Construction of the Interactive Educational Knowledge Graph and Classification of Student Groups

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Abstract—The attributes of the knowledge nodes in the interactive educational knowledge graph need to cater to students' online learning preferences, so understanding the composition and learning preferences of students in the online learning process is helpful to the development of more targeted learning paths. Currently, there are few existing research results on knowledge graph embedding methods based on students' interaction with respect to knowledge points, student group composition and their learning preferences. To this end, this paper studies the construction of an interactive educational knowledge graph and the classification of student groups. First, a knowledge recommendation idea was proposed based on the classification of student groups. Through the three types of interaction behaviors – human-computer, teacher-student, and student-student interactions that occur on the online learning platform, the depth of students' interactions with respect to the knowledge points in the interactive educational knowledge graph was characterized. The online learning effects of students were quantified by the interactive achievement of knowledge points mastered by students and the weights of knowledge points which represent their importance. Then, the effects of the differences in the interactions of students with respect to different knowledge points on the stability of the similarity prediction of students' learning preferences were explored, and based on the analysis results, students were classified into groups. The experimental results verified the effectiveness of the proposed model.

Keywords—interactive educational knowledge graph, online learning, knowledge point interaction, group classification

1 Introduction

The continuous development of online learning platforms have provided students with a variety of learning resources and tools and alleviated the uneven matching between the massive educational resources on the Internet and learners at different levels and from different sources. Therefore, the combination of online and offline education, which complement each other, has become the mainstream educational approach nowadays [1–10]. In order to make students' learning plans more scientific and their study time more flexible, more and more online learning platforms are mining professional knowledge systems, building interactive educational knowledge graphs, integrating fragmented knowledge modules, and recommending them to appropriate students [11–20]. The attributes of the knowledge nodes in the interactive educational knowledge graph need to cater to students' online learning preferences, and at the same time the knowledge points and learning resources need to be integrated and systematized. Understanding the composition and learning preferences of students in the online learning process is helpful to the development of more targeted learning paths.

Kobets et al. [21] analyzed and summarized the problems existing in higher education in the era of knowledge economy, and used the cognitive modeling method for weakly structured systems to construct a cognitive map of the educational process. The goal was to demonstrate the possibility of using cognitive modeling and cognitive maps in university knowledge management systems. In many cases, learners are confused about what knowledge is valuable and what they need to learn, and on the other hand, knowledge providers do not know how to update the outdated knowledge hierarchies or develop new knowledge products to meet the changing needs. To address this issue, Tang et al. [22] extended the topic map by adding a top-level knowledge requirement layer (KRL). This level of KRL can be used to guide learners to focus on the desired knowledge topics and push knowledge providers to redevelop or reconstruct outdated knowledge hierarchies. Adorni et al. [23] discussed a knowledge-based model for designing and developing learning units and teaching aids. The idea behind this model stemmed from the analysis of the open problems in instructional authoring systems and the lack of a clear process that can integrate instructional strategies with systems for the knowledge organization of the domain. Su and Wang [24] proposed the use of knowledge maps and appraisal of concept weights and other ICTs, and implemented an assessment system KMAAS to help primary school teachers in Taiwan or elsewhere properly create educational assessments. To compile an assessment, KMAAS analyzed the course material in the assessment scope and displayed a concept-weight-annotated knowledge map that embodied and visualized the importance of the concepts within the scope and the relationships between them. The experimental results confirmed the feasibility of the system in helping teachers compile educational assessments easily and accurately. Kolling da Rocha et al. [25] chose the sharing perspective, and attempted to expand the current knowledge on teaching authorship and learning practices in the context of higher education. It aimed to identify authorship profiles of undergraduate teachers at a university in south Brazil to validate the feasibility of creating a knowledge base to foster the development of innovative practices.

In the related literature on the construction of interactive educational knowledge graphs, domestic experts and scholars have focused on the construction of translation-based knowledge graph embedding models, while few have studied the knowledge graph embedding methods based on students' interactions with respect to knowledge points, student group composition and their learning preferences. To this end, this paper studies the construction of an interactive educational knowledge graph and the classification of student groups. Section 2 of this paper provides a knowledge recommendation idea based on the classification of student groups and characterizes the depth of students' interactions with respect to the knowledge points in the interactive educational knowledge graph through the three types of interaction behaviors – human-computer, teacher-student, and student-student interactions. Section 3 quantifies the online learning effects of students with the interactive achievement of knowledge points mastered by students and the weights of knowledge points which represent their importance. Section 4 explores the effects of the differences in the interactions of students with respect to different knowledge points on the stability of the similarity prediction of students' learning preferences, and then based on the analysis results, achieves the classification of student groups. The experimental results prove the effectiveness of the proposed model.

2 Knowledge point interaction and proficiency in the interactive educational knowledge graph

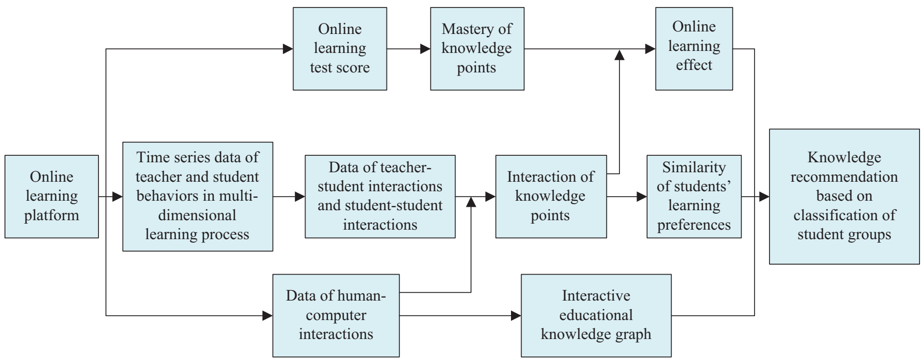


Fig. 1. Knowledge recommendation based on the classification of student groups

The ultimate goal of building an interactive educational knowledge graph and classifying student groups is to provide knowledge recommendation based on student groups. Figure 1 shows the idea of knowledge recommendation based on classification of student groups. First, build an interactive educational knowledge graph based on the time series data of teacher and student behaviors in the multi-dimensional learning process of the online learning platform. Second, perform collaborative analysis on the data of human-computer, teacher-student and student-student interactions, further analyze students' mastery and interaction of the knowledge points in the interactive educational knowledge graph, and obtain the calculation results of the online learning effect evaluation and learning preference similarity of students. Finally, provide knowledge recommendation based on group classification according to the constructed interactive educational knowledge graph and the calculation results of students' online learning effect evaluation and learning preference similarity.

This paper characterized the depth of interaction students' interactions with respect to the knowledge points in the interactive educational knowledge graph through the three types of interaction behaviors that occur in the online learning platform – human-computer interactions, teacher-student interactions and student-student interactions and also considered it to be the students' learning engagement, as the preparations for the evaluation of students' online learning effects.

Suppose that student v's frequency of interaction with the online learning platform in the process of learning knowledge point i is represented by $g_{SCv,i}$, that the interaction time of student v with the online learning platform in the process of learning knowledge point i by $p_{SCv,i}$, and that the frequency of pausing and dragging the timeline when student v's is interacting with the online learning platform learning knowledge point i by $t_{SCv,i}$. Based on the collected data such as $g_{SCv,i}$, $p_{SCv,i}$ and $t_{SCv,i}$ and other data in the learning process, calculate the human-computer interaction $RD_{v,i}$ of student v with knowledge point i:

$$RD_{v,i} = \beta \times g_{SC_{v,i}} + \gamma \times p_{SC_{v,i}} + \alpha \times t_{SC_{v,i}} \tag{1}$$

The main form of student-student interactions in the process of online learning is that students ask others questions and get answers when they encounter difficult problems. Therefore, the student-student interactions on the online learning platform can be regarded as a social network with students as nodes, and the behaviors of questioning and answering are the connection edges between nodes. The interactions between students with regard to knowledge points in the interactive educational knowledge graph can be characterized by the centrality of the social network. Since there are differences in the duration of students' questions and answers with regard to different knowledge points, certain weights were assigned to the node connection edges in this paper.

Suppose that the weight coefficient of student v and student u's interaction with regard to knowledge point i is represented by Q_{RRvui}, that the frequency of questions and answers between student v and student u in the learning of knowledge point i by g_{RRvui}, that the duration of questions and answers between student v and student u in the learning of knowledge point i by p_{RRvui}, and that the maximum duration of questions and answers between student v and other students in the process of learning knowledge point i by $max\{p_{RRv1i}, p_{RRv3i},...,p_{RRvmi}\}$. Based on the collected data of Q_{RRvui}, g_{RRvui} and p_{RRvui} in the learning process, calculate student v's student-student interaction $RR_{v,i}$ with respect to knowledge point i:

$$\begin{cases} RR_{v,i} = \sum_{u=1}^{n-1} Q_{RR_{u,v,i}} \times g_{RR_{v,u,i}}, v \neq u \\ Q_{RR_{v,u,i}} = \dfrac{p_{RR_{v,u,i}}}{max\left\{p_{RR_{v,1,i}}, p_{RR_{v,2,i}}, p_{RR_{m,n,i}}\right\}} \end{cases} \tag{2}$$

In the process of online learning, the main forms of teacher-student interactions include students asking questions and the teacher answering questions, the teacher asking questions and students answering questions, homework submission and correction, students' feedbacks on teaching effects, and the teacher's teaching optimization. Among them, students asking questions and the teacher answering questions, the teacher asking questions and students answering questions, and students asking and answering each other's questions are similar, except for the different interaction agents. Therefore, this paper calculates the two forms of interactions – students asking questions and the teacher answering questions, and the teacher asking questions and students answering questions, using the calculation method of $RR_{v,i}$. The home submission and correction, students' feedbacks on teaching effects and the teacher's teaching optimization are measured through the cognitive diagnosis model.

Suppose that the weight coefficient of student v's teacher-student interaction with respect to knowledge point i is represented by $Q_{RPv,i}$, that the student v's frequency of questions and answers with the teacher with respect to knowledge point i by $g_{RPv,i}$, that student v's homework performance with respect to knowledge point i by $HS_{v,i}$, that the number of students participating in online learning by n, the duration of questions and answers between student v and the teacher with respect to knowledge point i by $p_{RPv,i}$, and that the maximum duration of questions and answers between all students and the teacher with respect to knowledge point i by $max\{p_{RP1},p_{RP2},...,p_{RPv,i}\}$. Based on the collected data of $Q_{RPv,i}$, $g_{RPv,i}$ and $p_{RPv,i}$ and other data in the learning process, calculate the teacher-student interaction $RP_{v,i}$ of student v with respect to knowledge point i by the following formula:

$$\begin{cases} RP_{v,i} = Q_{RP_{v,i}} \times g_{RP_{v,i}} + \dfrac{HS_{v,i}}{\sum_{v=1}^{n} HS_{v,i}} \\ Q_{RP_{v,i}} = \dfrac{p_{ST_{v,i}}}{max\left\{p_{RP_{1,i}}, p_{RP_{1,i}}, p_{RP_{n,i}}\right\}} \end{cases} \tag{3}$$

Based on the human-computer interaction $RD_{v,i}$, student-student interaction $RR_{v,i}$, teacher-student interaction $RP_{v,i}$ and the weight coefficients ξ, δ and ω of the three forms of interactions, the interaction ILT_{vni} of student v with respect to knowledge point i can be expressed as follows:

$$ILT_{v,i} = \xi \times RD_{u,i} + \omega \times RR_{v,i} + \chi \times RP_{v,i} \tag{4}$$

The students' mastery of the knowledge points in the interactive educational knowledge graph is also calculated using the cognitive diagnosis model. Based on the collected data of students' online learning test scores, the score matrix R constructed by the scores of n students for l online learning test questions can be given by the following formula:

$$R = \begin{bmatrix} r_{14} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{l1} & \cdots & r_{ln} \end{bmatrix} \tag{5}$$

The correlation matrix G constructed by the correlations between l online learning test questions and m knowledge points is:

$$G = \begin{bmatrix} g_{11} & \cdots & g_{1l} \\ \vdots & \ddots & \vdots \\ g_{m1} & \cdots & g_{ml} \end{bmatrix} \tag{6}$$

Suppose the number of test questions for testing knowledge point i is represented by J, that the correlation value between knowledge point i and online learning test question j by g_{ij}, that the test score of student v for online learning test question j by r_{vj}, and that the full score of online learning test question j by HS_j, then the student v's mastery of knowledge point i can be expressed as:

$$NLT_{v,i} = \frac{\sum_{j=1}^{J} g_{ij} r_{vj}}{\sum_{j=1}^{J} g_{ij} HS_j} \tag{7}$$

3 Learning effect evaluation

Due to the complex structure of knowledge points in the interactive educational knowledge graph, the students' online learning effects were quantified in this paper through the interactive achievement of students with respect to the knowledge points and the weights of the knowledge points representing their importance. The interactive achievement of students with respect to the knowledge points can be divided into four levels: understanding, comprehension, mastery and application. Suppose the interactive achievement that enables student v to master knowledge point i is represented by $DLT_{v,i}$, which can be calculated by the following formula:

$$DLT_{v,i} = NLT_{v,i} \cdot ILT_{v,i} \tag{8}$$

The knowledge points in the interactive educational knowledge graph have different roles and importance for different majors and different courses, and therefore, in the process of online learning, there are differences in the average interaction of students in different majors and courses with respect to knowledge points. Let the weight coefficient of knowledge point i in different majors and courses be represented by θ_i, and the number of students who learn the knowledge point online by n, and then, the calculation formula of the weight coefficient is expressed as follows:

$$\theta_i = \frac{\sum_{v=1}^{n} ILT_{v,i}}{n} \tag{9}$$

Assuming that the weight coefficient of each knowledge point is represented by θ_i, and that the total number of knowledge points by m, the online learning effect KO_v of student v can be calculated by combining Eq. (8) and (9):

$$KO_v = \sum_{i=1}^{m} \theta_i \times ILT_{v,i} \tag{10}$$

4 Classification of student groups based on similarity calculation

The optimized similarity model takes into full account students' learning preferences, number of test questions, and sparseness of collected data to obtain a more scientific interactive educational knowledge graph for students. When the traditional similarity model is used for the similarity calculation of student groups, the differences in the interaction of students with respect to different knowledge points in the interactive educational knowledge graph are not considered much, so the stability in the prediction of similarities between students' learning preferences in the interactive educational knowledge graph are affected to some extent. In this paper, the interactions of 3 students with respect to 5 knowledge points were analyzed as an example to explore the impacts of the differences in the interactions of students with different knowledge points on the stability of the similarity prediction of students' learning preferences, and then based on the analysis results, the students were classified.

Based on the interactions between students (v,u) and between students (v,a) for $\{i_1,i_2,i_3,i_4,i_5\}$ obtained in the previous section, the prediction of v by the similarity of (v,u) was compared with the prediction of v by the similarity of (v,a) to examine the stability. The differences in the interactions of students with different knowledge points can be represented by the similarity correction factor ϕ shown in Eq.(11). Suppose that the interaction of student v with respect to knowledge point i is represented by $ILT_{v,i}$, that the interaction of student u with knowledge point i by $ILT_{u,j}$, and that the correction factor to the differences in the interaction of students with respect to different knowledge points by γ, then there is:

$$\gamma = x^{\left|ILT_{v,i} - ILT_{u,i}\right|} \tag{11}$$

The traditional similarity model only considers the interaction preferences of students when calculating the similarity of student groups, but lacks the consideration of the differences in the average interaction of students with respect to different knowledge points in the interactive educational knowledge graph. In this paper, average interaction of 2 students with respect to 5 knowledge points was analyzed as an example to explore the impacts of the average interaction of students with respect to different knowledge points on the prediction precision of the similarity between students' learning preferences, and then based on the analysis results, classification of student groups was carried out.

Based on the differences in the interaction between students u and v for the five knowledge points $\{i_1,i_2,i_3,i_4,i_5\}$, the average interaction with respect to the five knowledge points $\{i_1,i_2,i_3,i_4,i_5\}$ can be further compared. Based on the comparison results, the weight coefficients that characterize the differences of the average interactions with respect to different knowledge points can be obtained. Assuming that the interaction of student v with respect to knowledge point i is represented by $ILT_{v,i}$, that the total number of students by n, and that the total number of knowledge points by m, then the weight coefficient q_i of knowledge point i can be calculated by the following formula:

$$q_i = \frac{\sum_{v=1}^{n}\left(ILT_{v,i}/n\right)}{\sum_{i=1}^{m}\sum_{v=1}^{n}\left(ILT_{v,i}/n\right)} \tag{12}$$

Considering the differences in the interactions of students with respect to different knowledge points in the interactive educational knowledge graph, and the impacts of the differences in the average interactions with respect to different knowledge points on the calculation results of the similarity between students' learning preferences, a correction factor for the differences in interactions was set up in this paper, and the similarity model was optimized based on the weight coefficient corresponding to the correction factor. Suppose that the knowledge points learned by student v are represented by KP_v, that the knowledge points learned by student u by KP_u, that the knowledge points learned by both v and u by $KP_v \cap KP_u$, that the mean values of the interactions of v and u with respect to the knowledge points by λ_v and λ_u, and that the standard deviations of the interactions of v and u with respect to the knowledge points by ξ_v and ξ_u, and then the optimized similarity model can be expressed by Eq. (13):

$$\begin{cases} SIM(v,u) = R_1(v,u)\cdot R_2(v,u)\cdot R_3(v,u) \\ R_1 = \begin{cases} \dfrac{\sum_{i\in KP_v\cap KP_u} x^{\left(q_i\cdot\left|ilt_{v,i}-ilt_{u,i}\right|\right)}\cdot ILT_{v,i} - ILT_{u,i}}{\sqrt{\sum_{i\in KP_v} ILT^2_{v,i}}\cdot\sqrt{\sum_{i\in KP_u} IKP^2_{u,i}}}, if \quad SPR < \sigma \\ \dfrac{\sum_{i\in KP_v\cup KP_u} x^{\left(q_i\cdot\left|ILT_{v,i}-ILT_{u,i}\right|\right)}\cdot ILT_{v,i}\cdot ILT_{u,i}}{\sqrt{\sum_{i\in KP_v\cup KP_u} ILT^2_{v,i}}\cdot\sqrt{\sum_{i\in KP_v\cup KP_u} ILT^2_{u,i}}}, otherwise \end{cases} \\ R_2(v,u) = \dfrac{1}{1+exp\left(-\dfrac{\left|KP_v\cap KP_u\right|^2}{\left|KP_v\right|\cdot\left|KP_u\right|}\right)} \\ R_3(v,u) = 1-\dfrac{1}{1+exp\left(-\left|\lambda_v-\lambda_u\right|\cdot\left|\xi_v-\xi_u\right|\right)} \end{cases} \tag{13}$$

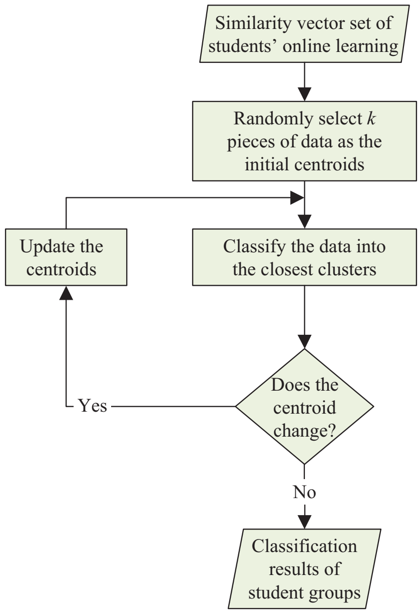


Fig. 2. Idea of student classification

The idea of student classification is shown in Figure 2. Based on the prediction results of the similarity between students' learning preferences, classify the students into different groups with the aid of the k-means clustering algorithm according to the characteristics of students' learning preferences. Repeatedly classify the students into clusters according to the similarity values of students' learning preferences, and then update the centroids until the centroid of each student group does not change, and in this way, student classification is achieved.

5 Experimental results and analysis

In this paper, the similarity between students' learning preferences was calculated based on the analysis results of the interactions with respect to knowledge points. First, the interaction data of nearly 1,500 students in Grade 1 to 4 in research institutions with respect to the knowledge points in the interactive educational knowledge graph during the online learning process were calculated, and then a training set and a test set were constructed in proportion to the data sets collected. The similarity of students' learning preferences in the training set was calculated by the similarity calculation model before and after optimization to verify the effectiveness of the model optimization. Since the number of students participating in the experiment affects the prediction performance of the proposed model, the model calculation errors MAE and MSE values before and after optimization under different numbers of students were summarized in this paper, as shown in Figures 3 and 4.

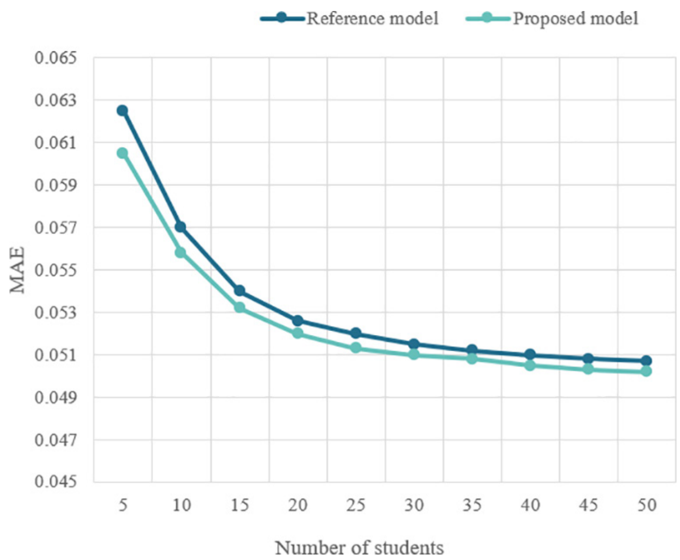


Fig. 3. MAE values of the model before and after optimization under different numbers of students

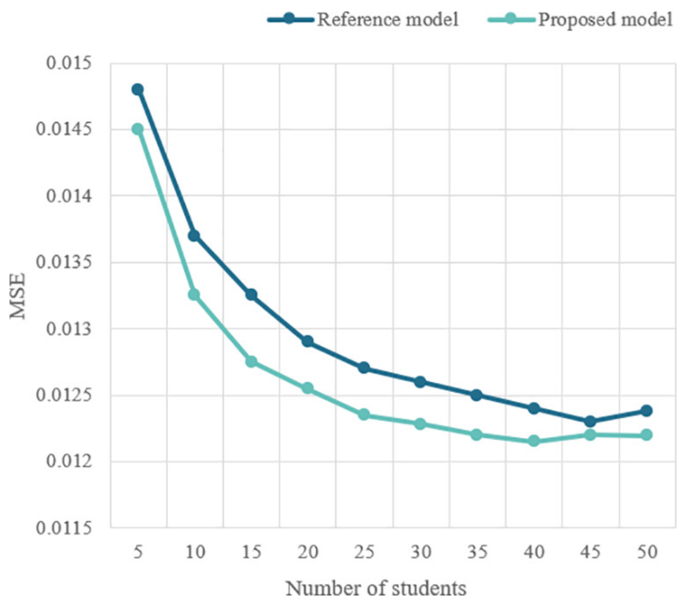


Fig. 4. MSE values of the model before and after optimization under different numbers of students

It can be seen from Figure 3 that the MAE values calculated by the similarity calculation model before and after optimization all decreased with the increase in the number of students, and that the downward trends of the MAE values began to flatten when the number of students exceeded 35. With the same number of students, the MAE value calculated by the optimized similarity calculation model was smaller than that by the one before optimization, indicating that the optimized similarity calculation model has higher precision in predicting the similarity of students' learning preferences.

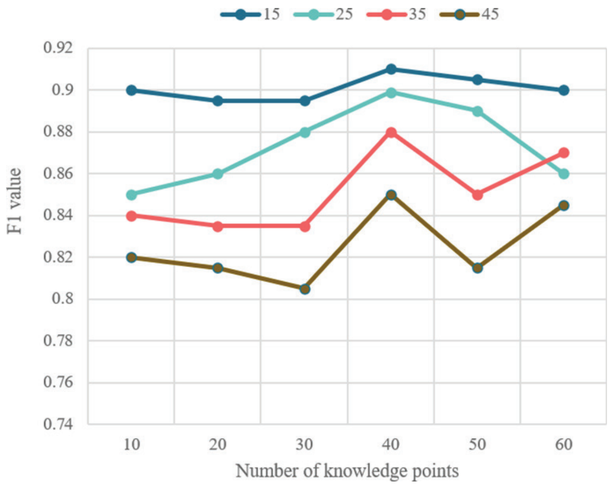
It can be seen from Figure 4 that the MSE values calculated by the similarity calculation model before and after optimization all decreased with the increase of the number of students, and the downward trends of the MSE values began to flatten when the number of students exceeded 35. With the same number of students, the MSE value calculated by the optimized similarity calculation model was smaller than that by the similarity calculation model before optimization, indicating that the optimized similarity calculation model has higher stability in predicting the similarity of students' learning preferences. To sum up, the performance of the optimized similarity calculation model is better than that of the one before optimization.

The number of knowledge points in the interactive educational knowledge graph has a certain impact on the prediction performance of the model with respect to learning preference similarity. In this paper, the students' interactions with respect to knowledge points ranking the 15th, 25th and 35th in terms of interaction were calculated, and the similarity of students' learning preferences was further calculated. Then, based on the calculation results, classification of student groups was performed and knowledge recommendation was achieved. The number of students also has a certain impact on the prediction performance of the model with respect to learning preference similarity. Therefore, in this paper, the learning preference similarity scenarios ranking the 20th, 30th, 40th, and 50th were chosen in the comparative experiment. The Precision, Recall, F1 value and MAE value of the prediction results of the similarity between students' learning preference are given in Table 1.

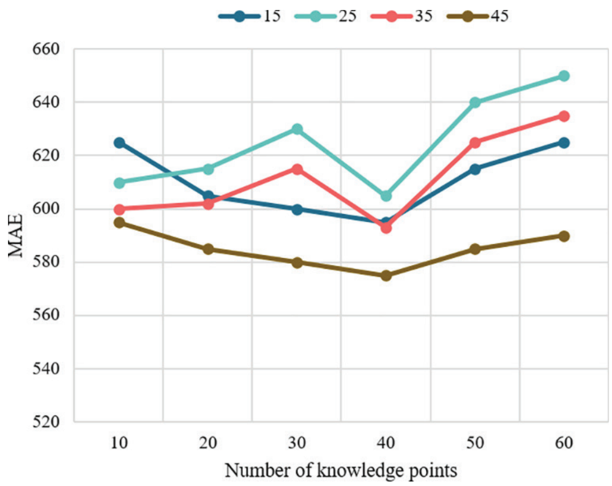
Table 1. Prediction performance of learning preference similarity

Learning Preference Similarity Ranking	**20**			**30**			**40**			**50**		
Knowledge Point Interaction Ranking	**15**	**25**	**35**	**15**	**25**	**35**	**15**	**25**	**35**	**15**	**25**	**35**
*F*1	0.8127	0.8152	0.8326	0.8251	0.8302	0.8472	0.8859	0.8326	0.8108	0.8162	0.8574	0.8162
Precision	0.8625	0.8027	0.8142	0.8695	0.8362	0.8847	0.8251	0.7362	0.8247	0.7012	0.7325	0.8947
Recall	0.8247	0.8362	0.8957	0.8821	0.8349	0.8162	0.8574	0.8628	0.8514	0.8836	0.8192	0.8647
MAE	625	541	597	516	548	503	529	583	527	506	592	568

In the above experiment, the similarity of learning preferences among students of different grades was calculated based on the knowledge points ranking the 15th, 25th, and 35th in the terms of interaction, and then based on the similarity calculation results, the students of different grades were classified. Figure 5 shows the experimental results of the student classification. According to the interactions with respect to the knowledge points in the interactive educational knowledge graph, the optimal student classification scheme was obtained with the fixed F1 value and MAE value.



(a) F1 value



(b) MAE value

Fig. 5. Effects of student classification

Through analysis of Figures 5a and b, it can be seen that, for students of the same grade, when the learning preference similarity ranking was 20, 30, 40, and 50, the F1 value of the student classification was the highest when there were 40 knowledge points of the interactive educational knowledge graph involved in the similarity calculation, and thus the classification effect was the best. When the learning preference similarity ranking was 20, 30, 40, and 50, the MAE value of student classification also reached the lowest and thus the classification effect was the best when there were 40 knowledge points of the interactive educational knowledge graph.

Taking the overall learning preference of the students as the dependent variable, and their learning behavior condition and group classification as the independent variables, a two-way analysis of variance (ANOVA) was carried out in this paper. At the same time, a one-way ANOVA was performed on the overall learning preferences of different learning groups to explore the differences in their learning preferences. Table 2 presents the descriptive statistics of the learning preferences of different experimental groups.

Table 2. Descriptive statistics of the learning preferences of different experimental groups

Group	*M*	*SD*	*N*
1. Non-synchronous learning behavior * non-classified	85.26	12.48	45
2. No learning behavior * classified	74.69	15.91	32
3. Synchronous learning behavior * classified	115.37	6.28	30
4. Non-synchronous learning behavior * classified	95.62	14.06	37
5. No learning behavior * non-classified	55.48	19.28	39
6. Synchronous learning behavior * non-classified	136.24	9.41	34
Total	86.11	25.64	258

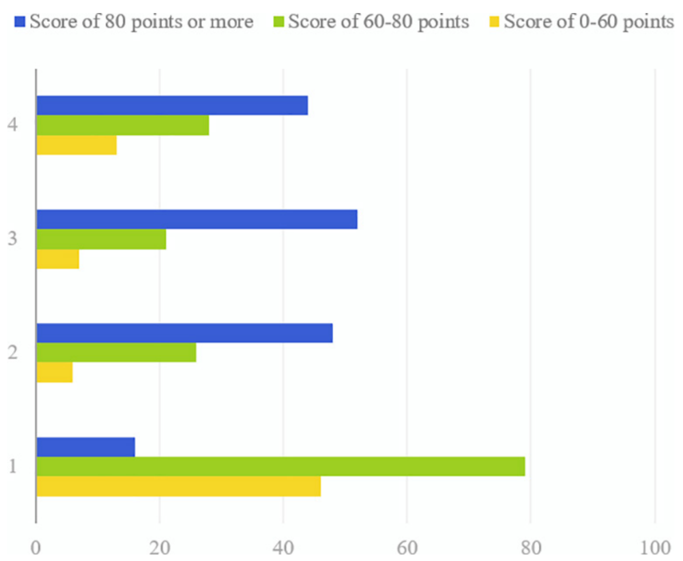


Fig. 6. Distribution of student groups corresponding to different ranges of online test scores

Next, a two-way ANOVA was performed on the learning behavior condition and group classification to find out the main effects and interaction between the two. It can be seen from the table that the main effects of the learning behavior condition and the group classification are both significant on students' learning preferences. At the same time, the interaction effect of learning behavior condition and group classification is also significant on students' learning preferences.

Figure 6 shows the distribution of student groups corresponding to different ranges of online test scores. It can be seen that the students' online test scores were inversely proportional to the precision of student group classification. This was because this study regarded the students' interactions with respect to the knowledge points in the interactive educational knowledge graph as their learning preferences, and then classified students based on their learning preferences and emotional attitudes. When students have a higher learning preference for a knowledge point, it is more difficult for the proposed model to extract students' learning attitudes, resulting in a lower precision of student group classification.

6 Conclusions

This paper studied the construction of an interactive educational knowledge graph and the classification of student groups. First, a knowledge recommendation idea was proposed based on the classification of student groups. Through the three types of interaction behaviors – human-computer, teacher-student, and student-student interactions that occur on the online learning platform, the depth of interaction between students and the knowledge points in the interactive educational knowledge graph was characterized. The online learning effects of students were quantified by the interactive achievement of knowledge points by students and the weights of knowledge points which represent their importance. Then, the effects of the differences in the interactions of students with respect to different knowledge points on the stability of the similarity prediction of students' learning preferences were explored, and based on the analysis results, students were classified into groups. Through an experiment, the MAE and MSE errors of the model calculation before and after optimization under different numbers of students were summarized, from which, it can be seen that the performance of the similarity calculation model after optimization is better than that before optimization. The scenarios where the learning preference similarity ranking was 20, 30, 40 and 50 were compared, and the Precision, Recall, F1 value and MAE value of the prediction results of the similarity between students' learning preference were given. The experimental results of student classification were presented. According to the interactions with respect to the knowledge points in the interactive educational knowledge graph, the optimal student classification scheme was obtained with the fixed F1 value and MAE value. In addition, descriptive statistics of the learning preferences of different experimental groups were provided, and the distribution of student groups corresponding to different ranges of online test scores were shown in the paper.

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