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Research on the Optimization Method of E-commerce Teaching Interaction Strategies Based on Reinforcement Learning Algorithms

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ABSTRACT
E-commerce classroom teaching is an important means to improve the quality and teaching effect of e-commerce teaching, and effective interaction in teaching is an important carrier of e-commerce teaching classroom activities. This study combines pan-reinforcement learning and reinforcement Q learning algorithms to recognize and analyze speech data in e-commerce teaching classroom, and uses head posture estimation algorithm to recognize interactive behaviors in e-commerce teaching classroom video, and combines the video and speech interaction data to get the e-commerce teaching interactive behavior recognition model. The model is then equipped with web application technology to design a visual analysis system for e-commerce teaching interaction, and the optimization strategy of e-commerce teaching interaction is realized with the assistance of this system. The results of the study show that the interactive behavior recognition model proposed in this paper can accurately identify the interactive behavior of teachers and students in each course of e-commerce teaching. It is also found that after the implementation of interaction optimization strategy in college e-commerce teaching classroom, the frequency of effective interaction behaviors of teachers and students increases from 351 to 391 times, and the meaningless classroom silence time is reduced. And the learners' cognition of knowledge is also improved under the influence of the improvement of the effect of interactive behavior. The visual analysis system of teaching interaction proposed in this paper based on reinforcement learning algorithm is of great significance for optimizing the effective interactive behaviors of teachers and students in e-commerce teaching and improving the degree of students' knowledge cognition.

Keywords: reinforcement learning algorithms; pose estimation algorithms; web application technology; interactive behavior; teaching e-commerce

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1. Introduction

Under the environment of this rapidly developing era, e-commerce has a far-reaching impact on social and economic development, business operation and other aspects. Therefore, the teaching of e-commerce has become very important, not only to meet the social demand for e-commerce talents, but also to cultivate talents adapted to this era and improve their comprehensive quality.

E-commerce teaching interaction through the creation of a multilateral interactive teaching environment, in the process of equal communication and discussion between the two sides of the teaching, to achieve a different point of view of collision and integration, and then stimulate the initiative of both sides of the teaching and exploration, to achieve to improve the effectiveness of the teaching of a teaching method [1]. To a certain extent, this solves some problems in the training of e-commerce talents, and improves students' innovative ability and practical ability. However, from the point of view of the practice of e-commerce teaching interaction, the effect of some teaching interaction is not very satisfactory, specifically the following performance.

First, the inertia and inertia of teachers' teaching hinder the application of teaching interaction [2]. In the field of e-commerce applications are always occurring new cases, constantly generate new models, this feature requires e-commerce teachers to have a positive learning attitude, keen observation and strong critical thinking ability [3]. Some teachers are used to the traditional injective education, unwilling to try to change in the form of teaching, can not pass new knowledge and new information in teaching, this inertia and inertia will inevitably hinder the application of teaching interaction in the classroom.

Secondly, teachers' insufficient knowledge reserves or lack of adaptability make it difficult to cope with some challenges in teaching interaction [4-5]. In teaching interaction, when the teacher raises a question, some students may raise new questions beyond the teacher's concern in the process of analyzing the question. If the teacher's knowledge reserve is insufficient, it may cause the classroom teaching to be out of control, and even affect the teacher's image in the students' minds, which will have a negative impact on the subsequent teaching.

Thirdly, some students treat teaching interactions negatively or lack in-depth thinking about the issues discussed, thus making it difficult to collide their thinking [6]. Nowadays, in most teaching situations, questioning and other interactive sessions become the stage for a certain number of students, and most students are onlookers. There is also the phenomenon that students' thinking is limited, and it is difficult to lead to in-depth analysis and viewpoints, which makes the effect of teaching interaction greatly reduced. Therefore, in the face of these situations need to optimize the interactive strategy of e-commerce teaching to better achieve the teaching effect.

Nowadays, most of the teaching mode is based on practice, in order to improve students' vocational ability, more in line with the demand of the talent market, and e-commerce teaching is no exception [7]. Practical teaching cannot be separated from the interactive mode, and e-commerce itself involves docking matters with customers, platforms, sellers, suppliers, etc., but the interaction between students and teachers, between classmates, and the marketing process is obviously insufficient [8]. Literature [9] uses e-commerce with interactions and transactions between participants in the food industry as a case study to assist students in understanding the importance of interactions between transacting parties and the evolution of e-commerce models in agriculture.

And some studies have shown that teaching e-commerce in a blended education model can improve the interaction between teachers and students [10]. And literature [11] mentioned that coursework can also enhance teacher-student interaction. Literature [12] shows that synchronous interactive network interaction mode has great effect in online interactive teaching of cross-border e-commerce English. In addition, nowadays, the highly popular live webcast marketing has become an important segment of e-commerce, and literature [13] shows that the interactivity and authenticity of e-commerce live broadcasting enhances consumers' purchase intention. Therefore, the interactive strategy in live e-commerce is also the focus of e-commerce teaching. However, at present, due to most of the teaching that e-commerce live interactive marketing is less different from offline interactive marketing, the teaching of this part is not so perfect. Therefore, it is necessary to continue to improve the interactive mode of each module of e-commerce teaching.

In this paper, the deep learning network module is used to classify and recognize interactive behaviors in teaching classroom speech data. And the accuracy of interactive speech recognition is improved according to the action-function value and action-reward value function strategies in the reinforcement learning module. Then the head gesture recognition algorithm and key frame image extraction method are used to recognize and analyze the interactive behaviors of teachers and students in the e-commerce teaching classroom, and the voice interactive data is combined with the video interactive data to realize the recognition of interactive behaviors in the e-commerce teaching classroom. Subsequently, based on the recognition model and web application technology to develop e-commerce teaching interactive visual analysis display system, timely feedback of interactive data in e-commerce teaching to assist in the optimization and adjustment of teaching interactive behavior, so as to obtain the optimization and enhancement of e-commerce teaching interactive strategy with the assistance of the system. After analyzing the effectiveness of the identification model of e-commerce teaching interactive behavior through testing, the interactive visualization system is applied to e-commerce teaching in a university to explore the effectiveness of the implementation of teaching interactive optimization strategy by analyzing the changes of effective interactive behavior and learners' cognition.

2. Method

2.1. Data Recognition Methods for Teaching Voice Interaction in E-Commerce

The model proposed in this paper for analyzing interactive voice data in e-commerce teaching is based on the SEN-ECRNN model and is composed by combining it with pan-reinforcement learning as well as reinforcement Q-learning algorithms [14]. E-commerce teaching voice interaction behavior recognition method is mainly composed of two modules, using deep learning network for classification recognition and reinforcement learning to dynamically change the training strategy, after completing the training of each batch, the model will be made according to each category to classify the calculation of the error rate, and according to the proportion of error dynamically change the proportion of the next batch of each classification.

Suppose there is a total of K category and the number of training samples in each batch is N, where $N\%K=0$, then at the beginning of training, there are N/K samples of each category in the batch, and after training each batch, the percentage of misclassification of each category in the current report is recorded, and the number of samples belonging to the k th category used for training in the next round is set to be:

$$N_k = N \cdot \left\lfloor \frac{C_k + \frac{1}{N}}{1 + \sum_{i=1}^{K} C_k} \right\rfloor \tag{1}$$

If it ends up $\Sigma_1^k N_k, N_k < N$, then update the category that has the fewest samples, then:

$$\arg\min_k N_k \leftarrow N - \sum_{1}^{\mathbf{k}} N_k \tag{2}$$

The algorithm can be considered as a reinforcement learning strategy that dynamically changes the distribution of training samples according to the misclassification proportion, the effectiveness of which is verified in the subsequent experiments in this section. However, the method of dynamically changing the samples according to the misclassification proportion can only be regarded as a model combined with reinforcement learning in a broad sense, and this study also proposes a model that jointly applies the original model with reinforcement Q-learning in reinforcement learning to update the network weights using a reinforcement Q-learning based approach.

Assuming that the training environment used for speech interaction behavior recognition in an e-commerce teaching classroom is E, the focus of the reinforcement Q learning approach is to select specific actions from the training environment to promote the optimization of the weighted sum of the final reward values obtained. In order to better apply reinforcement Q-learning to the model, it is proposed to use the categories of behaviors as the kinds of actions for reinforcement Q-learning. Thus, there are a series of actions a, observations s and reward values r in Environment E. In each round of iteration, the model performs the actions, i.e., the categories of behaviors, with a specific probability, and after forward transmission through the network, the agent will be awarded with a reward value r_i, r_i The larger the reward value is, the better the model fits the samples of the current batch. where the greedy selection method is set $\epsilon = 0.1$.

In general, the prediction of the entire model depends on the sequence of all previously learned samples, however the feedback obtained for each action may be available only after a delay of multiple rounds of iterative training. Assuming that the sequence of observations and actions is: $s_t = x_1, a_1, x_2, a_2, \ldots, a_{t-1}, \ x_t$, then the learned model ultimately depends on that discrete sequence as well. This discretely distributed sequence of states and actions forms a Markov decision process [15], and is therefore able to be applied to the Q-learning strategy, using the s_t sequence as a representation of the states in round t.

The ultimate goal of the model is to maximize the cumulative future reward value earned using optimal action selection. Assuming that future reward values are discounted by a factor of γ in each batch, the future reward value of the theorem t is:

$$R_T = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'} \tag{3}$$

where T is the number of training iterations. Make a certain action a in sequence s, then:

$$Q^*(s', a') = max_{\pi} E[\, R_t \mid s_t = s, a_t = a, \pi] \tag{4}$$

The main reason why the optimal action-function value function obeys Ford's equation is that if the optimal function $Q^*(s', a')$ is the optimal predicted value of action a' made by sequence s' in the next round, then the optimal choice strategy is to pick action a' to maximize the expected value of reward $r + \gamma Q^*(s', a')$:

$$Q^*(s,a) = E_{s' \sim \epsilon}\left[r + \gamma \max_{a'} Q^*(s', a') \mid s, a \right] \tag{5}$$

where $Q^*(s,a)$ denotes the optimal value, which is the expected maximum reward value for all of the strategies, and π is a mapping of sequences as well as a function of action selection.

To approximate the action-reward value function, the weights θ of the neurons in the network can be treated as a nonlinear approximation of the function, and the model is trained using a minimized error function $L_i(\theta_i)$, which changes i with each training iteration:

$$L_i(\theta_i) = E_{s,a \sim p(.)}\left[\left(y_i - Q(S, a; \theta_i) \right)^2 \right] \tag{6}$$

The target value for the i st round of learning is:

$$y_i = E_{s' \sim \epsilon}[r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) \mid s, a] \tag{7}$$

where $p(.)$ is the density distribution of action a and state s. When optimizing the loss function $L_i(\theta_i)$, the parameters of the last obtained iteration θ_{i-1} remain unchanged. Similar to regular deep learning networks, the final recognition still depends on the output of the network. Eventually, the derivation leads to the final gradient:

$$\begin{aligned}\nabla_{\theta_i} L_i(\theta_i) = E_{s,a\sim p(.);s^{'}\sim\epsilon}[(r+\gamma \max_{a^{'}} Q(s^{'},a^{'};\theta_{i-1})\\ -Q(s,a;\theta_i))\nabla_{\theta_i} Q(s,a;Q_i)]\end{aligned} \tag{8}$$

The calculation of the above gradient takes a large amount of computational effort, and the loss function can be optimized using stochastic gradient descent. Meanwhile, in the process of performing action selection, the $\epsilon-greedy$ selection strategy can be used, which has the following steps.

1) Generate random number rnd between [0, 1] randomly using uniform distribution.
2) If $rnd > \epsilon$, the action selection is $\max_a Q(s,a;\theta)$.
3) If $rnd \le \epsilon$, a random selection of actions is drawn from the action set.

2.2. Teacher-student interaction video data processing methods

2.2.1. Head pose recognition algorithm. In order to avoid the bias of the interactive behavior obtained from the analysis of the voice interaction data recognition method in e-commerce teaching, this paper proposes the interactive video data recognition method to assist the voice interaction data recognition method, and uses the combination of the two to analyze the interactive behavior in e-commerce teaching. From the video data of e-commerce teaching, the change of each person's head posture over time during the teaching process is extracted. The idea is to first extract the given keyframes from the video, and then identify the coordinate values of each key part of the target person from the keyframe images, and propose a rule-based algorithm to compute the head posture of the target person. Given a video V, consisting of a series of frame images:

$$V = \{F_1, F_2, ..., F_i, ..., F_N\} \tag{9}$$

where F_i is the i rd frame in V and N represents the total number of frames in V.

Each e-commerce teaching classroom video contains a large number of frames, and the information expressed by neighboring frames is almost the same. Therefore, this paper uses a uniform sampling method to remove a large number of redundant frames from the video. For example, given a video frame rate of 25 frames per second, two frames can be extracted uniformly in one second by downsampling the video by setting the sampling rate to 2/25, which can greatly reduce the computational cost without losing information. Second, the coordinates of the key points of the head are identified using the OpenPose model [16]. The head pose is determined based on the coordinate values of the left and right eye keypoints and the left and right ear keypoints identified by the model. In this paper, we define the type of head posture of students in e-commerce teaching as head up (up), head down (down), and head away (miss), then the head posture of the i th frame is calculated as:

$$HEADPOS_i = \begin{cases} up & Y^i_{reye} - Y^i_{rear} \ge T \quad \text{and} \quad Y^i_{leye} - Y^i_{lear} \ge T \\ down & Y^i_{reye} - Y^i_{rear} < T \quad \text{or} \quad Y^i_{leye} - Y^i_{lear} < T \\ miss & Y^i_{reye} - Y^i_{rear} = NaN \quad \text{and} \quad Y^i_{leye} - Y^i_{lear} = NaN \end{cases} \tag{10}$$

where $Y^i_{reye}, Y^i_{leye}, Y^i_{rear}, Y^i_{lear}$ are the Y -axis coordinates of the right eye keypoint, the left eye keypoint, the right ear keypoint, and the left ear keypoint at frame i, respectively, and NaN denotes undefined or unrepresentable values, usually due to missing values of the subtracted or subtracted numbers on the left side of the equation. T is an adjustable threshold parameter.

2.2.2. Key frame image extraction. In this paper, we use the OpenCV image processing module to extract key frame images of teacher-student interaction behaviors in e-commerce teaching videos, assuming that the input time array $T = [t_1, t_2, ..., t_i, ..., t_k]$, where t_i is the time point in the video at which the i key frame image needs to be extracted, in seconds. Then use OpenCV to parse the target video and traverse the time array T in order to calculate the frame index corresponding to each item t_i in the array, the frame index index is calculated as $index = t_i * fps$, where fps is the frame rate of the video. The frame index is then used to set the position of the video to be decoded, and finally the format of the frame image extracted by the module from the decoded position is converted from 3D BGR color matrix to PNG format and output.

2.3. Design of interactive visual analysis system for e-commerce teaching and learning

This paper uses web application technology [17] for the development of a visual analysis system for e-commerce teaching interactive data, equipped with the interactive voice and video data analysis methods proposed above, to realize the visual analysis of e-commerce teaching interactive data. Through the visual analysis results of the system, teachers and students in e-commerce teaching can find the interactive feedback and make adjustments in time, so as to achieve the purpose of optimizing the interactive strategy of e-commerce teaching. Compared with client applications, web applications have a shorter development cycle, do not need to be installed and deployed, and can be accessed anytime and anywhere through the browser. Second, the web community is more active, there are a large number of excellent open source visualization tools have been released in the community for developers to use for free, such as the front-end D3.js, AntV.js, three.js, etc. These visualization tools provide rich and easy to use APIs that allow visualization developers to use them to develop some highly customizable data views. Based on the above advantages, this paper uses web technology to develop a visual analytics system, the overall architecture of the system is shown in Figure 1. The overall architecture of the system in this paper is divided into four main modules, which are the front-end view module, the back-end module, the IO module, and the development tool module. The front-end view module consists of five parts, which are teaching progress view, student interaction view, student personal performance view, interaction behavior details view, and context view. The back-end module uses three main parts: the Python-based Flask web development framework, the MongoDB database, and the file system, where Flask as the web application framework is responsible for route mapping, data exchange between the front-end and the back-end, and calculating the results of a series of data mining algorithms used in this paper. In order to enable the system to respond quickly to user-given data while reducing the computation and loading time of repetitive data, different types of data are saved through MongoDB and file system. The MongoDB database is mainly responsible for storing the feature data that the front-end view needs to read repeatedly after secondary computation, such as students' personal performance characteristics, students' response relationships, etc. The file system is mainly responsible for storing the original multimodal data with large volume, such as the e-commerce teaching video and voice required for the recognition method of the voice interaction data and video interaction data. The IO module is mainly used to handle data reading and writing as well as responding to user input operations such as mouse clicks. The development tools module includes D3.js for view drawing, Material UI, a UI framework for page layout, and Python components for data processing, such as numpy, nltk, and gensim.

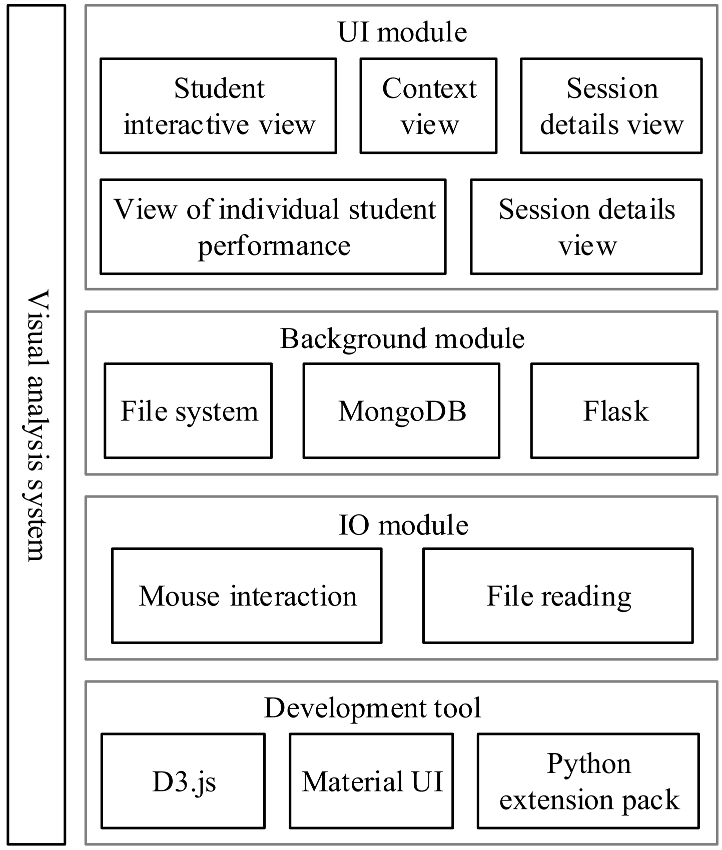


Fig. 1. Overall system architecture

3. Results and discussion

3.1. Validity Analysis of Interactive Behavior Recognition Models

In this section, the effectiveness of the proposed interactive behavior recognition model for e-commerce teaching based on reinforcement learning algorithm is first analyzed, and 30 videos are randomly selected from the videos of e-commerce teaching courses in a university for intelligent analysis and statistical results. The e-commerce teaching course videos of Marketing, Introduction to E-commerce, and Internet Marketing Fundamentals and Practice contain 10 videos each. At the same time, this paper also utilizes manual annotation for the analysis and processing of e-commerce teaching classroom videos to compare the effect of the proposed intelligent processing method with the manual method. The recognition comparison results of the interactive behaviors of e-commerce teaching classroom are shown in Table 1. From the analysis of the overall recognition situation, it can be seen that the 30 e-commerce teaching video interactive behavior recognition accuracy is high, and most of the classrooms show excellent recognition results. However, there are a small number of classrooms with lower accuracy rates, and in order to analyze the reasons for the decrease in the accuracy rate, this paper further carries out a detailed comparative analysis of the several classes with higher misclassification rates. Among them, from the perspective of interactive speech data recognition, not only the few classes with low accuracy rates, but also the classroom silence recognition values of all the classes (1.86%, 0.66%, and 5.05%) are lower than the manually labeled values (2.16%, 2.13%, and 5.43%), i.e., the speech segments that would have been noisy or silent are categorized into the clustering of a particular student or teacher. The reason for this error is that the classroom environment is noisy, the environmental clutter is sometimes similar to the characteristics of the recorded speaker, and the vocal information collected by the recording device is interfered with due to factors such as distance and occlusions. The combination of many factors reduces the accuracy of interactive speech recognition. From the point of view of video recognition, only the course "Internet Marketing Fundamentals and Practice" has a large difference ratio of 1.47% in action recognition. By comparing with the teaching video screen, it is known that the teacher uses the touch screen lever to interact with the whiteboard and instruct the students' behavior, so the angle of his/her human skeleton vectors is not in the judgment interval proposed in this paper. Therefore some of the actions are misjudged as other actions.

Table 1. Interactive behavior recognition test results

Course name	Processing mode	Teacher language	Student language	Classroom silence	Whiteboard interaction
Marketing	Artificial	65.23%	32.61%	2.16%	35.62%
	Algorithm	64.52%	33.62%	1.86%	35.96%
	Difference value	0.71%	1.01%	0.30%	0.34%
Introduction to e-commerce	Artificial	65.23%	32.64%	2.13%	34.58%
	Algorithm	66.39%	32.95%	0.66%	35.21%
	Difference value	1.16%	0.31%	1.47%	0.63%
Network marketing foundation and practice	Artificial	45.98%	48.59%	5.43%	36.95%
	Algorithm	46.87%	48.08%	5.05%	38.42%
	Difference value	0.89%	0.51%	0.38%	1.47%

3.2. Analysis of the optimization effect of e-commerce teaching interactive behavior

3.2.1. Results of Effective Interaction Behavior Analysis. This paper carries out the application of interactive visualization display system in the e-commerce teaching in this university to optimize the interactive behavior in e-commerce teaching, by collecting the classroom video data of e-commerce teaching before and after the application of the interactive visualization analysis system and carrying out a comparative analysis of the interactive behavior in order to explore the effectiveness of the optimization strategy of teaching interaction. The results of the analysis of the interactive behavior in the e-commerce teaching classroom before the application of the interactive visualization analysis system are shown in Table 2. From the analysis results of each code of the interactive behavior in the e-commerce teaching classroom, it can be found that the frequency of teaching interaction is low, while there is a long period of meaningless silence and confusion. The frequency of behaviors that produce direct influence on students in teacher verbal behavior (118 times) is greater than that of indirect influence (71 times), but the total duration of behaviors that produce direct influence (6.58 min) is shorter than that of indirect influence (10.10 min), i.e., the single duration of behaviors in teacher verbal behavior that produce indirect influence on students is longer. The passive responding behavior (12.62%) was lower than the active responding behavior (5.69%), which indicates that most of the students' verbal behaviors were in a passive way, whereas students need to take the initiative to express their ideas completely in good teaching classroom interaction behaviors. Meaningful classroom silence time accounted for 93.84% of the whole classroom session, while the length of meaningless silence and confusion amounted to 2.77min with a frequency of 12 times, which indicates that e-commerce teaching classroom interaction is poor.

Table 2. The analysis of the previous interactive behavior of the system

Classification	Statement	Coding	Effective	Total	Frequency

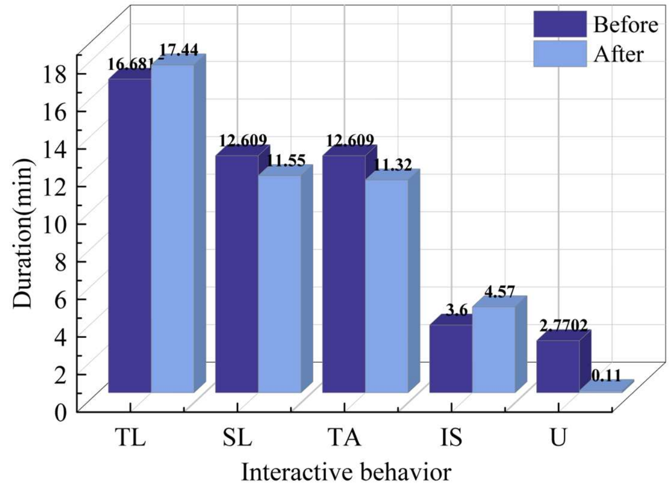
					percentage (%)	length (min)	
Teacher language	Indirect influence	Acceptance of students' emotions		1	——	——	——
		Praise		2	1.54%	0.69	16
		Take the student view		3	5.96%	2.68	32
		Question	Open	4	0.75%	0.34	9
			Enclosed	5	3.26%	1.47	25
		Ask		6	3.12%	1.40	36
	Direct influence	Teach		7	16.95%	7.63	45
		Prompt		8	5.49%	2.47	26
		Criticism		9	——	——	——
Student language		Passive response		10	12.62%	5.68	69
		Active response		11	5.69%	2.56	12
		Active question		12	0.15%	0.07	2
		Group discussion		13	9.56%	4.30	5
Technical application		Teacher control technology	Rendering	14	15.62%	7.03	36
			Display	15	——	——	——
			Guidance	16	1.49%	0.67	4
		Student manipulation	Notes	17	2.36%	1.06	5
			Assisted	18	——	——	——
			Display	19	1.28%	0.58	4
Silent silence		Student thinking		20	5.69%	2.56	4
		Instruction pause		21	2.31%	1.04	9
Meaningless silence and confusion					6.16%	2.77	12
Total time					100.00%	45	351

After applying the teaching interaction visualization analysis system, the analysis data of interactive behaviors in the e-commerce teaching classroom are shown in Table 3. With the auxiliary intervention of the interactive visual analysis system, the frequency of teachers' indirect influence behaviors (113 times) is higher than the frequency of direct influence behaviors (101 times), of which the duration of accepting students' emotional behaviors and adopting students' viewpoints behaviors are 0.57 min and 3.14 min, respectively. Teachers usually give affirmation to the students' ideas and increase the students' positive initiative to participate in classroom teaching and learning activities. In the course of classroom teaching, teachers give prompts or instructions at appropriate times to help students think and solve problems. In addition, the frequency of teachers asking closed questions and open questions is 28 times and 11 times respectively, but in terms of the percentage of time, teachers asking open questions account for a larger percentage (2.65%). Under the application of the interactive visualization system for applying e-commerce teaching, the length of meaningful classroom silence is 4.57min, and meaningless silence and confusion is only 0.11min.

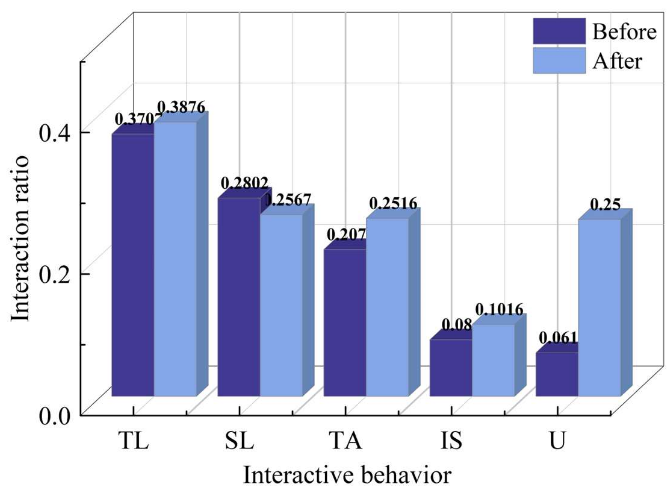
Table 3. The analysis of the interaction behavior of the system

Classification		Statement		Coding	Effective percentage (%)	Total length (min)	Frequency
Teacher language	Indirect influence	Acceptance of students' emotions		1	1.26%	0.57	5
		Praise		2	2.65%	1.19	22
		Take the student view		3	6.98%	3.14	35
		Question	Open	4	2.56%	1.15	11
			Enclosed	5	2.65%	1.19	28
		Ask		6	3.69%	1.66	41
	Direct influence	Teach		7	15.06%	6.78	51
		Prompt		8	2.65%	1.19	56
		Criticism		9	1.26%	0.57	6
Student language		Passive response		10	0.26%	0.12	4
		Active response		11	11.54%	5.19	36
		Active question		12	3.62%	1.63	19
		Group discussion		13	10.25%	4.61	7
Technical application		Teacher control technology	Rendering	14	8.59%	3.87	25
			Display	15	6.32%	2.84	14
			Guidance	16	2.45%	1.10	9
		Student manipulation	Notes	17	3.62%	1.63	6
			Assisted	18	2.54%	1.14	3
			Display	19	1.64%	0.74	5
Silent silence		Student thinking		20	6.92%	3.11	8
		Instruction pause		21	3.24%	1.46	4
Meaningless silence and confusion					0.25%	0.11	1
Total time					100.00%	45	391

3.2.2. Overall Comparative Analysis of Interactive Behavior. The results of the comparative analysis of the interactive behaviors before and after the application of the interactive visual display system for e-commerce teaching are shown in Figure 2, with (a) and (b) representing the results of the analysis of the percentage of interactive behaviors and the duration of interactive behaviors, respectively. As a whole, the e-commerce teaching classroom before and after the application of the interaction optimization strategy appeared to have 351 and 391 effective interaction behaviors of teachers and students, and all the effective interaction behaviors of teachers and students covered 93.84% and 97.25% of the classroom time, respectively. The percentage of total time spent on technology application in e-commerce classroom teaching increased from 20.75% to 25.16%, indicating a higher degree of classroom technology application, which suggests that teachers are good at using teaching equipment and designing teaching activities, and are able to provide richer teaching resources for students. Meaningful silence comparison results can also be clearly observed, the time it accounts for classroom instruction after the implementation of interactive optimization strategies increased from 41.4 min to 44.89 min, indicating that teachers give students time to think and also give teaching buffer time to pave the way for subsequent instruction.



(a) Interaction ratio



(b) Interaction ratio

Fig. 2. Interactive behavioral primary code analysis results

3.3. Analysis of Students' Cognitive Changes under Interactive Optimization Strategies

This section explores the changes of learners' cognition under the interactive optimization strategy in e-commerce teaching, so as to analyze the impact of the implementation of interactive optimization strategy in e-commerce teaching on students' cognition in e-commerce teaching more further. Cognitive presence is analyzed in four aspects, namely, exploration, integration, solution and others, and the results of the analysis of learners' cognitive presence in e-commerce teaching are shown in Figure 3. The mean scores of students' cognition of exploring, integrating, solving and other cognition of knowledge in e-commerce teaching before the implementation of interactive optimization strategy were 4.23, 5.26, 4.12 and 4.81, respectively. The mean scores after implementing the interactive optimization strategy increased to 8.75, 8.47, 8.80, and 8.61.

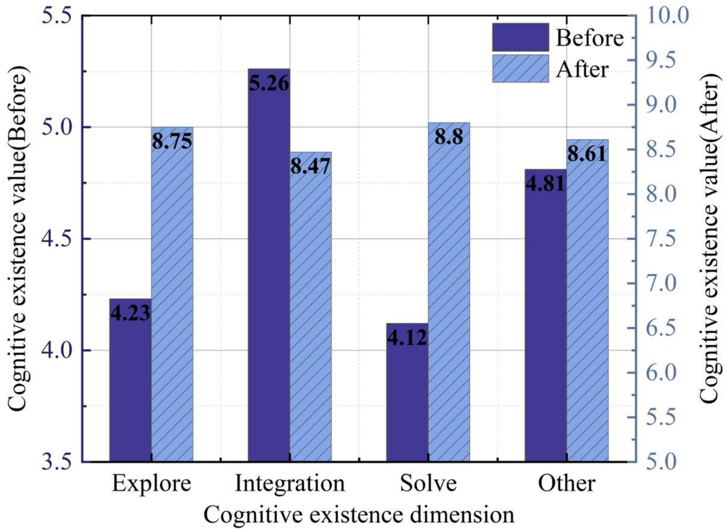


Fig. 3. The learners' cognitive existence analysis results

In order to analyze whether there are differences in the distribution of learners' cognitive presence before and after the implementation of the interactive optimization strategy, this study used multivariate analysis of variance (MANOVA) to analyze the results of cognitive presence analysis, and the results of the analysis are shown in Table 4. The univariate analysis showed that before and after the implementation of the interactive optimization strategy, learners' cognitive presence in exploratory cognition (F=18.526, P<0.001, η^2 = 0.003), integrative cognition (F=19.542, P <0.001, η^2 =0.002), resolving cognition (F=15.632, P<0.001, η^2 =0.005) and other cognition (F=17.524, P<0.001, η^2 =0.004) were significantly different. By comparing the means, it was found that the students' values of exploring, triggering, integrating, solving and other cognitions were significantly higher before the implementation of the interaction optimization strategy than before the implementation of the strategy, which indicates that the improvement of the effect of interactive behaviors in e-commerce teaching promotes the improvement of the learners' cognition.

Table 4. The learners' cognition was analyzed by MANOVA

Cognitive existence	Before		After		F	η^2	Sig.
	Mean	SD	Mean	SD			
Explore	4.23	0.62	8.75	0.62	18.526	0.003	0.000
Integration	5.26	0.82	8.47	0.59	19.542	0.002	0.000
Solve	4.12	1.24	8.8	0.78	15.632	0.005	0.000
Other	4.81	0.96	8.61	0.48	17.524	0.004	0.000

4. Conclusion

This paper combines the speech recognition technology based on reinforcement Q learning algorithm and the video recognition technology based on head posture estimation to recognize and analyze the interactive behaviors of teachers and students in e-commerce teaching classrooms, and develops and obtains the interaction visualization and analysis system to realize the optimization of the interaction strategies in e-commerce teaching. The analysis of the effectiveness of the interactive behavior recognition model finds that the model proposed in this paper has a high accuracy rate in recognizing interactive behaviors in 30 e-commerce teaching videos, and most of the classrooms show excellent recognition results. The analysis of interaction behavior before and after the application of interaction optimization strategy in e-commerce teaching in a university found that the e-commerce teaching classroom appeared to have 351 and 391 effective interaction behaviors of teachers and students, respectively, and the effective interaction behaviors covered 93.84% and 97.25% of the classroom time, which indicates that after the implementation of the interaction optimization strategy, teachers can give students time to think in e-commerce teaching and at the same time, give the buffer time to the teaching The It was also found that before and after the implementation of the interactive optimization strategy, there was a significant difference between the learners' cognition of exploring, integrating, solving and other cognition of e-commerce teaching (P=0.000), which indicates that the improvement of the effect of interactive behaviors in e-commerce teaching promotes the improvement of the learners' cognition.

In summary, the interactive optimization strategy assisted by the visual analysis system of interactive behavior in e-commerce teaching can promote the high-quality development of effective interactive behavior of teachers and students in e-commerce teaching classroom, and effectively help to set up the construction of teachers' and students' awareness of effective interaction and the guidance of students' in-depth thinking.

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