The Online Teacher-Student Interaction Level in the Context of a Scenario-Based Multi-Dimensional Interaction Teaching Environment

https://doi.org/10.3991/ijet.v17i12.32083

Yinchun Chen
College of Foreign Languages, Shanghai Jianqiao University, Shanghai, China
chenyc@gench.edu.cn

Abstract—For teachers of online courses, figuring out the features of teaching content, setting proper teaching scenarios, and mobilizing students' learning enthusiasm via multi-dimensional interaction are necessary works. This paper analyzed the online teacher-student interaction level in the context of a Scenario-based Multi-Dimensional Interaction (SMDI) teaching environment. At first, this paper divided the evaluation indexes of the said interaction level into four aspects. Then, this paper built a teacher-student interaction behavior preference feature model based on the Graph Convolution Neural Network (GCNN) and a teacher-student interaction relationship model based on multi-task learning, thereby realizing the accurate description of the preference features of teacher-student interaction behavior. After that, this paper elaborated on the method for accurately constructing the teacher-student interaction relationship. At last, the effectiveness of the models was verified by the experimental results.

Keywords—scenario-based multi-dimensional interaction (SMDI), interaction level, graph convolution neural network (GCNN), teacher-student interaction relationship, interaction behavior, preference feature

1 Introduction

The Scenario-based Multi-Dimensional Interaction Teaching (hereinafter as the SMDI approach) is a teaching method which takes scenarios as the basis for teaching, by creating specific virtual, semi-real, or real scenarios [1-6], students are invited to participate in various teaching scenarios and learn the problem situations [7-11]. The SMDI approach can trigger students' interest in learning, motive them to cope with problems to be happened in the scenarios actively, thereby cultivating their thinking and ability to solve the problems effectively [12-18]. For teachers of online courses, figuring out the features of teaching content, setting proper teaching scenarios, and mobilizing students' learning enthusiasm via multi-dimensional interaction are necessary works [19-22]. In links such as course introduction, key point consolidation, and knowledge extension, teachers can design proper question scenarios for different teaching objectives.

Regarding scenario-based teaching, field scholars have done a lot of relevant research works, for example, in higher education institutions, students generally lack some specific math knowledge required for certain courses, and this situation is more frequent for introductory-stage courses of engineering science subjects, and advanced mathematics is particularly important for these disciplines; to solve this problem, Barros Costa and Perkusich [23] developed a blended learning scenario for the fundamental courses of electrical engineering major which is conductive to imparting math knowledge in the courses of this major, then they conducted a questionnaire survey to investigate students' acceptance with visualized teaching and its influence on the exam scores, and drew conclusions for the target problem. Teacher-student interaction is an inevitable question in education, interaction can stimulate learners to continue learning, however, compared with traditional education mode, the interactive discussion in an online learning environment is much more complex. Mohammad et al. [24] analyzed the interaction types and methods, and introduced electronic interactive learning tools; their survey results showed that students and teachers can benefit from these interaction methods and tools, and overcome obstacles via electronic interaction. With the advent of the flipped classroom, teachers now have a new teaching mode for reference, it's generally believed that teacher-student interaction is influenced by teaching mode and it is the key indicator in teaching efficiency improvement. After reviewing relevant literatures, Liu and Qi [25] built a research model to explain disadvantages in teacher-student interaction in the flipped classroom of oral English class. Yu et al. [26] discussed the influence of an immersive-style VR interaction feedback system on the learning interest and performance of students in the coffee brewing class, and their research results indicated that the said system can trigger sub-dimensions of situational interest to an average level except for the challenge dimension, while it also improves learners' learning achievement. Multimedia can create an efficient learning environment, give full play to students' learning initiative, and make the classroom teaching more flexible and effective. Cao [27] analyzed the theories and application of multimedia in English teaching, and studied the scenario-based interactive English class in the multimedia network environment.

Studies on scenario-based teaching and on teacher-student interaction have received more attention in recent years, but few studies have combined the two topics, and there is a blank in the research on the teacher-student interaction behavior in scenario-based teaching. Under the condition of online environment, the scenario-based interactions between students, and between teachers and students are all conducted on the online learning platforms, so it's necessary to research the online teacher-student interaction in the scenario-based teaching environment. For this reason, taking English teaching as an example, this paper analyzed the teacher-student interaction level in the SMDI teaching environment. In the second chapter, this paper divided the evaluation indexes of the said interaction level in the SMDI teaching environment into 4 aspects, and constructed an online teacher-student interaction model for the SMDI approach. In the third chapter, this paper built a teacher-student interaction behavior preference feature model based on GCNN (abbreviated as GCNN-based feature model) and a teacher-student interaction relationship model based on multi-task learning (abbreviated as relationship model), and realized the description of the teacher-student interaction behavior preference features based on the dimension of teacher-student interaction behavior/teaching scenario and the dimension of teacher-student interaction relationship. In the fourth chapter, this paper elaborated a method for accurately constructing the teacher-student interaction relationship, which takes the clustering of teacher-student interaction behaviors as the primary task, and the prediction of learning behavior preferences as the secondary task. At last, the effectiveness of the models was verified by experimental results.

2 The online teacher-student interaction model for SMDI approach

The SMDI approach can imperceptibly and gradually bring students into the optimal interaction state. Because the teaching is conducted online, teachers need to apply various methods to create proper teaching scenarios to interact with students and trigger their thinking, for instance, teachers can use language description and multimedia to set or stimulate the scenarios of the stories. In the preset teaching scenarios, teachers can pose a few questions to increase interactions in the classroom and guide students to discuss the set situations, and these are important implementation methods in the SMDI approach. In English class that applies the SMDI approach, teachers need to instruct students to master the method of summarizing and consolidating knowledge by themselves, so that they could build their own knowledge system based on the knowledge-related discussions they conducted during the SMDI teaching. Then teachers should encourage and guide students to apply the English knowledge they learnt to various real-life scenarios, thereby excising their knowledge transfer and application abilities and English communication skills. After the class, course summery and assessment are required. The self-summary of teachers and students are individual activities: students need to reflect on themselves based on their self-summary and the comments given by teachers, and improve their learning ability; while teachers also need to reflect on themselves based on their self-summary and the comments given by students, thereby designing more reasonable and effective teaching scenarios in the future and improving the teaching effect of the SMDI approach.

According to above analysis, this paper divided the evaluation indexes of the online teacher-student interaction level in the SMDI teaching environment into 4 aspects: code of conduct for teachers (Code for teachers), code of conduct for students (Code for students), code of conduct for information exchange between teachers and students (Code for information exchange), and code for other conducts (Code for others), the details of each aspect are given below:

The Code for teachers includes: 1) Asking, encouraging, and praising students; 2) Accepting students' opinions; 3) Proposing instructive or summative questions; 4) Giving lectures and demonstrations; 5) Organizing and carrying out scenario-based teaching activities; 6) Assessing student performance and giving feedback.

The Code for students includes: 1) Answering questions proposed by teachers actively; 2) Participating in scenario-based teaching activities actively; 3) Joining in group discussions actively; 4) Commenting on themselves and others actively; 5) Reflecting on the teaching process and giving feedback.

The Code for information exchange includes: 1) The ability of teachers to use IT tools for teaching; 2) The ability of students to use IT tools for learning.

The Code for others includes: 1) Whether a time section has been set in the class for students to think about the teaching scenarios; 2) Whether the interaction in the classroom is harmonious.

Figure 1 gives an interaction model for constructing indexes for evaluating the online interaction level of teachers and students in the SMDI approach. To improve said interaction level, it's necessary for online learning platforms to effectively figure out students' behavior preferences so as to form a better teacher-student interaction relationship in the SMDI approach. However, existing similarity correlation discovery methods usually take the clustering result as the optimization goal of the algorithm, which will result in large noise in the extracted preference features of teacher-student interaction behavior.

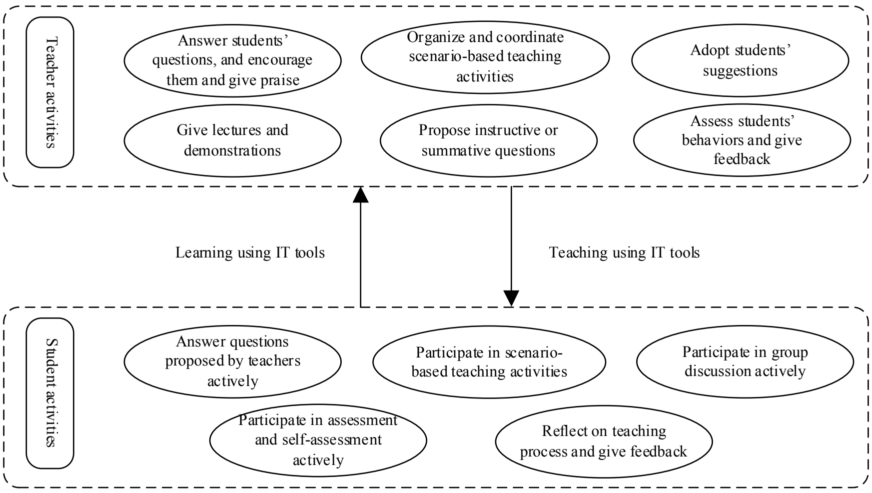

Fig. 1. Online teacher-student interaction model for the SMDI approach

Since the information of online teacher-student interaction in the SMDI approach is mostly graph-structured, this paper adopted a novel GCNN to learn the various information of the interactions between students, and between teachers and students. The constructed model was used to explicitly encode the teacher-student online interaction information into the teacher-student interaction behavior preference features, which solved the problem of computation delay caused by the direct encoding of online teacher-student interaction information. This paper also proposed a method for accurately constructing the teacher-student interaction relationship which takes the clustering of teacher-student interaction behavior as the primary task and the prediction of learning behavior preferences as the secondary task, with the help of this method, the preference features of the teacher-student interaction behavior could be modified and the relationship of teacher-student interaction could be constructed accurately.

3 Description of the preference features of teacher-student interaction behavior

This paper built a feature model based on GCNN to describe the preference features of teacher-student interaction behavior, and built a relationship model to accurately describe the teacher-student interaction based on multi-task learning. The feature model gave a comprehensive analysis from two dimensions (one dimension is the interaction between students, and the other is the interaction between teachers and students), in the two dimensions, the multi-layer convolution operation of the model can effectively describe the features of students' learning behavior, and fully explore the potential similarities in the interaction behavior of teachers and students. The relationship model adopted two tasks: the clustering of teacher-student interaction based on self-supervised learning, and the prediction of students’ behavior preference, the two tasks were trained together to complete the modification of the preference features and the accurate construction of teacher-student interaction relationship.

3.1 Based on the dimension of teacher-student interaction behavior/teaching scenario

When embedding the features of teacher-student interaction behavior, the behavior attribute information and the implicit feedback information was taken as the input so as to fully learn the features of the interaction behavior. The free embedding of the interaction behavior of teachers and students was mainly realized via matrix decomposition and was used to describe the collaborative latent features.

Assuming: n_x represents the free embedding of a single teacher-student interaction behavior; m_i represents the free embedding of a single teaching scenario; a_x represents the attribute features of the given teacher-student interaction behavior; a_i represents the attribute features of the given teaching scenario; Q_v and Q_u represent transformation matrices to be learned in parameter estimation; then, based on the free embedding of teacher-student interaction behavior and the attribute features, the merged embedded features shown as following formulas could be generated:

$$v_x^0 = [n_x, a_x \times Q_v] \tag{1}$$

$$u_i^0 = [m_i, a_i \times Q_u] \tag{2}$$

Figure 2 gives the structure of the feature embedding propagation layer of the model. The input of the feature embedding propagation layer is the embedded features $v^0{}_x$ and $v^0{}_i$ of teacher-student interaction behavior and teaching scenario. Assuming: $v^l{}_x$ and $v^l{}_i$ represent the embedded features of teacher-student interaction behavior x and teaching scenario i in the l-th layer, then based on the embedding of the l-th layer, the operation of continuing to merge with the existing embedded features of teacher-student interaction behavior in the l-th layer is called the feature embedding of a specific teacher-student interaction behavior in the l+1-th layer. Assuming: S_x represents the set of teaching scenarios in which a teacher-student interaction behavior x exists; R_i represents the set of teacher-student interaction behaviors that exist in teaching scenario i; Q^{l+1} represents the transformation matrix in the propagation process, then the following formula gives the specific calculation process of feature embedding in the l+1-th layer:

$$v_x^{l+1} = \left(v_x^l + \sum\nolimits_{j \in S_x} \frac{u_j^l}{|S_x|} \right) \times Q^{l+1} \tag{3}$$

$$u_i^{l+1} = \left(u_i^l + \sum\nolimits_{y \in R_i} \frac{v_y^l}{|R_i|} \right) \times Q^{l+1} \tag{4}$$

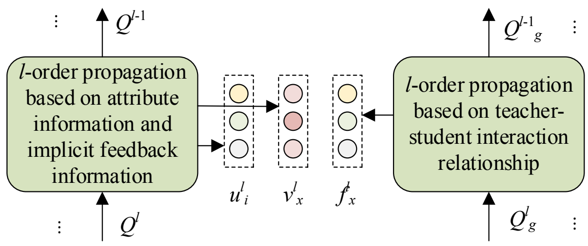

Fig. 2. Structure of the feature embedding propagation layer

To better describe the propagation process of feature embedding, above formula can be converted into the matrix form. Assuming: X represents the adjacency matrix of the bipartite graph of teacher-student interaction behavior/teaching scenario with N+M nodes, then there is:

$$X = \begin{bmatrix} S & 0^{M \times N} \\ 0^{N \times M} & S^P \end{bmatrix} \tag{5}$$

Assuming: V^l and U^l represent the merged embedding matrices of teacher-student interaction behavior and teaching scenario in the l-th layer; E represents the degree matrix of X used to smooth the embedding of node neighbors; then Formula 6 gives the expression of merged embedding matrix in the l+1-th layer:

$$\begin{bmatrix} V^{l+1} \\ U^{l+1} \end{bmatrix} = \left(\begin{bmatrix} V^l \\ U^l \end{bmatrix} + E^{-0.5} X E^{0.5} \times \begin{bmatrix} V^l \\ U^l \end{bmatrix} \right) \times Q^{l+1} \tag{6}$$

Assuming: $\{v^0_x,...,f^K_x\}$ is the multiple representation of teacher-student interaction behavior x; $\{u^0_i,...,u^K_i\}$ is the multiple representation of teaching scenario. After propagating through K layers, it can get $\{v^0_x,...,f^K_x\}$ and $\{u^0_i,...,u^K_i\}$. The features of teacher-student interaction behavior obtained in different layers are the merged information of teacher-student interaction behavior obtained from neighbors of different orders. For example, assuming v^0_x represents the feature embedding of behavior x itself; v^1_x represents the information of the first-order neighbors of x in the interaction graph of teacher-student interaction behavior/teaching scenario; v^l_x represents the information of the l-order neighbors of x; ||*|| represents the join operation, therefore, for the teacher-student interaction behavior x or the teaching scenario i, the finally obtained features of teacher-student interaction behavior can be expressed by the following formulas:

$$v_x^* = v_x^0 \| \cdots \| v_x^K \tag{7}$$

$$u_i^* = u_i^0 \| \cdots \| u_i^K \tag{8}$$

3.2 Based on the dimension of teacher-student interaction relationship

For each teacher-student interaction behavior a, besides attaining the effective features from the interaction graph of teacher-student interaction behavior/teaching scenario, the representation of teacher-student interaction behavior features could be further enriched by the teacher-student interaction relationship. The underlying features of each teacher-student interaction behavior are affected by the students, and every student is affected by other students in the teacher-student interaction relationship. This paper also used GCNN to model the propagation process of feature embedding in the interaction graph of teacher-student interaction behavior/teaching scenario. The model input f^0_x is the merged embedding v^1_x of first-order neighbors of the teacher-student interaction behavior in the teacher-student interaction relationship.

Assuming: f^l_x represents the feature embedding of teacher-student interaction behavior x in the l-th layer; g_x represents neighbors of teacher-student interaction behavior x in the l-th layer; Q_g^{l+1} represents the transformation matrix in the propagation process, then the process of attaining embedded features of a specific teacher-student interaction behavior in the l+1-th layer could be expressed by Formula 9:

$$f_x^{l+1} = \left(f_x^l + \sum\nolimits_{p \in g_x} \frac{f_p^l}{|g_x|} \right) \times Q_g^{l+1} \tag{9}$$

Similarly, the final features of x based on the dimension of teacher-student interaction relationship can be expressed as:

$$f_x^* = f_x^0 \| \cdots \| f_x^K \tag{10}$$

After the features of teacher-student interaction behavior were attained from two dimensions (namely the dimension of teacher-student interaction behavior/teaching scenario, and the dimension of teacher-student interaction relationship), the features of the two dimensions need to be further merged to extract richer structural features of teacher-student interaction behavior in the SMDI approach. Assuming: Q' represents the transformation matrix for merging the teacher-student interaction behavior preference features of the two dimensions; w_i represents the final structural features of teaching scenario i, and it satisfies $w_i=u^*_i$. Taking attaining the final structural feature t_x of teacher-student interaction behavior x as an example, Formula 11 gives the feature merging process:

$$t_x = \left(v_x^* \middle\| f_x^*\right) \times Q' \tag{11}$$

4 The accurate modelling of teacher-student interaction relationship

The prediction of teacher-student interaction behavior preference is the secondary task in the accurate modelling of teacher-student interaction relationship. In this task, the preference degree of teacher-student interaction behavior i to teaching scenario j could be calculated as follows:

$$\hat{s}_{ij} = sigmoid\left(t_i^{\,T} w_j\right) \tag{12}$$

Assuming: H represents the training set; H_i represents the training set related to teacher-student interaction behavior i; j represents the positive samples of teacher-student interaction behavior i in the training set, it can be denoted as $(j,r)\in H_i$ (there is teacher-student interaction behavior v_i in teaching scenario u_j); sr represents the negative samples of teacher-student interaction behavior i in the training set (there isn't teacher-student interaction behavior v_i in teaching scenario u_j), then the value range of the differences between the predicted scores of the teaching scenario with and without interaction is $s_{ijr}^*=s_{ij}^*-s_{ir}^*$. This paper adopted a regression-based pairwise sorting method, and the objective function of accurately modelling the teacher-student interaction relationship is given by Formula 13:

$$K_{pre} = \sum\nolimits_{i\in H} \sum\nolimits_{(j,r)\in H_i} \left(s_{ijr} - \hat{s}_{ijr}\right)^2 = \sum\nolimits_{i\in H} \sum\nolimits_{(j,r)\in H_i} \left(\hat{s}_{ij} - \hat{s}_{ir} - 1\right)^2 \tag{13}$$

For the cluster sample i of teacher-student interaction behavior and the d-th cluster, the student p-distribution was taken as the kernel distance function to measure the similarity between the feature representation T_i of teacher-student interaction behavior i and the cluster center λ_d. Assuming: u represents the degree of freedom of student p-distribution; $\sum_{d'} w_{id'}=1$; w_{id} represents the probability that a sample i is assigned to the d-th cluster, then there is:

$$w_{ij}=\frac{\left(1+\frac{\left\|T_i-\lambda_d\right\|^2}{u}\right)^{-\frac{u+1}{2}}}{\sum_{d'}\left(1+\frac{\left\|T_i-\lambda_d\right\|^2}{u}\right)^{-\frac{u+1}{2}}} \tag{14}$$

After obtaining the distribution W of the clustering results of teacher-student interaction behavior, in order to improve the cohesion of the cluster, namely to ensure that the feature representation of teacher-student interaction behavior can get closer to the cluster center as much as possbile, it's necessary to construct an assisting target distribution T. Assuming $g_d=\sum_d w_{id}, g_d$ represents the soft clustering frequency, then the calculation process of the target distribution T is given by Formula 15:

$$t_{id}=\frac{\frac{w_{id}^2}{g_d}}{\sum_{d'}\frac{w_{id'}^2}{g_{d'}}} \tag{15}$$

The calculation formula of element t_{id} in T contained a high-order term w^2_{id}, which was mainly to ensure the high confidence degree of the clustering distribution of teacher-student interaction behavior; to make the clustering distribution W get close to T constantly, this paper defined the objective function based on KL divergence as follows:

$$K_{clu}=KL(T\|H)=\sum_{i\in H}\sum_d t_{id}log\frac{t_{id}}{w_{id}} \tag{16}$$

5 Experimental results and analysis

In terms of the teaching effect of the SMDI approach, there're significant differences between different grades (freshman, sophomore, and junior), so this paper performed One-way ANOVA on the evaluation criteria of different online interaction levels of teachers and students in the three grades, and the results are listed in Table 1. According to the data in the table, except for the "Code for information exchange" whose significance value was greater than 0.05, the significance values of the other three (Code for teachers, Code for students, and Code for others) were all smaller than 0.05, indicating significant differences. In terms of the four evaluation criteria, the SMDI approach got better effect on freshman and sophomore students than on junior students. Throughout the entire process, the effect of the SMDI approach was always in a good state; while for junior students, since they were facing the pressure of job-hunting and the postgraduate entrance exam, the effect of the SMDI approach was slightly weaker compared with students in the other two grades. Since sophomore students had already experienced online teaching in colleges and universities, they were not motivated enough to cooperate with the SMDI approach, and the effect was not as good as that of the freshman students.

Table 1. One-way ANOVA for different evaluation criteria

Variable	Code for teachers			Code for students			Code for information exchange			Code for others		
Option	1	2	3	1	2	3	1	2	3	1	2	3
N	43	37	41	48	33	40	49	33	41	47	34	46
Mean	17.81	17.23	16.82	15.52	14.74	13.95	18.24	17.81	17.68	19.13	16.42	15.83
F	7.815			4.829			2.817			3.928		
Significance	0.027			0.039			0.174			0.038		
Comparison	1>2,3>2			2>1,1>3			2>3,3>1			2>1,3>1		

To test the impact of the structural parameters of the constructed model on the feature representation performance of the model, experiment was conducted, during which the number and list length of the constructed teacher-student relationship were set as 40 and 10, respectively, and the impact of the dimension and merge ratio of the features of teacher-student interaction behavior on the Normalized Discounted Cumulative Gain (NDCG) index was determined.

The feature dimension of teacher-student interaction behavior was set as 10, 20, 40, 80, and 160, respectively, and Figure 3 shows the changes in the NDCG index under different features dimensions, as can be seen from the figure, the teaching effect was relatively idea when the feature dimension was less than 80, when it exceeded 80, the discounted gain of the teaching effect increased, which was mainly because that the too-high dimension can easily lead to overfitting of the model, and the too-low dimension can lead to insufficient representation of the features of teacher-student interaction behavior.

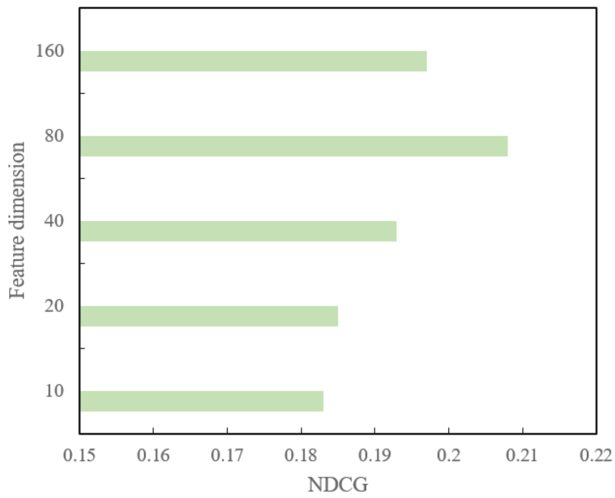

Fig. 3. Changes of the NDCG index under different feature dimensions

During model training, the clustering loss and preference prediction loss of the teacher-student interaction behavior had both been optimized, and the merge ratio could balance these two kinds of loss. According to Figure 4, the NDCG increased with the increase of merge ratio, indicating that a too-low merge ratio would lead to insufficient representation and modification of the features of teacher-student interaction behavior, the potential similarity of teacher-student relationship was low, and the effect of the constructed teacher-student relationship was not good; moreover, a too-high merge ratio would easily lead to sample skew, resulting in that the effect of the constructed teacher-student relationship was not good as well, so a merge ratio between 1 and 1.5 would be appropriate.

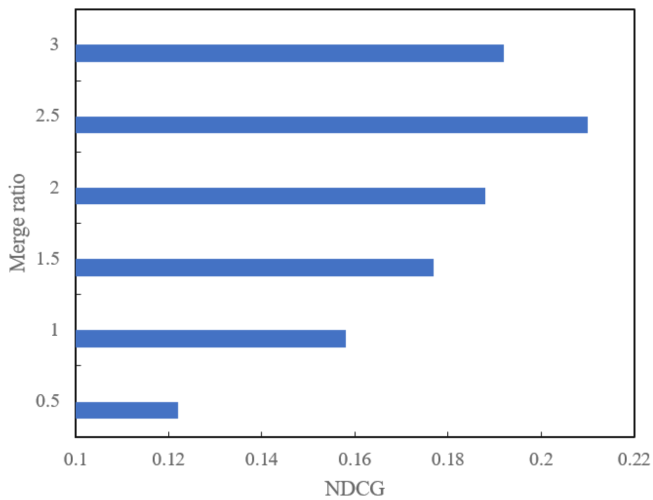

Fig. 4. Changes of the NDCG index under different merge ratios

To verify the effectiveness of the teacher-student relationship construction algorithm proposed in this paper, this paper compared it with a few reference algorithms including the random search algorithm, Bayesian search algorithm, auto-encoding clustering algorithm, and K-means clustering algorithm. The experimental results are shown in Figures 5 and 6 below. In terms of the error sum of squares and the CH clustering evaluation index, the proposed algorithm outperformed the other four methods under the condition of different numbers of teacher-student relationship.

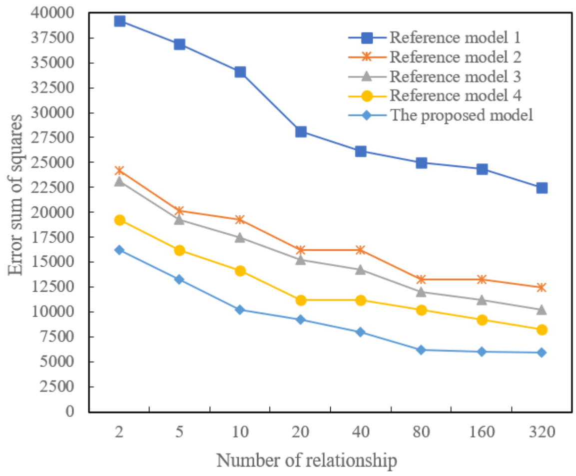

Fig. 5. The error sum of squares under different numbers of teacher-student relationship

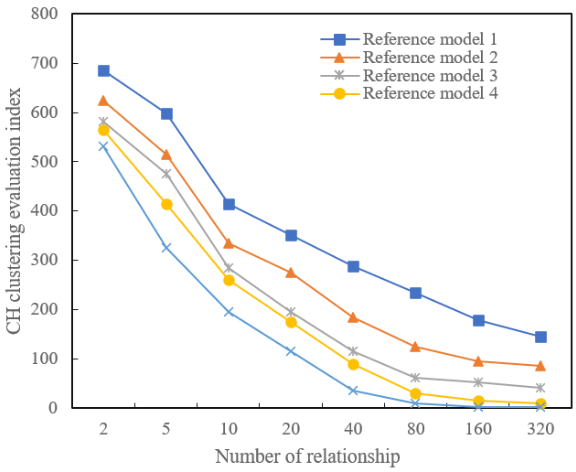

Fig. 6. The CH index under different numbers of teacher-student relationship

Table 2 shows the teaching effect of the SMDI approach after reasonable teacher-student relationship has been constructed. The effect of the SMDI approach has a direct influence on students' enthusiasm to participate in the next SMDI learning activity. After the SMDI learning activities have been implemented, teachers and students could form a more harmonious relationship, the English communication ability of students could be effectively improved, the knowledge of English vocabulary and grammar could be mastered better, and students would expect the next SMDI class. According to the experimental results, more than 58% of the students believed that the SMDI approach could help them get higher scores in English, only about 8.9% of them did not approve of the teaching effect of the SMDI approach. The results proved the advantages of the SMDI approach, which is the key for the continuous development of the SMDI approach.

Table 2. Teaching effect of the SMDI approach

Option	Not consistent at all	Not consistent	Not sure	Consistent	Completely consistent	Total
Frequency of interaction	3	15	55	66	18	162
Percentage	1.2	9.5	31.7	44.8	13.1	115
Effective percentage	1.7	9.8	34.1	47.2	13.8	137
Cumulative percentage	1.2	11.6	48.6	88.4	127	153

6 Conclusion

This paper analyzed the online teacher-student interaction level in a SMDI teaching environment, and divided the evaluation indexes of such interaction level into 4 aspects. In the texts, a GCNN-based feature model and a relationship model based on multi-task learning were built to describe the preference features of teacher-student interaction behavior, and the method for accurately constructing the teacher-student interaction relationship was introduced in detail. Then, combining with experiments, this research performed one-way ANOVA on different evaluation criteria, and the results suggested that there're significant differences in the teaching effect of SMDI approach between different grades. After that, the changes in the NDCG index under different feature dimensions and merge ratios were given, and the appropriate feature dimension and merge ratio were selected; the changes in the error sum of squares and the CH clustering evaluation index under different numbers of teacher-student relationship were given, which had verified that proposed teacher-student relationship construction algorithm outperformed the other four methods under different numbers of teacher-student relationship. At last, this paper analyzed the teaching effect of the SMDI approach, and the experimental results showed that more than 58% of the students believed that the SMDI approach had helped them get higher scores in English, which had demonstrated the advantages of the SMDI approach.

7 References

[1] Xia, B. (2017). A study of English situational teaching in the context of multimedia network. Boletin Tecnico/Technical Bulletin, 55(6): 766-771.

[2] Liang, K., Hao, Y., Zhao, J. (2021). An empirical study on the effect and quality of situational English teaching. International Journal of Emerging Technologies in Learning, 16(21): 74-86. https://doi.org/10.3991/ijet.v16i21.26863
[3] Yordanova, M. (2021). Application of the situational teaching method in the electrical safety education. In 2021 56th International Scientific Conference on Information, Communication and Energy Systems and Technologies (ICEST), 215-216. https://doi.org/10.1109/ICEST52640.2021.9483514
[4] Li, Y.F. (2020). Visual Education of Music Course for College Students Based on Human-Computer Interaction, International Journal of Emerging Technologies in Learning, 15(2): 175-186. https://doi.org/10.3991/ijet.v15i02.12535
[5] Wu, R., Xu, J., Qian, P. (2021). Situational inquiry method in the research teaching mode for ideological and political courses. Journal of Intelligent & Fuzzy Systems, 40(2): 3631-3642. https://doi.org/10.3233/JIFS-189398
[6] Wang, Y. (2021). On the application of situational education in prose teaching. In 2021 2nd International Conference on Computers, Information Processing and Advanced Education, 908-911. https://doi.org/10.1145/3456887.3457102
[7] Schledermann, K., Pihlajaniemi, H., Sen, S., Hansen, E.K. (2018). Dynamic lighting in classrooms: A new interactive tool for teaching. In Interactivity, Game Creation, Design, Learning, and Innovation, 374-384. https://doi.org/10.1007/978-3-030-06134-0_41
[8] He, X., Zhang, C., Chen, Z., Wu, K., Fang, J. (2019). Dynamic interactive gesture design and its application in classroom teaching. In Recent Developments in Intelligent Computing, Communication and Devices, 1159-1167. https://doi.org/10.1007/978-981-10-8944-2_135
[9] Wang, D., Yuan, L. (2019). An interactive teaching model for wisdom classroom based on learning situation analysis. In 2019 IEEE International Conference on Computer Science and Educational Informatization (CSEI), 5-11. https://doi.org/10.1109/CSEI47661.2019.8939001
[10] Dai, S. (2019). ARS interactive teaching mode for financial accounting course based on smart classroom. International Journal of Emerging Technologies in Learning, 14(3): 38-50. https://doi.org/10.3991/ijet.v14i03.10104
[11] Fu, X., Tan, A., Zhang, B., Fu, G., Bi, W. (2017). Exploration of multidimensional interactive classroom teaching for CCD principle and application course. In Education and Training in Optics and Photonics, 104524L. https://doi.org/10.1117/12.2268527
[12] Zhou, N., Zhang, Z.F., Li, J. (2020). Analysis on course scores of learners of online teaching platforms based on data mining. Ingénierie des Systèmes d'Information, 25(5): 609-617. https://doi.org/10.18280/isi.250508
[13] Raheb, K.E., Stergiou, M., Katifori, A., Ioannidis, Y. (2019). Dance interactive learning systems: A study on interaction workflow and teaching approaches. ACM Computing Surveys (CSUR), 52(3): 1-37. https://doi.org/10.1145/3323335
[14] Wu, Y.F., Yuan, M.H., Peng, Z.C. (2019). Research on the cultivation of students' autonomous learning ability based on MOOC-based network interactive teaching. International Journal of Continuing Engineering Education and Life Long Learning, 29(1-2): 72-86. https://doi.org/10.1504/IJCEELL.2019.099250
[15] Singh, A.K., Kumar, S., Bhushan, S., Kumar, P., Vashishtha, A. (2021). A proportional sentiment analysis of MOOCs course reviews using supervised learning algorithms. Ingénierie des Systèmes d'Information, 26(5): 501-506. https://doi.org/10.18280/isi.260510
[16] Luo, J., Zhu, Y. (2019, August). Analysis and solution of interactive problems in rural synchronous music live classroom teaching. In 2019 IEEE International Conference on Computer Science and Educational Informatization (CSEI), 200-204. https://doi.org/10.1109/CSEI47661.2019.8938842
[17] Amir, O., Kamar, E., Kolobov, A., Grosz, B. (2016). Interactive teaching strategies for agent training. In In Proceedings of IJCAI 2016.
[18] Ma, Z., Shi, L. (2016). Application of visual interactive concept map in college english

writing teaching. International Journal of Emerging Technologies in Learning, 11(11): 32-36. https://doi.org/10.3991/ijet.v11i11.6248
[19] Zhao, Q., Chen, D. (2013). Design of interactive spoken English teaching platform in MCALL model. In Information Technology and Computer Application Engineering: Proceedings of the International Conference on Information Technology and Computer Application Engineering (ITCAE 2013), 85.
[20] Zhang, W.M., Zhang, E. (2013). Application of interactive multimedia-internet-based teaching system in college English teaching. International Journal of Emerging Technologies in Learning, 8(3): 17-22. https://doi.org/10.3991/ijet.v8i3.2690
[21] Zhang, Y. (2011). Web CT-based platform design for interactive college English teaching. In 2011 International Conference on Mechatronic Science, Electric Engineering and Computer (MEC), 1298-1301. https://doi.org/10.1109/MEC.2011.6025707
[22] Wen, J., Wei, X.C., He, T., Zhang, S.S. (2020). Regression analysis on the influencing factors of the acceptance of online education platform among college students. Ingénierie des Systèmes d'Information, 25(5): 595-600. https://doi.org/10.18280/isi.250506
[23] Barros Costa, E.D., Perkusich, A. (1996). Modeling the cooperative interactions in a teaching/learning situation. In International Conference on Intelligent Tutoring Systems, 168-176. https://doi.org/10.1007/3-540-61327-7_113
[24] Mohammad, N.M., Sara, F., Zahra, T., Mojtaba, H. (2013). The study of the teacher's role and student interaction in e-learning process. In 4th International Conference on e-Learning and e-Teaching (ICELET 2013), 130-134. https://doi.org/10.1109/ICELET.2013.6681659
[25] Liu, Y., Qi, W. (2021). Application of flipped classroom in the era of big data: what factors influence the effect of teacher-student interaction in oral English teaching. Wireless Communications and Mobile Computing, 2021: 4966974. https://doi.org/10.1155/2021/4966974
[26] Yu, S.J., Hsueh, Y.L., Sun, J.C.Y., Liu, H.Z. (2019). The effect of an immersive virtual reality interactive feedback system on university students' situational interest and learning achievement: The case of a pour over coffee brewing lesson. In 27th International Conference on Computers in Education, ICCE 2019, 622-627.
[27] Cao, A. (2017). Research on the interactive classroom of English situational teaching based on multimedia network. Boletin Tecnico/technical Bulletin, 55(4): 132-138.

8 Author

Yinchun Chen, female, born on April 4, 1980 in Huanggang, central China's Hubei Province, is an associate professor. In 2003, she graduated from Yanshan University with a bachelor of arts degree in English. In 2008, she received a master's degree in English language and literature from Yanshan University. Her teaching career began in July, 2003 in Yanshan University. Since 2012, she has been working in Shanghai Jian Qiao University. So far, she has published more than 10 papers in English teaching, literature, and translation, co-edited several textbooks and CET4 tutorials, authored a book titled Innovative Development and Research of English-Chinese Translation in Cross-Cultural Context, participated in a state-level research project, and hosted a municipal-level research project (email: chenyc@gench.edu.cn).

Article submitted 2022-03-21. Resubmitted 2022-05-03. Final acceptance 2022-05-05. Final version published as submitted by the author.