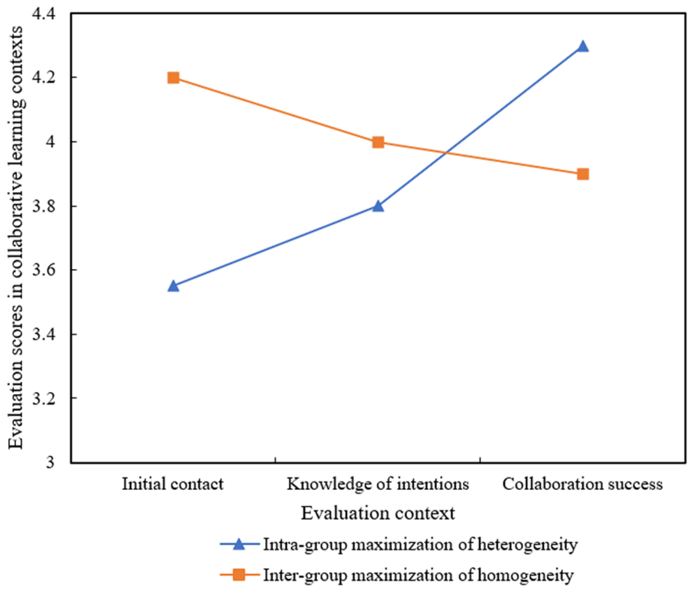

Fig. 5. Comparison of learners' evaluation scores of other members in the group at different collaborative grouping stages

Next, the case of collaboration failure is also analyzed, where the evaluation context also has three levels, and it is found that the interaction of all three factors is not significant.

Table 2. Descriptive statistics of interactive effects in different modes

Modes	*N*	Interactive Effects			
		Average	Standard Deviation	Minimum Value	Maximum Value
Random	7	51.2741	5.24179	46.25	62.47
Rotation	5	53.6297	5.25142	41.37	55.21
Group leader-led	21	75.8425	6.32514	62.51	86.39
Novice-led	9	52.6142	4.62592	48.67	61.45
Experience-led	11	77.5926	5.34271	75.48	85.27
Total	63	62.3413	15.26258	46.35	81.64

In order to get a better interactive model of collaborative learning in the context of online English teaching, this article first gives a descriptive statistical analysis of 50 collaborative learning groups' interactive evaluation based on the improvement of learners' achievements. The results are shown in Table 2. In terms of the average scores of interaction effects, the scores of the five collaborative learning interaction modes are in the following order: experience-led > group leader-led > rotation > group leader > novice-led > random. Herein, the "group leader-led" and "experience-led" modes with higher average scores of interaction effects are called efficient modes, while the "random", "rotation" and "novice-led" modes are called inefficient modes. The results of multiple comparative tests are conducted on the five collaborative grouping modes, and the results further show that there are significant differences in the interactive effects of collaborative learning groups between the efficient and inefficient modes in online English teaching context. There are no significant differences within either the inefficient mode or the efficient one.

Table 3. Multiple comparison test results for the interaction outcomes of the five collaborative learning interaction modes

Mode 1	Mode 2	Interactive Effects	
		Average Difference (I–J)	**Significance**
Random	Rotation	–2.51741	0.326
	Group leader-led	–15.62385	0.041
	Novice-led	–4.25174	0.158
	experience-led	–13.62597	0.012
Rotation	Random	2.51748	0.362
	Group leader-led	–16.52984	0.025
	Novice-led	–1.35247	0.594
	experience-led	–11.62519	0.014
Group leader-led	Random	15.28492	0.063
	Rotation	11.60257	0.051
	Novice-led	8.62591	0.062
	experience-led	–0.23152	0.246
Novice-led	Random	4.51284	0.131
	Rotation	1.62397	0.584
	Group leader-led	–8.52613	0.014
	Experience-led	–8.52741	0.011
Experience-led	Random	26.35291	0.036
	Rotation	28.54174	0.047
	Group leader-led	2.61538	0.085
	Novice-led	24.35126	0.091

The examination of collaborative learning interactions in this article focuses on the output part of the collaborative learning task based on learning preferences, which is divided into the overall learning effect and the mutual identification of learners. Combining the classroom observation and the above analysis results, it can be found that in efficient modes "group leader-led" and "experience-led" learning groups with similar learning preferences can quickly complete the tasks and solve problems. Moreover, they can also actively discuss the content of the task and agree on the steps to implement the task. Therefore, learning groups in these two modes have a more reliable interactive relationship in any learning session and perform better in terms of interaction relevance and completeness.

6 Conclusions

This article focuses on studying collaborative grouping and interactive relationship construction of college students based on group preference. A collaborative learning grouping algorithm based on group preference is proposed, considering the differences in learners' learning preferences and the preference of learning groups in a balanced way, and the problems in collaborative grouping of college students are described. A group preference-based collaborative learning grouping algorithm is designed, the main ideas and implementation process of the algorithm are expounded, experiments are designed to compare the intra-group difference degree of different grouping algorithms, and the algorithm's evaluation method is introduced. The experimental results of different collaborative grouping stages with different group goals are given, and the evaluation scores of different collaborative grouping stages with different group goals are compared, and the corresponding analysis results are given, which verifies the effectiveness of the proposed algorithm. The descriptive statistics of the evaluation of 50 collaborative learning group' interactive effects based on the improvement of learners' achievements are carried out, thus obtaining the collaborative learning interactive modes with better interactive effects in online English teaching contexts. The experimental results show that the learning groups in the "group leader-led" and "experience-led" modes have more reliable interactive relationships in any learning sessions and perform better in terms of interaction relevance and completeness.

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