

Research Article

Emotional Interaction and Behavioral Decision-Making Mechanism in Network Science Education Based on Deep Learning

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With the globalization of network education and the design and construction of all aspects of engineering, network science education is playing an increasingly important role in higher education and even the lifelong education system of college students. The purpose of this article is to study emotional interaction in deep learning network education and analyze the status quo of its behavioral decision-making mechanism. It uses research literature method, algorithmic statistical method, and questionnaire survey method to investigate specific groups of people; analyzes the status quo of emotional interaction and behavioral decision-making mechanism; improves statistical algorithms; and explores an old style emotional cognitive decision-making model. In this paper, a questionnaire survey of a university shows that the proportion of students whose online learning time is 1.5–2 hours is about 10.3% and the proportion of 1–1.5 hours is about 6.8%. The study time of students' online courses is mainly concentrated. The study time between 0.5 and 1 hour accounts for about 83.2%; about 2.3% of learners rarely use the Internet, less than 0.5 hour; and 1% of students hardly use online courses and may rely more on traditional classroom teaching. Further research showed the behavior of their emotional interaction: interactive teaching network in six modules reached the upper level, the peak value of the curve was 0.737, the bottom value was 0.115, and the transitivity was above 0.115. From deep statistical learning algorithms to completing network science education, designing or modifying more comprehensive and faster bpq-l learning algorithms based on traditional learning algorithms can allow us to find target sentiments.

1. Introduction

With the rapid development of network technology, multimedia technology, comprehensive, high-level technology, online education has undergone profound changes. The advantages of educational resources as the main aspect of the field of online education are gradually showing up and attracting attention from all over the world. In order to guarantee a high level of online education, it is necessary to develop a high-quality online teaching model, but how to apply the emotions of teachers and students to online courses is a difficulty that needs to be solved by the founders of online courses. Compared with traditional classrooms, online teaching has unparalleled benefits. In traditional teaching, teachers can have back-to-back conversations and emotional integration with students and make improvements in time based on students' feedback. However, on the

network platform, the spatial separation between teachers and students prevents students from expressing their inner feelings to teachers, being unable to conduct extensive and in-depth research with teachers, which makes them feel lonely. Such a network environment will affect the effectiveness of learning to a certain extent.

The development of contemporary social infrastructure can completely provide technical support for the delivery of online education, but how to measure students' thoughts in online lectures and online classes and realize eclectic emotional interaction characterized by human-human interaction has become a problem worthy of research in the current modern network teaching. Linking emotional algorithms to online teaching can enable teachers to adjust their behaviors and teaching policies according to the changes in students' states and emotions, so as to achieve the best teaching effect. Based on the current shortcomings of

online teaching, this article has made an in-depth discussion on the theories and key factors of emotional computing and transferred emotional algorithms to online education. Based on software technical support, it studies emotional interaction and behavior in order to build an emotional transmission system. Aiming at the high-level model widely existing in the difficult path of online teaching, the teaching FPBDI model is proposed. At the same time, it achieves emotional behavioral actions, so that teachers can appropriately adjust their own methods according to the changes in students' class status, that is, by changing classroom strategies to mobilize students' learning goals, improve their learning ability, and achieve a more stable network emotional transmission method, with the help of simple and practical human-computer communication methods, to achieve emotional transmission and expression in network education.

The research by Hu in 2016 analyzed how different social statuses given to mathematics competitions affect the sense of fairness during the subsequent asset allocation in the "Ultimatum Game" (UG). Behavioral data shows that participants in a higher state are more likely to reject unfair UG offers than participants in a low state. This influence of social status is related to the activity in the right anterior island (rAI) and the functional connection between rAI and areas in the anterior cingulate gyrus cortex, indicating that these two brain regions are essential for integrating background factors and social norms. In addition, there is an interaction between the social status in the amygdala and thalamus and the fairness provided by UG, which implies the role of these areas in the adjustment of social status to the perception of fairness. However, to collect the data, only mathematical participants were chosen [1]. In 2017, Basuki proposed two multicriteria decision-making methods involving both subjective and objective criteria for warehouse location selection. The Brown and Gibson model is used to integrate subjective factor measurement (SFM) and objective factor measurement (OFM) to estimate the warehouse location selection index. A comparative study of the results and sensitivity analysis were carried out. The study found that the proposed method as a multicriteria decision-making (MCDM) tool is very useful and effective for evaluating and selecting warehouse locations in the supply chain. However, this research focuses on decision-making methods rather than optimization algorithms, and the proposed algorithms are still not easy to understand and not easy to apply widely [2]. In 2016, Shao used a card guessing game that can independently manipulate the perceptual control and gambling results of 29 healthy female participants. They observed IoC and GF-type behaviors, as well as the interaction of previous control and previous results. GF-type behavior is only after the result of computer selection, not the result of self-selection. According to their records, the imaging results suggest that ACC and the left anterolateral prefrontal cortex (LAPC) are involved in surrogate processing, while the cerebellum and right DLPFC are involved in the previous outcome processing. Crucially, the lower right intense pulsed light showed obvious gambling-related activities on the interaction of the previous control and the previous

results and showed more positive signals for the outcome of the previous computer selection, but the reverse mode of self-selected results and the feedback process did not respond to the interaction of control and results. They also found that the participants' behavioral sensitivity to the interaction of prior control and prior results was associated with the correct IPL signal and the functional connectivity of the neural network associated with the agent and prior results processing. However, there are errors in his research process, leading to deviations in the results [3].

The innovations of this article are as follows: (1) This article studies the users of online teaching platforms from the perspective of experience value. On the one hand, the current domestic research on the Internet is mostly carried out from the perspective of education and computer and from the perspective of users and sales; on the other hand, my country's offline research is mostly concentrated on online products, with fewer scholars. (2) This article creates a possible model of the user trend of the online teaching platform. Based on the model, this paper successfully creates an influence model on user behavior intentions. (3) This paper compares the network with reality and obtains a more comprehensive result.

2. Design and Implementation Methods Based on Emotional Interaction and Behavioral Decision-Making Mechanisms in Online Education

2.1. Online Education. Education also includes online education, but the operating environment needs to be achieved through the network [4]. At present, regardless of the country, the generalizations and statements of online education are different at home and abroad. Among them, the most generalized, most influential, and most representative definitions are as follows.

The Modern Online Education Resources Construction Management Committee of the Ministry of Education of my country has conducted an in-depth investigation and research on this issue and concluded the following points: We believe that the so-called modern online education refers to the education in which students incorporate all teaching knowledge through the Internet [5]. It has two components: the application of specific teaching strategies and the co-construction of course teaching objectives, which is to master the content and realization of network course teaching. Supportive environment mainly refers to courses and practices that can be assisted and can be taught online with the help of learning resources and network means [6].

Yu and Lin believe that what we call online education is to play a role through the Internet. First, it is a course in itself, which is the same as the traditional course; second, according to its characteristics, it can reflect its advantages; that is, it can use the network to complete the characteristics of learning [7]. According to the educational content of the "New American Education Encyclopedia," it can be understood as follows: "realistic education in its sense refers to

the purposeful guidance of school teachers to students, which leads to the collection and integration of student learning activities, including: teaching content, goals and activities, even including evaluation methods and methods are a concept.” The process of using online education also requires changes in the way of disseminating educational information [8]. While preparing, to a large extent, relevant educational models, concepts, methods and varieties will appear.

Similarly, Wu of Normal University thinks so. According to its related academic theories and under its guidance, asynchronous self-study courses are set up through the Internet. It is to complete the goal of a certain subject within a certain range and design the sum of network-related activities and content on this basis [9].

It can be seen from the above definition that although online education is carried out in a network environment, it has all the basic characteristics and attributes of the course, so online education is also a course, and we can also realize that the teaching objectives of online education are determined by the content of teaching and the network environment [10].

2.2. Interaction and Emotional Interaction. Transmission is a concept introduced from literature to teaching [11]. For “interaction,” the interaction expressed in this way is first of all a process composed of several stages of self-interaction, human interaction, and tripartite interaction [12]. Many scholars have given various explanations and descriptions of interaction in the domestic and foreign research on teaching delivery, among which the more typical definitions are the following:

From the perspective of the characteristics of the transmission pathway, Professor Riel believes that “the transmission in learning is a process of simultaneous, changing, and mutual giving between the lecturer and the recipient, including relevant information.” From the perspective of emphasizing the motivation of transmission, Professor Lisser believes that “transmission is the continuous two or more individuals to explain and challenge the views on both sides” [13]. From the perspective of emphasizing the long-term meaning of the transmission behavior, Professor Simon believes that “transmission is a two-way communication between two or more individuals in the environment to complete their tasks or create social relationships.”

The above-mentioned professors have given their own definitions of transmission from their level. The authors believe that these definitions have no essential difference, and they only explain interaction from different perspectives according to the needs of research. Transmission in online teaching can be understood as the communication and transmission between the learner and the online teaching for the purpose of constructing the correct thoughts of the students on the content in the network. Emotion transmission refers to the interaction of emotions [14]. Emotion transmission in online teaching refers to the active tendency and relevance of emotions, attitudes, evaluations, etc. of both

parties and other individuals in online courses, and it reflects all the communication and exchanges between each other in online teaching.

2.3. Emotional Model and Cognitive Decision-Making. In the high-level field, the number of scholars who pay attention to the experimental cognitive process of the cognitive process is increasing, and it is increasingly clear that emotion is a factor for impressions, learning, behavior, and all other related models. However, the current influence of computational models on people and subjective decision-making and learning is relatively small, and the applied research in this area lags behind the research in its field [15]. Most of the calculation models are still based on cognitive models to analyze and simulate human experience, predictions, and decisions. Traditional models are based on expected utility theory, assuming that people make decisions based on cost-benefit analysis [16].

The emotional cognition model is an extension and integration of the existing theoretical prospect theory and reinforcement learning theory and emphasizes the role of emotion in decision-making and neural-based human decision-making behavior [17]. In the emotional cognition model, the assumed preference for decision-making is mainly obtained from subjective experience in similar situations in the past (that is, experience-based mode) and effectively predicts the result of future emotional influence selection (that is, predictive mode) [18]. Generally speaking, the experience-based model is a reflection, association, and automatic process, while the prediction model is a goal-oriented reflection process. The model mainly explains how the current state (including cognition and emotion) uses empirical models and predictive models to influence decision-making choices [19].

The purpose of the network hierarchy emotional cognitive decision is to address the emotional dimension of decision-making in cognitive learning. Its essence is to subdivide emotional cognitive decision-making, so that each aspect of emotion has its own goal, and each decision biased towards low-level emotional cognition only needs to address a smaller aspect, and the learning strategies of low-level emotional cognition decisions can in turn be invoked by high-level emotional cognition decisions, thus speeding up decision-making efficiency.

As shown in Figure 1, AC model frame is composed mainly of a number of probability formulas. The x , y , y_a , z , x' , y' in the framework represent the current cognitive state (x), the current emotional state (y), the probability distribution of the current emotional state (y_a), the current selected low-level emotional cognitive decision (z), the next cognitive state (x'), and the next emotional state (y') after the current low-level emotional cognitive decision. In the model, emotional cognitive decision-making includes cognitive module, emotional module, decision-making module, cognitive reward module, and emotional reward module. The basic framework of the model is shown in Figure 1 [18].

No matter when the low-level emotional cognitive decision-making is executed, the external reward from the

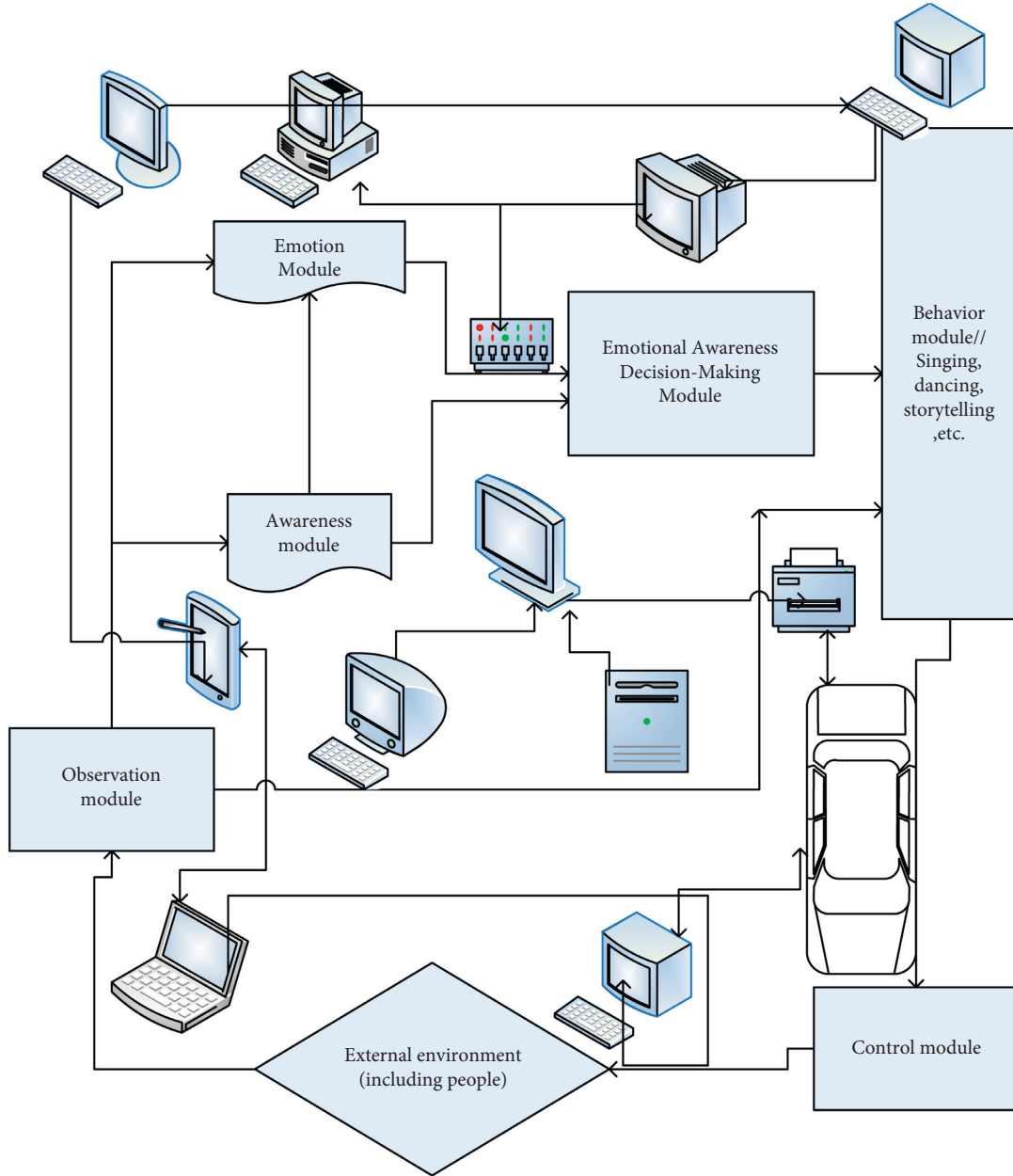


FIGURE 1: AC model basic frame structure diagram.

external environment will be evaluated and used to update the internal self-motivation model of emotional cognitive decision-making. The observation module is also included in the emotional cognitive decision-making, which is mainly used to extract useful features from the external environment, such as identifying the body's posture and facial expression features of the interactor. Therefore, each emotional cognitive decision has its own objective observation model, where the observation model uses the facial expression recognition system [19].

Suppose that in a certain time window, there is only one cognitive state in emotional cognitive decision-

making (because the external world is partially observable) and the cognitive state of emotional cognitive decision-making is obtained from the observation model. The cognitive reward model is $Q_{xq}(x')$, and the cognitive state transition model is

$$Ks(x'|x, z). \quad (1)$$

The emotion model is

$$Ks(y'|x', y). \quad (2)$$

The emotion conversion model is

$$Ks(y'|y_k, x, z) = \sum_{r=1}^{|\alpha|} Ks(y'|x' = r, y_k)Ks(x' = r|x, z) = \sum_{r=1}^{|\alpha|} \sum_{h=1}^{|\beta|} y_{kg} Ks(y'|x' = r, y = g)Ks(x' = r|x, z). \quad (3)$$

Affective cognitive decision-making model is

$$U_{ZN}(x, w, z) = U_{yaj}(x, z) + U_{rmc}(x, w, z), \quad (4)$$

$$Ks(z = g|x, w) = \frac{yfk(\omega U_{ZN}(x, w, z))}{\sum_{o=1}^{|\mathcal{Z}|} yfk(\omega U_{ZN}(x, w, o))}. \quad (5)$$

In (5), ω is the reversal temperature of the bolt selection strategy. The emotional cognitive decision-making algorithm is executed in a self-loop, and the specific implementation steps are as follows:

- (1) Initialize the inner emotional state space set XY in the emotional agent to be happy and unhappy and the external emotional state space set XB to be joy, sadness, fear, anger, and cognitive states. Therefore, the cognitive state can be temporarily ignored in the implementation, and the external emotion probability distribution of the emotional subject can be initialized at the same time.
- (2) The emotional agent obtains the emotional state of the interactor through the observation module and updates the external emotional probability distribution of the emotional agent xw :

$$xq_l = Qs(x = l|w, xq_{new}) = \sum_{n=1}^{|\mathcal{F}|} Qs(x = l, x_{new} = n|w, xq_{new}). \quad (6)$$

- (3) Send the current emotional state probability distribution to the input layer of the HK neural network, and use the G function in the hidden layer of the HK neural network to calculate the intrinsic cognitive reward value $D_{ecs,a}$

$$D_{ecs,x} = G_{XY}(x, z). \quad (7)$$

- (4) Intrinsic emotional reward value $D_{ecs,qv}$ is as follows:

$$D_{ecs,qv} = G_{QVY}(qt, x, z) = \sum_{n=1}^{|\mathcal{Q}|} qtG_{QVY}(n, x, z). \quad (8)$$

- (5) Calculate the intrinsic reward value D_{ecs} :

$$D_{ecs} = \eta_x(z) \times D_{ecs,x} + \eta_Q \times D_{ecs,qv}. \quad (9)$$

- (6) The maximum output value of the intrinsic reward HK neural network is calculated, and the appropriate emotional agent decision Z is selected to perform emotional behavior

$$Ks(z = q|x, d) = \frac{yat(\varepsilon P_{ZN}(x, d, z))}{\sum_{m=1}^{|\mathcal{Z}|} yat(\varepsilon P_{ZN}(x, d, m))}. \quad (10)$$

- (7) After executing decision Z , the observation module obtains the external reward s_{yam} and then uses the model S_{yam} to update the external reward:

$$S_{yam} \leftarrow (1 - \mu)S_{yam}(x, z) + \mu s_{yam}. \quad (11)$$

- (8) Use the emotional model $P_{YYS}(t, x, z)$ of extrinsic reward to update the probability distribution of extrinsic emotional state [20].

- (9) Use the emotional cognitive decision-making model $P_{ZN}(t, x, z)$ to update the correspondence between external emotional states and emotional behaviors.

- (10) Return to step (2) to continue execution.

Classification algorithms are the core of face recognition. Its basic idea is to organize and classify the feature components by constructing a b-weak classifier to organize and classify the feature components from the ICA component of the hot area of the face [21]. The ADAB algorithm is completed by loops. The only requirement for weak classifiers is that their classification accuracy is greater than 0.45. If there are s independent components $T = (t_1, t_2, \dots, t_s)$, for the n -th training image, there are corresponding s projection coefficients $Q_n = (q_{n1}, q_{n2}, \dots, q_{ns})$, and the input vector is the obtained projection coefficient Q_n and the corresponding number Z_n . In this article, each independent component may constitute a weak classifier. First, a simple test is done through the recognition effect of independent component Euclidean distance to find those independent components that can truly constitute a weak classifier.

For the D training image problem of class X , there are D projections $Q_{x(n),i}, x = n, \dots, x, n = 1, \dots, D_x$, on the i -th independent component, and the class mean is $p_i(x), x = 1, \dots, x$, where D_x is the number of samples of the x -th class, so there is $\sum_{x=1}^x D_x = D$.

We can see from the following formula that

$$\sum_{n=1}^{D_x} l(Q_{x(n),i}) > \left[\frac{D_x}{2} \right]. \quad (12)$$

This independent component is then considered to form a classifier on the x th [22]. Among them

$$l(Q_{x(n),i}) = \begin{cases} 1, & \text{if } q_{x(n),i} > w_i(x), \\ 0, & \text{something else.} \end{cases} \quad (13)$$

Once the G independent components are selected and all form the corresponding weak classifiers, the continuous multiclass adab algorithm is used for the whole range. The weak classifier should be configured with a feature L and a threshold α_x .

$$k(l, x) = \begin{cases} 1, & \text{if } l > \alpha_x, \\ 0, & \text{something else.} \end{cases} \quad (14)$$

Using β to represent the sample space and χ to represent the label space, a simple multitype and multilabel problem can use data to represent (a, b) , where $a \in \beta, b \in \chi$ are defined as $B[m]$:

$$B[m] = \begin{cases} 1, & \text{if } m \in b, \\ -1, & \text{if } m \notin b. \end{cases} \quad (15)$$

Then, the icab classification algorithm can be defined as follows:

$$G(Z, m) = \text{sign} \left(\sum_{n=1}^n \eta_n g_n(Z_n, m) \right). \quad (16)$$

In the above process, η_n is the performance factor of the low-performance classifier $g_n(Z_n, m)$ generated after the n -th round, which is determined by the sum of the misclassified data β_n generated by the action of $g_n(Z_n, m)$ on the data, and η_n is the reduction function of β_n . The smaller the β_n , the larger the η_n , and the greater the importance of $g_n(Z_n, m)$ [23]. It should be noted here that when the classification error $\beta_n \geq 0.45$, the algorithm will abbreviate the low-performance classifier generated in this round, and the algorithm will stop. Because at this time, the training step redefines the sample weight, the "difficult" sample weight decreases, the "easy" sample weight increases, and the weight update mechanism cannot function. That is, the data set samples are classified correctly; at this time, all data weights are zero, and the sample weights are invalid. The final high-performance classifier $G(Z, m)$ is obtained by weighted summation of all low-performance classifiers $g_1(z_1, m), g_2(z_2, m), \dots, g_n(z_n, m)$.

3. Implementation Method Experiment of Emotional Interaction and Behavioral Decision-Making Mechanism in Online Education

3.1. Survey Object and Purpose. The development and use of online courses only create teaching and learning conditions for e-learning, but this is only a basic condition and does not play its real role. If you want to play its role to a greater extent, it also depends on its specific application status in reality. It also depends on its specific application status in reality. The survey of this research was carried out in the form of questionnaires, aiming to understand the real needs of current learners of online courses, timely discover the problems in the implementation of online courses and find out the reasons, formulate improvement strategies for the existing problems, so that the online courses can truly give

full play to their effect, provide better reference value for emotional interaction design in online courses, and make it play its due role.

This survey is based on 16-level students in engineering majors of a normal university. A total of 150 questionnaires were sent out, and 110 questionnaires were retrieved, of which 105 were valid questionnaires, and the questionnaire efficiency was about 95%. Most of the participants participated in the survey. Because students have taken online courses and the time is guaranteed to be at least one academic year, they can participate in a questionnaire for the educators, so as to know and understand the real attention and needs of the current online course recipients.

3.2. The Overall Design of the Questionnaire. The questionnaire used in this study is "a questionnaire about a sample survey of the current status of online teaching." This questionnaire is anonymous and includes two questions, single-choice and multiple-choice questions. The questionnaire includes 40 questions in total. The questionnaire has six components.

This questionnaire is divided into five parts: The design and analysis ideas of the questionnaire are shown in Table 1.

We find out how long learners spend during online courses. Question 3 of the questionnaire aims to understand the time that learners log on to the online course each time. The survey results are shown in Figure 2.

As shown in Figure 2, the time for students to learn online is mainly between half an hour and 1 hour, accounting for about 83.2%. There are also about 2.3% of the recipients who rarely use online courses, and the time is less than 0.5 hours, which may much more depend on traditional classroom teaching.

4. Experimental Results Based on the Design and Implementation of Emotional Interaction and Behavioral Decision-Making Mechanisms in Online Education

4.1. Survey Content and Sample Analysis. Online teaching is one of the supports of contemporary education mode, and its development and design have always been the core of far contemporary teaching research. The author investigated the relevance of online courses from pe, pd, hci and nd through questionnaires. The relevance statistics are shown in Table 2.

According to the interactive data of online courses in Table 2, draw the interactive curve as shown in Figure 3.

It can be seen from Figure 3 that the correlations of pe, pd, nd, h-ci, ci and fd in online teaching have all reached the upper-middle level. The peak of the curve is 0.737, the trough is 0.1, and the correlations are all above 0.1. The peak of the curve is question 2, which shows that the students think that the network teaching is the best intersecting in the creative aspect of the interface, and the students are satisfied. Font size, color, template, and other pd are the key factors that affect the recipient; in particular, the feelings of novices who are not familiar with the Internet will be

TABLE 1: Questionnaire design and analysis ideas.

Questionnaire design content	
The basic situation of the survey object	(1) The status quo of learners using online courses. (2) The time and purpose of learners to learn online courses.
Online course teaching content	(1) The learner evaluates the text, image, video, sound, and other pages of the online course. (2) The learner evaluates the page design, playback effect, human-computer interaction, navigation design, and other aspects of the online course. (3) The degree of satisfaction and evaluation of the learners regarding the teaching content of the current online courses.
Online course learning resources	(1) The main difficulty learners experience in using online course learning resources. (2) The time when learners encounter difficulties in the process of online learning, help objects, and feedback methods. (3) The interactive methods provided by current online courses.
Online course learning support services	(1) The learner's connection with the teacher in the course of online course learning. (2) Learners' expectations of teachers in online courses.
Interactive aspects of online courses	(1) The human-computer interaction for learners to learn online courses. (2) The interactive content of the learner's online course learning. (3) The interactivity between learners and peers when learning online courses.
Online courses for learning evaluation and others	(1) The type of online courses that current learners like. (2) How learners learn online. (3) Learners' expectations for improvements in current online courses.

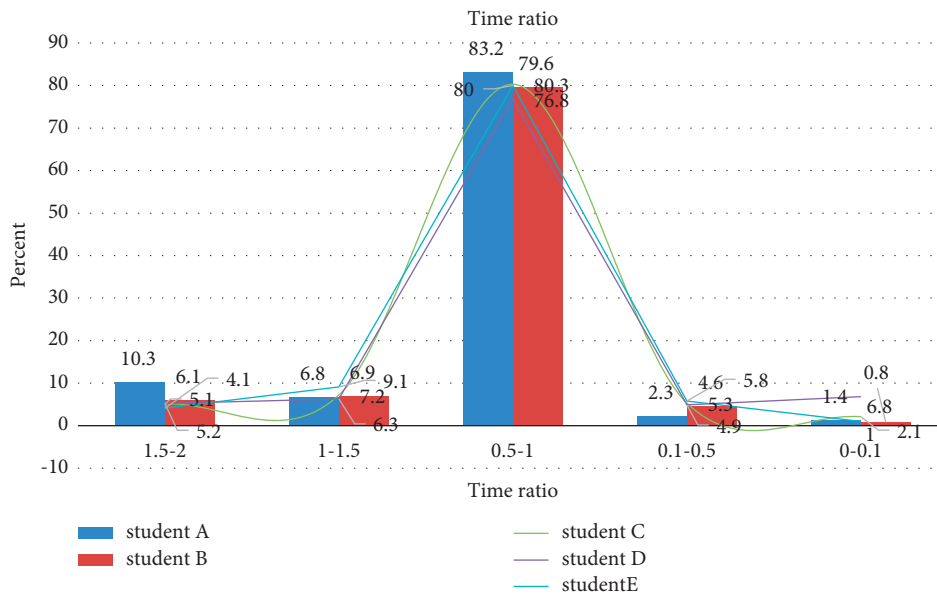


FIGURE 2: Finding out how long learners spend during online courses.

TABLE 2: Interactivity of online courses.

	4.5 Good	3.5 Can	2.5 Bad	1.5 Relatively poor	Interactivity
(1) Play effect	14	28	18	3	0.619
(2) Page design	15	31	14	7	0.737
(3) Human-computer interaction	13	30	10	9	0.652
(4) Navigation design	21	25	11	4	0.669
(5) Content interactivity	7	22	16	5	0.731
(6) Feedback	12	19	17	8	0.7

affected by these factors. Related pd especially reduces the learning effect of learners. A good pd can improve the efficiency of students, thereby improving their abilities. The

trough of the curve is problem 1, which shows that students think that online courses are the worst on pe, and they need to be improved.

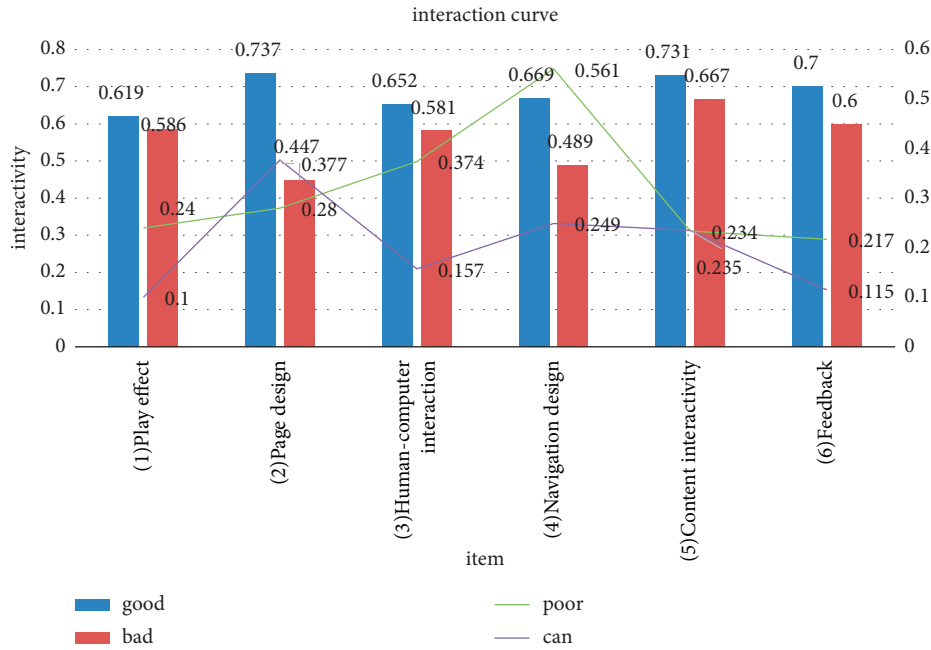


FIGURE 3: Interactive curve of online courses.

According to the four key factors of pd, behavior setting, cp, and mav system, in four stages, 100 students were tested to connect the evaluation data with mathematical simulation and the degree of satisfaction of the simulation experiment products in their stages was compared and analyzed. The results are shown in Figure 4.

According to the analysis in Figure 4, the four designs of university experiments have significantly improved id, bs, plat, and mae. In particular, the degree of preference for id and mae has increased by 19.8% and 15.2% compared to before design. From this, it is understood that the recipient can better grasp the structure, principle, procedure, method, and other steps of the experimental apparatus through observation and operation in the simulated experimental environment; at the same time, the effects and actual conditions of the virtual experiment scene are observed. The design of simple hands-on and other aspects have a great impetus to achieve the efficiency and effect of virtual experiment steps.

4.2. Expression Algorithm and Test. This paper uses JAF facial expression database to test the algorithm. The Jaf facial expression database has collected 15 people's expression images, a total of 200 images, and the resolution of each image is very clear, and all images are used for testing. For the clear images in the facial expression database, using the method in this paper to recognize facial expressions has a faster speed, and each image takes about 0.9 s on average, which makes real-time video processing possible. At the same time, the classification accuracy of the algorithm for simple expressions, as shown in Table 3, can basically meet the needs of practical applications.

Table 3 compares the expression recognition rates of ica and icab algorithms. The results show that the recognition

accuracy of icab algorithm is significantly higher than that of ica algorithm.

At the same time, this paper compares the results of the icab algorithm with the expression recognition results of the pca and gab features and the support vector machine method. The results are shown in Figure 5.

From the experimental results in Figure 5, the following conclusions can be drawn.

- (1) icab has obvious advantages over pca. The main reason is that icab makes full use of the effectiveness of ica in feature extraction and the excellent characteristics of ada algorithm classification in feature classification, and the algorithm effectively reduces the dimensionality of traditional algorithm features, with improved calculation efficiency.
- (2) Expression recognition based on gab features has a higher recognition rate for excitement and happiness, but the recognition rate for frustration and disgust is lower than the svm algorithm.
- (3) The support vector machine method has high recognition of the six expressions. The main reason is that the training sample and the test sample space overlap in the experiment. There are 190 of the 200 sample libraries participating in the training, which is not satisfied in practical applications.

The emotional processing process of the intelligent agent assistant is divided into two emotional modules. The first module judges the type and intensity of emotions based on external input, while the second module generates corresponding behavioral responses based on emotions of different intensities. Its emotional response is determined by three factors, the type of emotion, the intensity of emotion, and the external environment. In this way, the intelligent assistant will

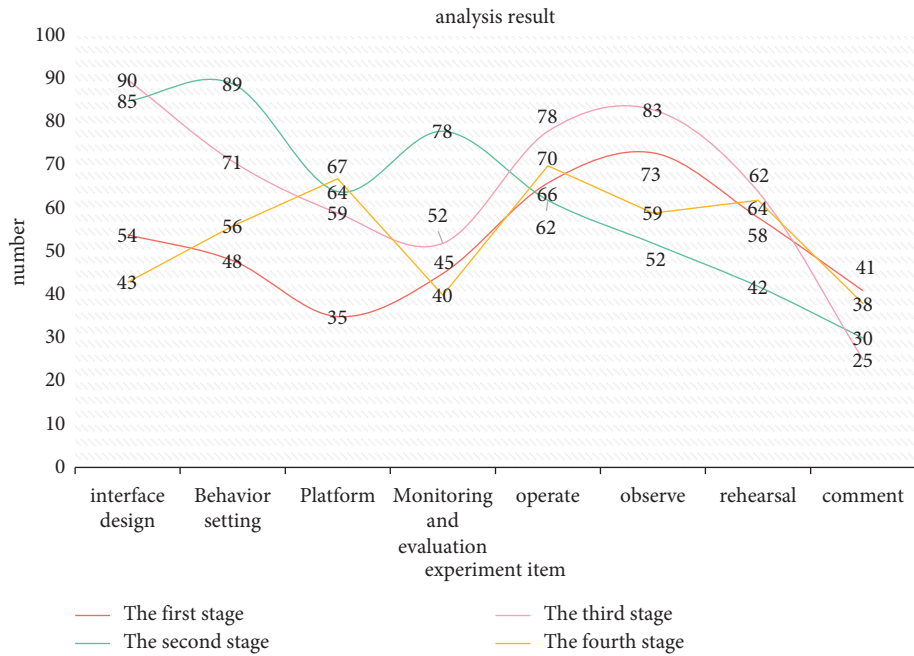


FIGURE 4: Four-stage student satisfaction evaluation and analysis results of the college physics experiment project.

TABLE 3: Comparison of facial expression recognition rate.

	Exciting	Happy	Ica/icaboost Peaceful	Frustrated	Angry
	u	v	w	x	y
u	87.3/89.3	3.41/3.41	2.71/0.1	2.57/0.1	4.23/3.41
v	8.5/6.55	83.9/85.6	3.55/2.71	0.1/0.1	0.1/0.1
w	0.1/0.2	6.55/6.55	81.9/96.9	6.02/6.13	0.1/0.1
x	0.1/0.2	2.99/0.1	11.11/0.1	80.7/85.3	6.35/4.99
y	3.41/3.41	2.24/3.41	3.46/0.1	11.3/10.5	88.9/90.9

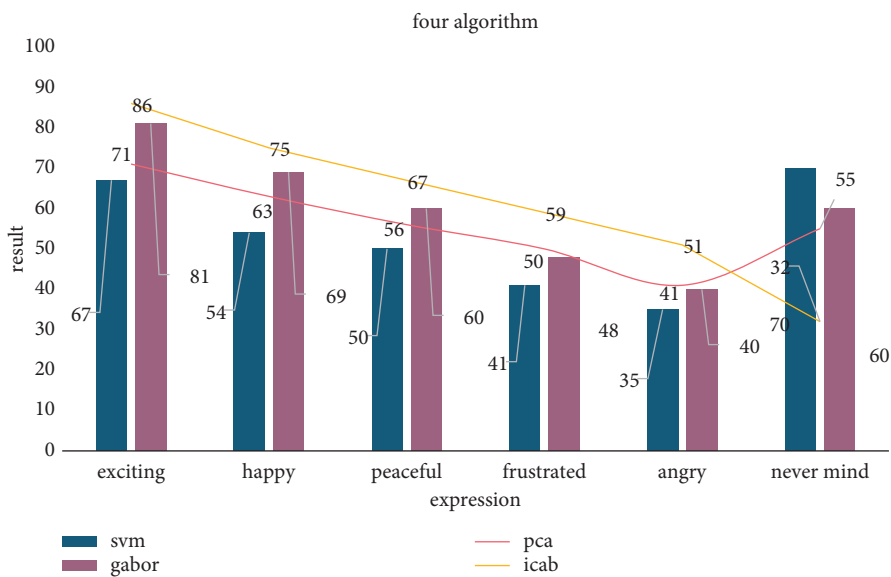


FIGURE 5: Recognition results of four algorithms in JAFFE library.

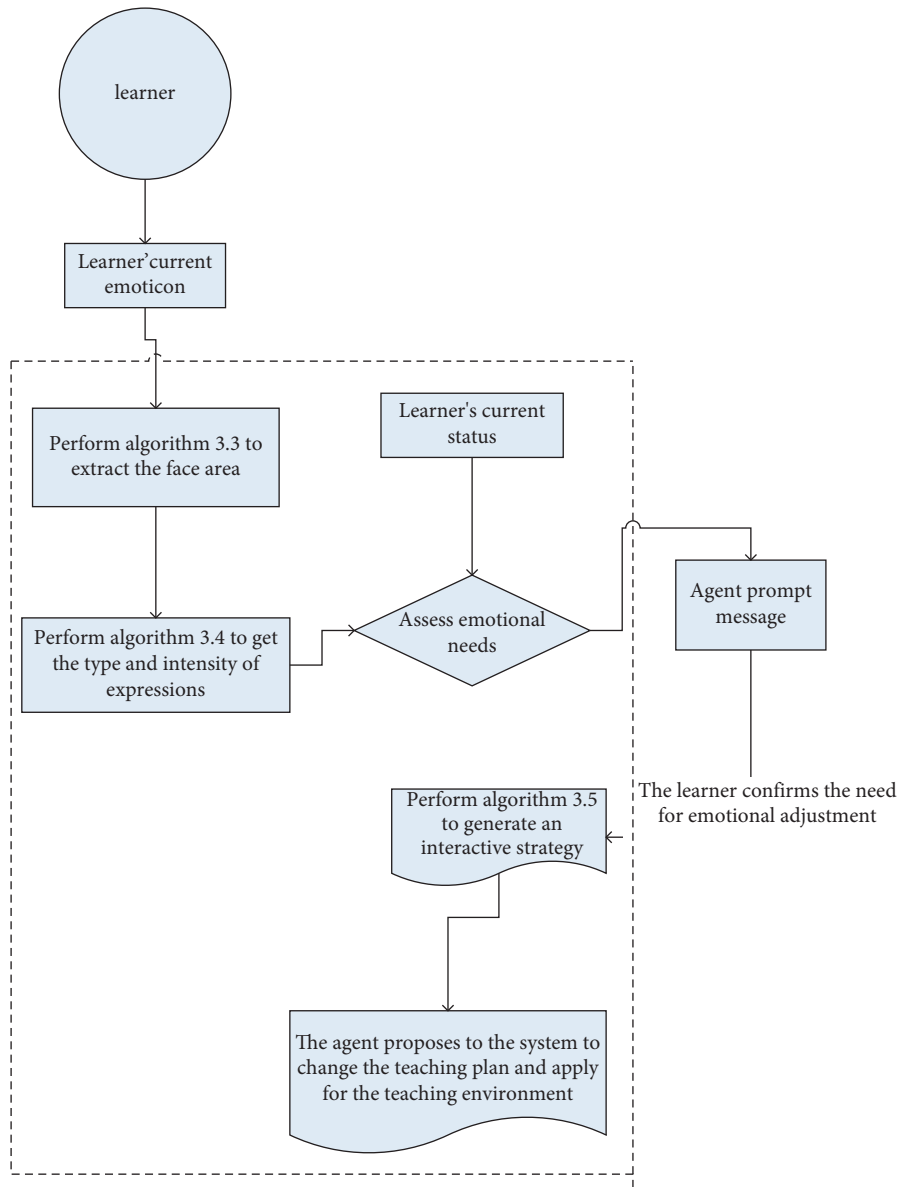


FIGURE 6: Agent emotion processing mechanism.

dynamically generate different emotions for the learners' various learning behaviors, and different emotions will affect the learning assistance strategies of the emotional intelligent assistant for the learners. The intelligent assistant's learning assistance strategy for learners in the system is generated based on corresponding rules and behaviors.

The emotion processing flowchart of the agent assistant is given in Figure 6.

It can be seen from Figure 6 that the agent assistant runs on the client and runs in the background by default. It is the interface between learners and the teaching system for emotional interaction.

In order to verify the improved operability of the algorithm, the algorithm is validated in a virtual reality environment. You can directly see the path and movement of the experimental agent in the test run to achieve a certain purpose. The agent can quickly find the target through sentry

in the maze and successfully escape the danger encountered in the process of searching. When the agent obtains the current situation through observation, it then selects the response method and Z algorithm through BOL to calculate the possibility and executes the corresponding action; if it does not encounter obstacles during the movement, it will be rewarded (external reward and internal reward). If you encounter obstacles, you will be punished, and the agent will make behavior decisions again and execute corresponding actions.

In the programming environment, write a grid of 25 rows and 25 columns, place a number of small squares (obstacles) in it to form a small maze, and then let the agent automatically bypass the obstacles in the maze from the starting point to find the target and walk through this. The labyrinth experiment verified the improved algorithm, and the results of the algorithm operation experiment are shown in Figure 7.

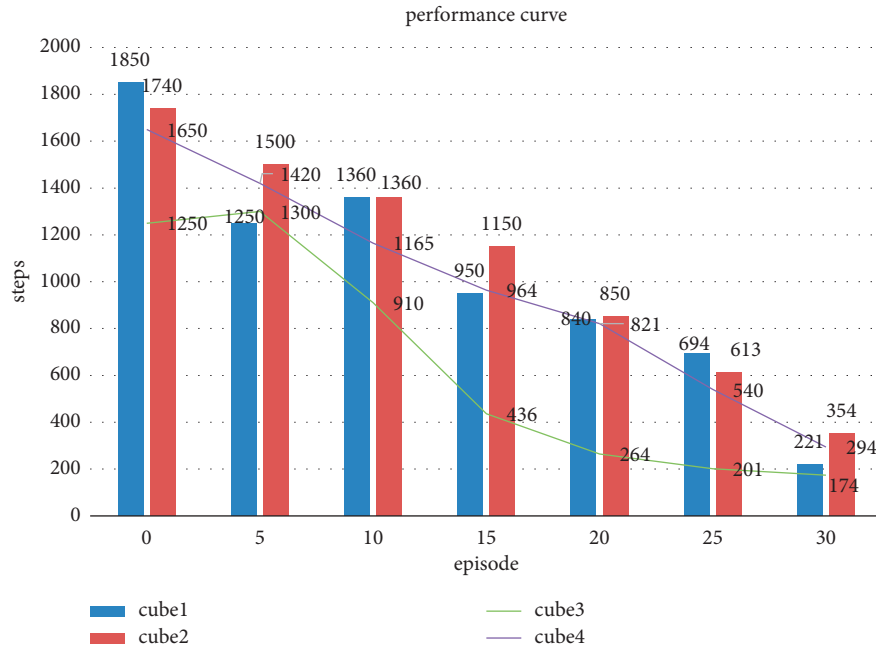


FIGURE 7: The experimental results and performance curve of the agent looking for the target.

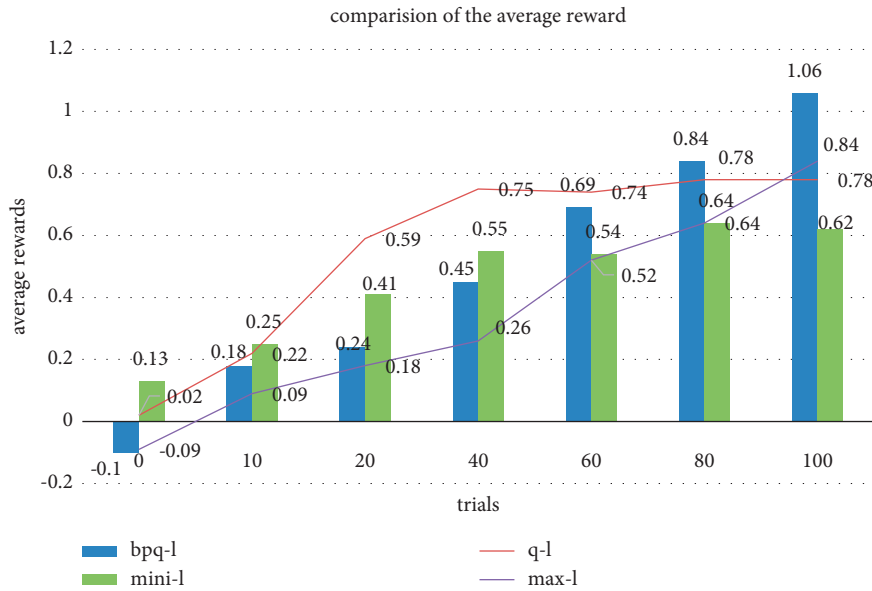


FIGURE 8: Comparison of the average reward value of improved Q learning and traditional Q learning.

As shown in Figure 7, the experimental results of the agent looking for the target in the maze, the agent can successfully avoid the obstacles encountered in the search process after many trials in the maze and finally find the target. The parameter selection in the improved algorithm is as follows: $\alpha = 0.2$; $\gamma = 0.85$; temperature parameter $T = 90$. Judging the input layer of the z-function neural network is to see if there are obstacles left, right, up, and down and the output layer has four actions: up, down, left, and right. In order to observe the effectiveness of the improved algorithm more clearly, it is compared with the experimental results of the traditional algorithm in finding the target in the maze, as shown in Figures 8 and 9.

When the agent finds the target in the maze, when comparing the traditional algorithm experiment with the improved algorithm experiment, the parameters of the four algorithms are set the same. Figures 8 and 9 are the average award after comparing the results of traditional algorithm and improved sentiment in the policy algorithm to find the target agent obtained and the number of attempts to find success goals.

It can be seen from Figure 8 that the performance of the improved algorithm is better than that of the traditional algorithm, because for the traditional algorithm, the smaller the segmentation, the better the performance. When $\alpha = 0.05$, after about 250 trials and training, the average

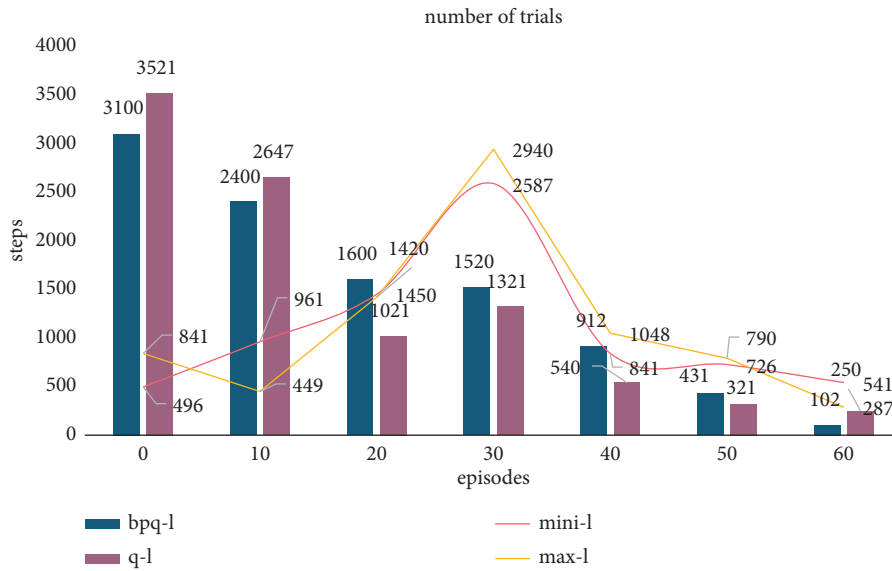


FIGURE 9: Comparison of trial times between improved Q learning and traditional Q learning.

reward can reach 0.8, and the average reward of the improved algorithm can reach 1.06. Therefore, it is obvious that the agent using the improved algorithm obtains a higher reward in the trial process of finding the target than the agent using the traditional algorithm.

Figure 9 shows the comparison result of the number of attempts of the agent to find the target during the process of using two different algorithms to find the target.

As can be seen from Figure 9, the two algorithms for finding the target after the mood have almost the same number of attempts in the first action, but with the increase in the number of operations, the improved algorithm attempts to find the target emotions less and less. It shows that the learning ability of the improved algorithm is stronger and faster than the learning ability of the traditional algorithm, but with the increase of the number of acts, the number of trials of the traditional algorithm can almost be the same as the number of trials of the improved algorithm.

5. Conclusions

The research on the decision-making aspects of emotional cognitive behavior in online teaching reminds us that the real change from books to online courses is to change the pedantic methods of teaching students in the past, so that students' ability in the Internet and real life will be improved. Then, we must pay attention to the dual lack of emotion and behavior in online courses. In order to better solve this problem, this article uses the literature method, algorithmic calculation method, and sample survey method to investigate specific populations and refine the statistical algorithm, and it explores an old style emotional cognitive behavior decision model. In this paper, a questionnaire survey of a university shows that the proportion of students whose online teaching time is 1.5–2 hours is about 10.3% and the proportion of 1–1.5 hours is about 6.8%. The study time of students' online courses is mainly concentrated. The study

time between 0.5 and 1 hour accounts for about 83.2%; there are also about 2.3% of the recipients who seldom use online courses, with the time being less than 0.5 hour; and 1% of students hardly use online courses to learn. On the basis of online teaching, further research has been done on its emotional relevance, and the results show that the intersection of the 6 modules given in online teaching has reached the upper-middle level, the peak of the curve is 0.737, and the trough is 0.115. The intersecting properties are all above 0.115. The highest point of the curve is pd, which shows that students think that online teaching is the most relevant in pd. This means that the improved receptive ability is stronger than the previous algorithm's receptive ability and the learning speed is faster. The shortcomings of this paper are as follows: Due to the authors' lack of ability and level, the calculation level of this paper only stays on the book, and the model proposed in the paper has not been tested in a wider range of practice, so it has wide applicability. The actual operation is not sure. Secondly, this study did not further divide the dimensions of behavioral intention variables, and the division method is not scientific enough. Therefore, in the future, the model will continue to be simplified and refined and the national online course platform can be integrated to conduct larger data analysis and scientific dimension division, making the emotional interaction and behavior decision-making mechanism based on deep learning network education representative and scientific.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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