Students' Willingness to Participate in Interactive Teaching in the Context of Distance Education

https://doi.org/10.3991/ijet.v17i18.34179

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Abstract—Figuring out students' willingness to participate in interactive teaching activities is conductive to promoting the application of distance education, thereby assisting teachers to better formulate and implement their teaching plans of distance education. In common practical research on teacher-student and student-student interactions in the context of distance education, the interactive behavior data are mostly collected at certain fixed time points, and the influence of the information technology of distance education platforms on students' motivation and willingness to participate in interactive teaching activities has been ignored. To make up for these shortcomings, this paper aims to analyze students' willingness to participate in interactive teaching in the context of distance education. At first, this paper built a hidden Markov model to describe the changes from the current state to the future state of students' willingness to participate in interactive teaching. Then, based on the data of teacher-student and student-student dialogues, this paper built a prediction model to identify students' willingness to participate in interactive teaching. At last, the effectiveness of the constructed models was verified by experimental results.

Keywords—distance education, interactive teaching, willingness, hidden Markov model, prediction

1 Introduction

As new education information applications are being developed and updated constantly, the conventional off-line classroom teaching has transformed to "smart class" and "distance education" which are formed based on online learning behaviors [1–8]. Distance education is very different from the conventional off-line classroom teaching in terms of organization form, mode, method, and tool [9–15]. With such transformation, the teaching interaction method gradually changes from the simple teacher-student interaction to the interaction among three parties: teachers, students, and distance platforms [16–18]. Regardless of off-line or on-line education, classroom interaction is still the primary teaching method that has the greatest and direct impact on teaching effect and learning quality [19–24]. For distance education platforms, due to their special teaching environment, they rely more on students' active participation, and the main driving factors of the interactive behavior of students would determine teachers' decisions in distance education to a large extent [25, 26]. Therefore, figuring out students' willingness to participate in interactive teaching activities is conductive to promoting the application of distance education, thereby assisting teachers to better formulate and implement their teaching plans of distance education.

Based on the theory of distributed cognition, Chen and Huang [27] employed several cases to analyze the influencing factors of content, tools, and contextual interactions during online learning and discuss college students' willingness to engage in online learning under distributed cognition, their paper serves as a guidance for the experience design of education platforms. Students' willingness to participate in blended learning has always been an interesting topic in higher education, Zhang et al. [28] conducted a large scale questionnaire survey to investigate the said willingness and find its influencing factors, they received 1903 effective replied questionnaires and interviewed nine students, and the results reveal that blended learning hasn't been widely implemented in China yet. Islam et al. [29] discussed how to motivate students to participate more actively in classroom teaching, and their paper offers great help for teachers, students, guardians, and education professionals. The outbreak of COVID-19 pandemic in 2019 has impacted the entire world, and a side effect is the popularization of online learning and distance education. Dascalu et al. [30] proposed a new-version Reader Bench framework based on cohesion network analysis, which can be used to assess students' online activities as a plug-in feature to Moodle. The authors adopted a recurrent neural network with LSTM cells that integrates global features (including participation and initiation indices) with a time series analysis on timeframes, and used the network to forecast students' grades and create sociograms to observe their interaction patterns. Kaliisa and Dolonen [31] introduced a tool called the Canvas Discussion Analytics Dashboard (CADA) which was designed using human-computer interaction approaches and can provide teachers with real-time insights into students' online discussions and discourses. The tool supports automatic extraction and analysis of forum posts and interactions from the Canvas LMS and provides visualized results, also, it creates links between participation rate, use concepts and cognitions, and gives clear and detailed display to the contribution and sentiment scores of every participant.

After carefully reviewing the existing literatures, we found that as the information-based education has penetrated deeper into classroom teaching, world field scholars have developed and applied various interactive analysis tools to construct classroom teaching interaction models applicable to different teaching scenarios. However, in common practical research on teacher-student and student-student interactions in the context of distance education, the interactive behavior data are mostly collected at certain fixed time points, and the influence of the information technology of the distance education platforms on students' motivation and willingness to participate in interactive teaching activities has been ignored. Thus, to make up for these shortcomings, this paper aims to analyze students' willingness to participate in interactive teaching in the context of distance education. In the second chapter, this paper built a hidden Markov model to describe the changes from the current state and future state of students' willingness to participate in interactive teaching. Then, based on the data of teacher-student and student-student dialogues, the third chapter built a prediction model to identify students' willingness to participate in interactive teaching. At last, the effectiveness of the constructed models was verified by experimental results.

2 Description of students' willingness to participate in interactive teaching activities

The target problem, namely students' willingness to participate in the interactive teaching activities of distance education (hereinafter referred to as "participation willingness" for short), can be described by the features of the decisive relationship between adjacent states in the hidden Markov model, that is, this model can well reflect the changes between the current state and future state of students' participation intension of interactive teaching activities.

Hidden Markov models are usually used to describe Markov processes with hidden unknown parameters, and the two types of chains, observable state chains and hidden state chains, are determined by initial probability distribution, state transition probability distribution, and observation probability distribution. Assuming: W represents the set of all possible participation willingness; u represents the set of all observable participation willingness; M represents the number of possible participation willingness; N represents the number of observable participation willingness, then there are:

$$W = \{w_1, w_2, ..., w_M\} \tag{1}$$

$$U = \{u_1, u_2, ..., u_N\} \tag{2}$$

Assuming: Q represents the sequence of participation willingness; S represents the length of the sequence; E represents the observation sequence corresponding to Q; M represents the length of the observation sequence, then there are:

$$Q = \{q_1, q_2, ..., q_S\} \tag{3}$$

$$E = \{e_1, e_2, ..., e_M\} \tag{4}$$

Specifically, the matrix variables of the Markov chain include X, Y, and Z, which are called the three elements of the hidden Markov model, and they respectively represent the transition matrix, the observation probability matrix, and the initial probability vector of participation willingness, X can be expressed as:

$$X = \{x_{ij}\}_{M*N} \tag{5}$$

Assuming: at time moment p, under the condition that the participation willingness is w_i, then the occurrence probability x_{ij} of w_i is:

$$x_{ij} = t(i_{t+1} = w_j \mid i_t = w_i) \tag{6}$$

$$i = 1, 2, ..., M;\ j = 1, 2, ..., N \tag{7}$$

At time moment $p = 1$, the occurrence probability of w_i is D_i, that is, the initial state probability vector can be written as:

$$D = (D_i), D_i = (T_1\ \ i =)_i\, w = 1, 2, ..., i \tag{8}$$

In the hidden Markov model, D and X determine the state sequence of participation willingness, its observation sequence is determined by Y, then the hidden Markov model can be expressed by Formula 9:

$$\mu = \{X, Y, Z\} \tag{9}$$

Taking three distance education interactive learning groups X, Y and Z and three interactive teaching forms 1, 2, and 3 that about to be applied as examples, by randomly selecting students from the three learning groups, random interactive learning group sequence and student sequence could be constructed, which correspond to the hidden state chain and the observable state chain of the hidden Markov model.

In this case, assuming: interaction probabilities among groups X, Y, and Z are all 1/3, which is the state transition probability. Assuming: the probability of X participating in interactive teaching form 1 is 1/3, the probability of X participating in interactive teaching form 2 is 1/4, the probability of X participating in interactive teaching form 3 is 1/5; the probability of Y participating in interactive teaching form 1 is 1/2, the probability of Y participating in interactive teaching form 2 is 1/2, the probability of Y participating in interactive teaching form 3 is 1/3; the probability of Z participating in interactive teaching form 1 is 1/4, the probability of Z participating in interactive teaching form 2 is 1/5, the probability of Z participating in interactive teaching form 3 is 1/4, then, the initial probability distribution is:

$$\Omega = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right) \tag{10}$$

The state transition probability matrix is:

$$X = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{pmatrix} \tag{11}$$

The output probability matrix is:

$$Y = \begin{pmatrix} \frac{1}{4} & \frac{1}{5} & \frac{1}{6} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{4} & \frac{1}{5} & \frac{1}{4} \end{pmatrix} \tag{12}$$

According to maximum likelihood estimation, the participation willingness of students was divided into three states: passive state, average state, and active state.

The three states respectively represent that the number of interactive teaching behavior performed by a student during 1 class hour is less than 2, between 3 and 8, and more than 8. If this number is less than 2, then the student is considered to be in a passive state; if this number is between 3 and 8, then the student is in an average state; if this number is more than 8, then the student has an active participation willingness.

A student's participation willingness state at time moment $p-1$ can be switched to the hidden state with a fixed probability, and this probability is the transition probability, and the switching probability of the student's participation willingness state from time moment $p-1$ to time moment t is the output probability. The captured data were fitted.

The participation willingness states of 100 students during a week were investigated and divided into the three above-mentioned states: passive, average, and active, and the states of these students were regarded as the hidden state of the model. Then, after one week, the number of interactive teaching behavior of these 100 students was taken as the criterion to divide their participation willingness states, and the students' participation willingness states in this week were regarded as the observable state of the model. The participation willingness states of students (participants of distance education) after another one week can be predicted by the constructed hidden Markov model, and the students' participation willingness states in this week can be used to verify the effectiveness of the model.

The set of output probabilities is:

$$\Omega_1 = (0.81, 0.11) \tag{13}$$

The probability distribution of students' participation willingness is:

$$\Omega_2 = (0.82, 0.10) \tag{14}$$

3 Prediction of students' willingness to participate in interactive teaching activities

Students' participation in interactive teaching activities will generate a lot data of teacher-student and student-student dialogues based on which the prediction model could be constructed to identify students' willingness to participate in interactive teaching. Figure 1 shows the structure of the prediction model. The model has two parts: the semantic information extraction of a single dialogue, and the semantic information extraction of dialogue sequence. In the teacher-student and student-student dialogue scenes, generally, the students' participation willingness during the entire conversation process is unchanged. Therefore, during a single teacher-student or student-student dialogue, each time a student sends a piece of dialogue information, the model will identify the student's participation willingness. However, considering the continuity of teacher-student and student-student dialogues, the complete dialogue sequence should be input into the constructed prediction model.

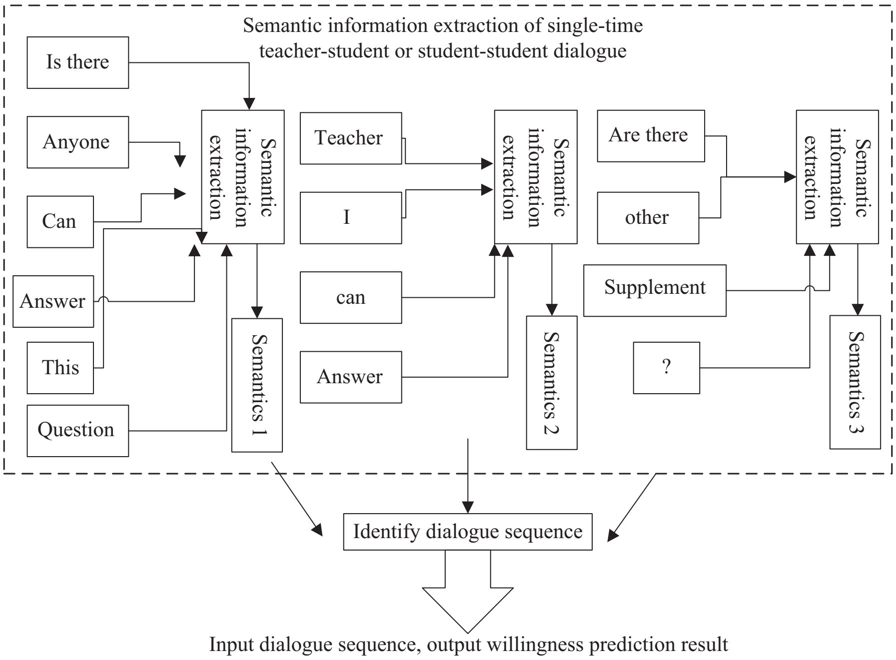

Fig. 1. Structure of the prediction model

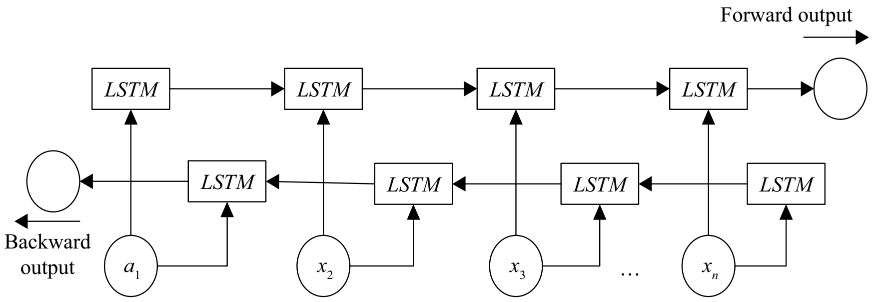

Fig. 2. Structure of the *BiLSTM* model

Assuming: a_i represents dialogues initiated by student; a'_i represents dialogues initiated by teacher, then Formula 14 gives the expression of teacher-student and student-student dialogues:

$$A_n = \left[a_0, a'_1, a_2 \cdots a_1, a'_{i+1} \cdots a_{n-1}, a'_n\right] \tag{15}$$

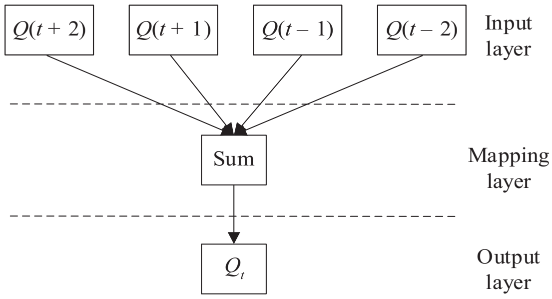

Fig. 3. Diagram of the *Word2Vec* model

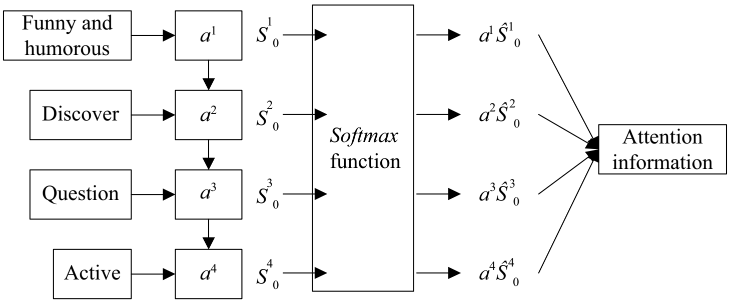

Fig. 4. Flow of the *Attention* algorithm

The semantic information extraction of single dialogue adopts a dual-model mode, the *Word2Vec* algorithm for word vectorization and the *Attention* algorithm for accuracy and efficiency improvement of sematic extraction were introduced into the *BiLSTM* model to attain the prediction model *BM* of student participation willingness based on teacher-student and student-student dialogue sequence. Figure 2 gives the structure of the *BiLSTM* model, and Figures 3 and 4 give the *Word2Vec* model and the flow of the *Attention* algorithm. The adopted *Word2Vec* model has 256 dimensions. For a single dialogue a consisting of multiple words q initiated by student, it could be expressed as:

$$a = \left[q_0, q_1 \cdots q_i \right] \tag{16}$$

Vector e is formed after the conversion of q:

$$e = Word2Vec(q) \tag{17}$$

Figure 5 shows the execution flow of the word embedding model combined with the time sequence model. The *BiLSTM* model was used to extract semantic information from the dialogue text with embedded words, and the adaptive *Attention* algorithm was used to summarize the attained semantic vector sequences to create a comprehensive semantic vector, which can be expressed as:

$$\left[r_{blstm}^0, r_{blstm}^1, r_{blstm}^2, \cdots r_{blstm}^i \right] = BiLstm\left(\left[e_0, e_1, \cdots, e_i \right] \right) \tag{18}$$

The *Attention* algorithm was used to summarize and extract $[r^0_{blstm}, r^1_{blstm}, r^2_{blstm}, \dots r^i_{blstm}]$ to get the semantic vector r^*:

$$r^* = Attention\left(\left[r_B^0, r_B^1, r_B^2, \cdots r_B^i\right]\right) \tag{19}$$

The model performance evaluation steps are:

STEP 1: Extract associated information from the content of teacher-student and student-student dialogues to generate the output associated information e_1 and e_1' of each dialogue sentence, e_1 and e_1' respectively correspond to dialogues initiated by student, and dialogues initiated by teacher or other students:

$$\left[e_0, e_1', e, \cdots, e_i, e_{i+1}' \cdots e_{n-1}, e'_n\right] = BM\ (A_n) \tag{20}$$

STEP 2: Eliminate associated information output corresponding to dialogues initiated by teacher and other students and process the category information generated by the associated information through the *Softmax* function, then the participation willingness probability t under the condition of student-initiated dialogues could be attained; assuming q and y represent linear transformation parameters used to generate category information based on the associated information, then there are:

$$\left[K_0, k_2, \cdots, k_i\right] = \left[e_0, e_1', e_2, \cdots, e_i, e_{i+1}' \cdots e_{n-1}, e_n'\right] \times q + y \tag{21}$$

$$\left[t_0, t_2, \cdots, t_i\right] = Softmax\left[k_0, k_2, \cdots, k_i\right] \tag{22}$$

In this paper, the loss function of the model was defined as the average cross entropy of each position to be identified in the teacher-student and student-student dialogue content. Assuming: m represents the number of positions to be identified, then there are:

$$F(A) = -\sum_{i=1}^{2} T(a_i) log(T(a_i)) A = (a_1, a_2) \tag{23}$$

$$loss = \frac{\sum_{i=0}^{m} F_i(A)}{m} \tag{24}$$

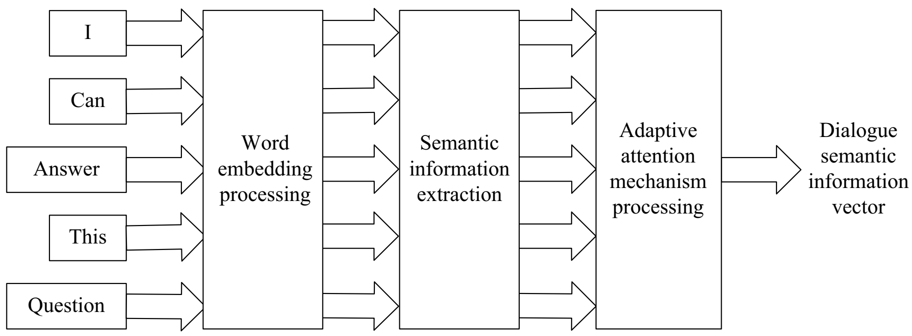

Fig. 5. Execution flow of the word embedding model combined with the time sequence model

4 Experimental results and analysis

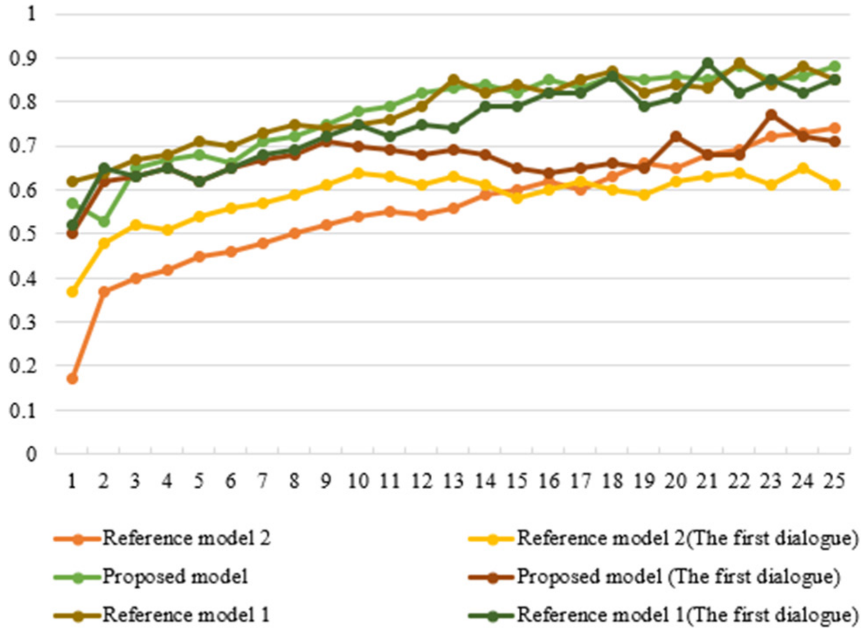

Fig. 6. Training process of different models

Figure 6 shows the training process of different models. Reference model 1 is a prediction model based on un-optimized *LSTM* architecture, and Reference model 2 is a prediction model based on optimized *LSTM* architecture. In Figure 6, the horizontal axis is the number of training times, and the vertical axis is the $F1$ value of positive examples (students who have the willingness to participate in interactive teaching). In the experiment, the judgment threshold of participation willingness was set as 0.5, a value greater than 0.5 can be judged as "a position is identified as having participation willingness", and a value less than 0.5 can be judged as "a position is identified as not having participation willingness". In each round of model training, the prediction performance of the model was tested, and the average value of the $F1$ values of all positive examples at identified positions and the positive examples of first teacher-student and student-student dialogues was taken as the test indicator. The optimal model prediction performance is the test result of model prediction performance when the average $F1$ value is the largest, see Table 1 for details.

According to Table 1, the identification effect of the prediction model based on un-optimized *LSTM* architecture is better than that of the other two models, but its execution time is longer and its application is more difficult. As for the prediction model based on optimized *BiLSTM* architecture proposed in this paper, its execution time is close to that of the prediction model based on optimized *LSTM* architecture, but its prediction effect is better, indicating that the proposed model is effective.

Table 1. Experimental results

Model	Un-optimized *LSTM* architecture	Optimized *LSTM* architecture	Optimized *BiLSTM* architecture
$F1$ value	0.623	0.581	0.692
Recall ratio	0.617	0.567	0.548
Precision ratio	0.791	0.528	0.693
$F1$ value (first time)	0.695	0.508	0.638
Recall ratio (first time)	0.625	0.582	0.674
Precision ratio (first time)	0.609	0.526	0.642
Average identification time	452.8	55	81

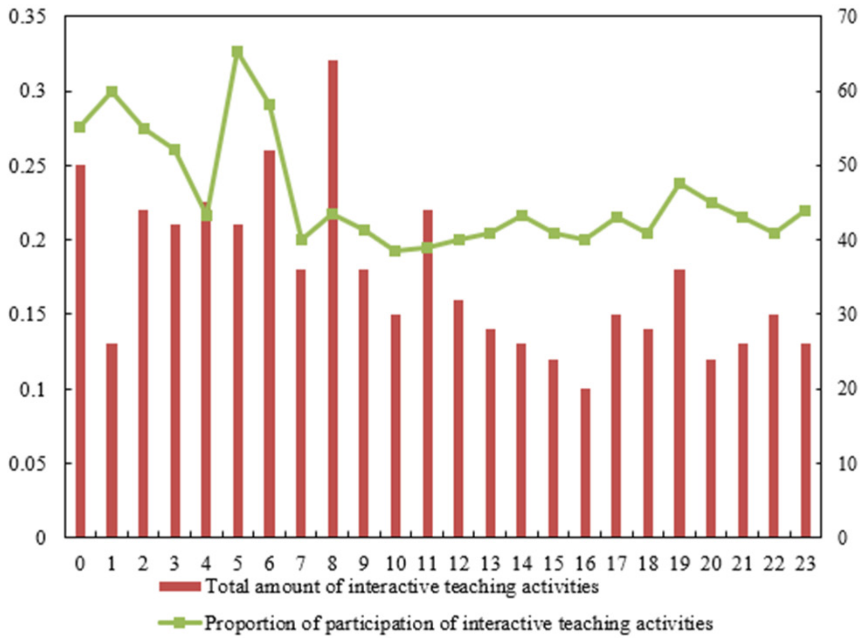

Fig. 7. The total amount of interactive teaching activities and the proportion of participation of interactive teaching activities

Since categorical variables such as the participation frequency, and release time of interactive teaching activities can affect students' participation willingness, they were converted into dummy variables and taken as the control variables of the model for analysis. Taking the release time of interactive teaching activities as an example, the value of the release time is the time distribution of 24 class hours of a course. Under the condition of different class hours, there are differences in students' willingness to participate in interactive teaching. Figure 7 shows the total amount of interactive teaching activities and the proportion of participation of interactive teaching activities, the horizontal axis in the figure is the class hour, the vertical axis is the proportion of the participation of interactive teaching activities, and the columns in the figure represent the total amount of interactive activities organized by teacher under the condition of different class hours. As can be seen from the figure, there is little difference in the proportion of participation of interactive teaching activities under different class hours, and the students' participation willingness is slightly higher at the beginning of the course.

Figure 8 shows the proportions and relationships of students' participation purposes and interaction methods. Table 2 shows the cross analysis of participation purposes and interaction methods. According to Figure 8 and Table 2, during distance education, the participation purpose "encourage students to think" takes the largest proportion, among students who hold this purpose, the most frequently-adopted interaction methods are "Teacher proposes question and student answers it" and "Group discussion", followed by "Student proposes question and teacher answers it"; for students who often participate in online interactive activities, their thinking could be effectively promoted, which has activated the classroom atmosphere to a certain extent, and this indicates that other online interactive activities can meet students' personalized requirements for interactive teaching activities, and they provide new activity options for students who lack learning initiative.

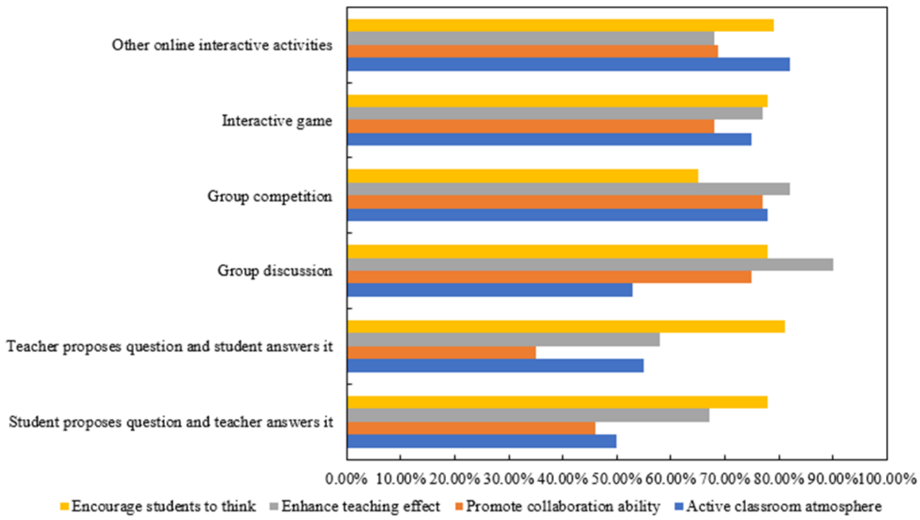

Fig. 8. Proportions of participation purposes and interaction methods

Table 2. Cross analysis of participation purposes and interaction methods

Participation Purposes		Encourage Students to Think	Enhance Teaching Effect	Promote Collaboration Ability	Active Classroom Atmosphere
Interaction methods	Student proposes question and teacher answers it	78	67	46	50
	Teacher proposes question and student answers it	81	58	35	55
	Group discussion	78	90	75	53
	Group competition	65	82	77	78
	Interactive game	78	77	68	75
	Other online interactive activities	79	68	68	82

5 Conclusion

This paper studied students' willingness to participate in interactive teaching in the context of distance education. To probe into this topic, at first, this paper built a hidden Markov model to describe the changes from the current state to the future state of students' participation willingness. Then, based on the data of teacher-student and student-student dialogues, this paper built a prediction model to identify students' participation willingness, explained the training process of the model, and gave the experimental results. In the experiment, the proposed model outperformed the prediction model built based on optimized *LSTM* architecture in terms of prediction effect, and the total amount of interactive teaching activities and the proportion of participation of interactive teaching activities were counted, and the results revealed that there is little difference in the proportion of participation of interactive teaching activities under different class hours, and the students' participation willingness is slightly higher at the beginning of the course. At last, this paper plotted the participation purposes and interaction methods of students into a histogram, and gave a cross analysis on the participation purposes and interaction methods of students.

6 Acknowledgment

(1) General research project of ideological and political theory teachers in colleges and universities in 2021(21JDSZK099). Project Name: Research on teaching Mode reform of Ideological and Political Course in Higher Vocational Colleges.

(2) Major project of basic research of Philosophy and Social Sciences in Colleges and universities of Henan Province in 2022(2022-JCZD-09). Project Name: Research on the Cultivation System of Vocational College Students' core literacy from the perspective of Type education.

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Article submitted 2022-07-13. Resubmitted 2022-08-08. Final acceptance 2022-08-09. Final version published as submitted by the authors.