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Language Teaching Evaluation Based on Multimodal Theory in Artificial Intelligence Scenarios

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Abstract Teaching evaluation is an indispensable and important part of the whole classroom teaching process. With the development of network information technology, the multimodal theoretical teaching mode has entered the classroom teaching. The traditional single-modal teaching evaluation mode is too boring and low in interactivity, which can no longer meet the requirements of modern teaching mode. In order to solve this problem, this paper introduces the multimodal theory under the artificial intelligence scenario into language teaching, and builds a student-centered multimodal theoretical language teaching evaluation system based on the multimodal discourse analysis theory. Through 18 weeks of unimodal, bimodal and multimodal language teaching in the three classes respectively, the students in the three classes were tested after the teaching. The results show that the students' attention in class has been improved by multimodal teaching, and the students' performance has improved by 8.8%. The satisfaction of teachers and students has been improved to a certain extent. Language teaching based on multimodal theory can fully mobilize and give full play to students' subjective initiative and enthusiasm for learning, improve teaching quality, which makes teaching evaluation more abundant, comprehensive, objective and effective.

Index Terms Language Teaching, Multimodal Theory, Artificial Intelligence, BP Neural Network

I. Introduction

With the support of multimedia technology, the new teaching mode represented by multimodal theory in artificial intelligence scenarios has gradually attracted widespread attention. In the form of multi-modal teaching, it is necessary to use a variety of symbol sources such as text, images, and sounds to enhance students' different perceptions of teaching so as to attract students' interest in learning and enhance students' learning initiative as well as improve students' quality, which can achieve effective language teaching effect. As a new science and technology, artificial intelligence has an extremely wide range of applications. It is used in language teaching of multiple modal resources. It drives students into the classroom through auditory, visual and tactile senses, brings closer the relationship between students and teachers, and improves the degree of interaction between teachers and students, so the classroom efficiency can be improved.

In order to improve students' academic level, many researchers have devoted themselves to multimodal theory language teaching evaluation research. Deng X has studied language pedagogy, discussing how scholars can acquire knowledge of language and pragmatics to produce correct and appropriate, capture compatible grammar, and determine the relationship between productive opportunities and needs development in the classroom environment [1]. Sadhya D explored the possibility of incorporating multimodal practice into initial language teacher training at a university in Vietnam and found that the concept of multimodality and the application of a multimodal approach to language teaching have many advantages [2]. Abdel-Raheem A analyzed the application value of multimodal theory, and then discussed the application of multimodal theory in college English classroom from the aspects of textbook reform, teaching activity design, and learning transformation [3]. On the basis of discussing the necessity of multimodal discourse analysis research in ESP teaching, Tahmasebi A constructed a multimodal analysis framework for the ESP teaching method, and analyzed the crew members in English. It is found that the multimodal theory teaching has the characteristics of dynamics, authenticity and diversity [4]. Vermenych Y discussed the application of multimodal discourse analysis theory in classroom teaching, and found that multimodal theory teaching is beneficial to stimulate students' interest in learning and bring students a diversified classroom learning atmosphere [5]. Abbas studied the characteristics of a range of patterns in school science classrooms, theorizing the role of images, gestures and interaction with objects. It provided a methodologically innovative framework for analyzing teaching and learning, curriculum and knowledge across all communication styles [6]. Kachorsky D constructed a teaching video research framework based on sociosemiotic visual grammar theory and power distance theory, and applied the framework to the analysis of award-winning teaching videos in China to find out the characteristics of teaching videos [7]. The above research shows that multimodal theoretical teaching can improve teachers' teaching efficiency.

Artificial intelligence technology is continuously applied in various fields, and many scholars have certain cooperative research in artificial intelligence. Lu H explained the work of artificial intelligence by defining intelligent agents and their functions in production systems, reactive agents, real-time conditional planners, neural networks, and decision-theoretic systems. Agent learning was also explained as an extension of programmers' influence in unknown environments [8]. Hassabis D calculated the artificial intelligence system guide and found that almost all books on artificial intelligence were expressed in computer science, mainly containing complex algebraic tables and variational equations [9]. Rongpeng believed that in artificial intelligence, the process of searching for a solution to a problem could be implemented without domain knowledge in many cases, while in other cases this process can also be implemented with knowledge of the domain [10]. Liu R discovered the relationship between randomness and ambiguity, and the uncertain state and its changes can be measured by entropy and hyperentropy respectively. Using entropy and hyperentropy, the uncertainty of various evolution and differentiation of chaotic, fractal and complex networks was further studied [11]. Glauner P proposed an electromyographic (EMG) pattern recognition method to identify motor commands for controlling prosthetics through evidence accumulation based on multiparameter artificial intelligence. Integral absolute values, variances, autoregressive (AR) model coefficients, linear cepstral coefficients, and adaptive cepstral vectors were extracted from several time periods of the EMG signal as feature parameters [12]. Thrall J H has developed a number of AI-based machining monitoring systems for optimizing, predicting or controlling machining processes [13]. Research showed that artificial intelligence promotes the generation of experimental results and promotes technological development and innovation.

Multimodal theory emerged in the west at the end of the 20th century. As a new teaching theory, it has attracted much attention in the academic circles in recent years. Multimodal theory is a phenomenon that uses the human body's multiple sensory functions, such as hearing, vision, touch and other senses, to communicate through various data resources such as sound, pictures, and actions.

II. Multimodal Theory of Language Teaching Evaluation Methods

(1) Framework design of artificial intelligence language teaching system

The artificial intelligence simulation program is guided by numerical control technology and training, and is divided into numerical simulation management system, course and data system. The numerical simulation management system is used to realize the simulation and course design of teaching. The course and data system is mainly used to save the materials used in the course and the user's personal information. The numerical simulation management system, course and data system realize data connection and data storage through the database system. The system architecture is shown in Figure 1:

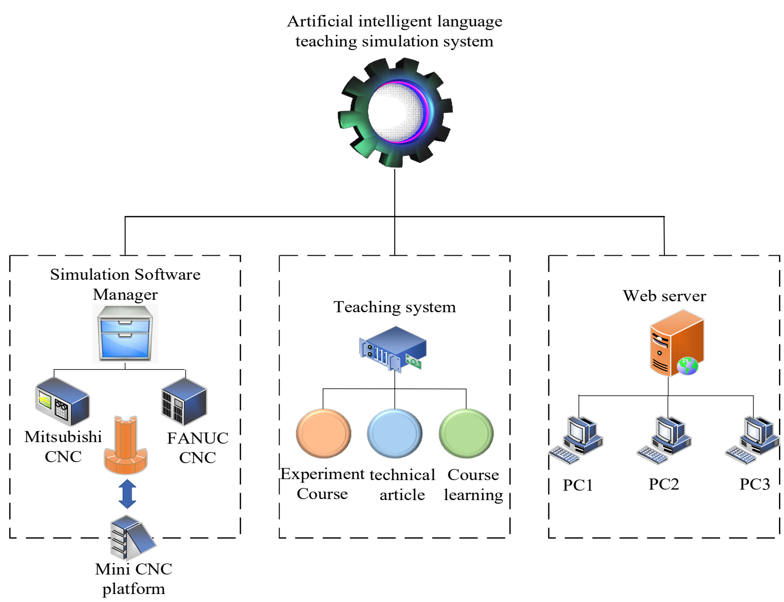


Figure 1: Artificial intelligence language teaching system framework design

The NC emulator runs on the Linux operating system as a client and uses the emulator as a program access point. The simulation software manager provides the interface of different numbers to simulate the control software. When the user simulates the software manager, the user selects the number to control the software and test the number to start. The CNC simulation software is controlled based on the movement identified by the LinuxCN control system. In the simulation mode, the control system displays the feedback signal to achieve the simulation effect. When the application platform is connected to the physical operation, the control system sends control signals to the application platform, and the application platform transmits real-time data through sensors. The general-purpose system is deployed on personal web servers and computers, which are used to run the learning system and MySQL database [14]. A control number simulator is installed on each computer, and students use the computer simulator to connect the computer to the MiniCNC application platform to perform physical operations.

(2) Application of PCOSM method in artificial intelligence teaching system

In the artificial intelligence language teaching system, each module function of PCOSM has an extremely important role in the system, and each module function affects each other to provide a better learning system for students. Specifically as shown in Figure 2.

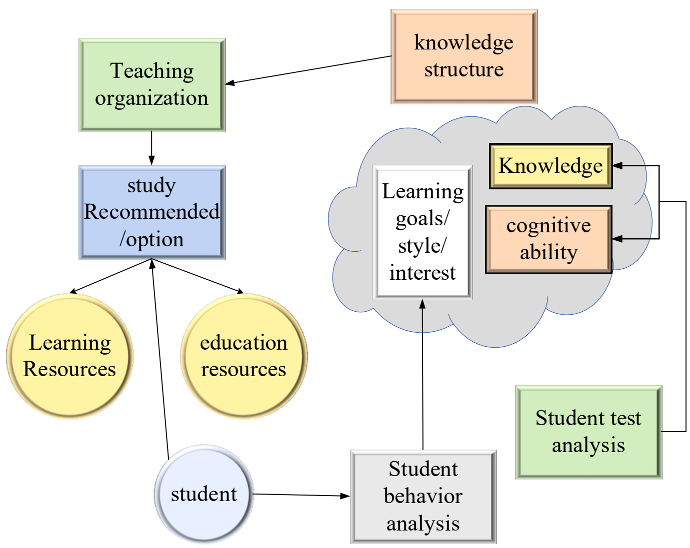


Figure 2: Use of PCOSM

The student interest model allows the system program to select the most popular educational resources according to the different educational needs of students and recommend them to them, thereby improving the effectiveness and efficiency of education. Physical modeling allows programs to select different characters for students to learn based on differences in students' learning styles, or to provide options for students to choose from with different insights into classroom language skills, or to analyze areas of understanding on a case-by-case basis. The student acquisition teaching mode allows the program to not only understand students more comprehensively, but also help each student's weaknesses, as well as provide a basis for students to organize their own learning ideas. The education system needs to provide the courses that students want to learn through the choices of students, and the different choices of different students will affect the course setting, education resource update and verification and other links [15]. Therefore, the student model should be presented to students and other observers, such as teachers, in a clear manner so that students always have a clear personal understanding of the learning process and can also be used when the course model is inaccurate.

(3) Artificial intelligence language teaching system function

The modules of the artificial intelligence training plan mainly include training and testing, resource search, reward and evaluation, etc. The functional framework of the artificial intelligence language teaching system is shown in Figure 3.

a) Learning and testing

Students can choose different subjects to study in the system, they can check books and watch courses. Subject learning tests can be conducted after the course study to review and check the knowledge learned. The tests include paper-based tests, question-and-answer tests and practice tests.

b) Resource recommendation

System education resources include: classroom videos, books, practice questions, listening, wrong question sets, classic test questions, etc. There are certain levels of recommended resources. The higher the level is, the higher the usage authority will be. Users can select training resources according to their own preferences or reference indicators. The recommended source information includes at least: subject, topic, short introduction, text volume, difficulty level, and number of views. Once the user selects the course resource, the program should provide the content of the course resource, such as text, etc. In the process of resource identification, related services such as play, pause, subscription, sharing, and preference should be provided. When playing video and audio sources, the corresponding subtitles should be synchronized. For text display features, such as objects or subtitles, users can flag words they don't know or understand, and then make queries.

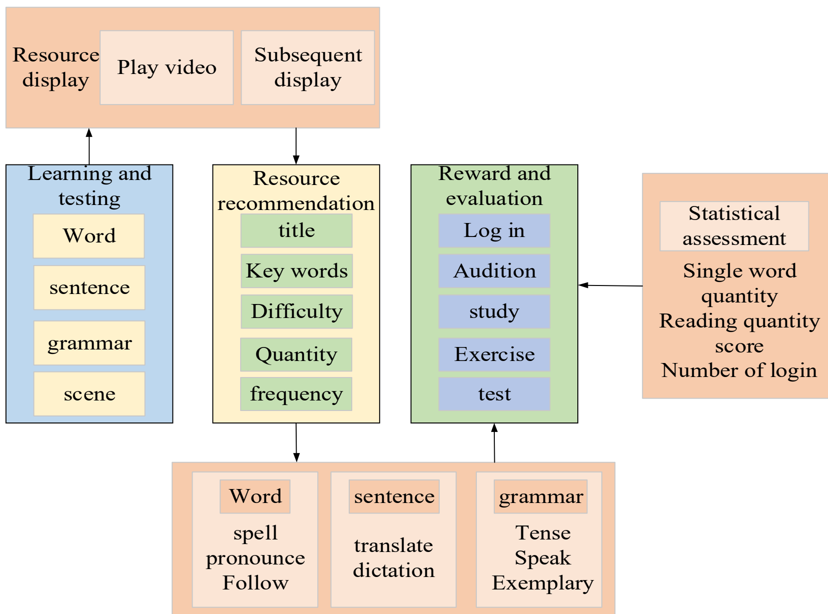


Figure 3: Artificial intelligence language teaching system function

c) Reward and evaluation

Rewards are a way to improve students' interest. Rewards include course completion rewards, login rewards, problem-solving rewards, and competition rewards. Students can compare their own academic status with the academic status of the same students around them so as to stimulate students' competitive psychology to surpass others. Evaluation is a kind of recognition for students when they have completed the learning content. When students encounter problems, they help students to solve them. When students get rewards, they give praise to students.

(4) Multimodal teaching process

Each teaching in the system has a different degree of effect. A specific process can determine the expression and communication of a specific meaning, and choosing different methods can increase the duration of interpretation, so there are various ways to choose in teaching. When choosing a combination, it is imperative to use such programs for educational activities and to determine which is the primary position and which is the secondary position. Since different methods have different uses and functions, interactions are required during use to empower individuals to use multiple modes of expression and communication [16], [17]. According to the three principles of multimodal classroom learning, teachers and students use symbols and sensory methods suitable for different classroom teaching levels. Through demonstrating relevant media, multimodal knowledge can be fully integrated into practical learning. The multi-modal teaching process is shown in Figure 4.

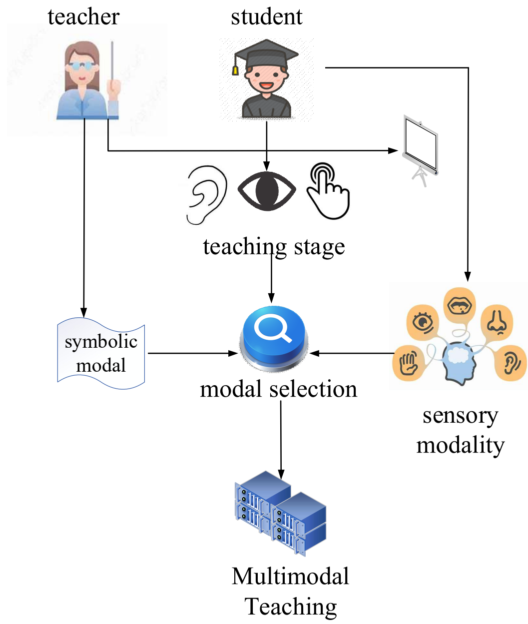


Figure 4: Multimodal teaching process

(5) Common language teaching evaluation algorithms

a) BP neural network

BP neural network is the most widely used artificial neural network. It is a multi-level feedback network that takes in through error training and backtracking computing, and uses a charge function to run backwards through the network to compute the slope [18]. BP neural network includes two parts: one is forwarding the message, and the other is the switching error between the expected output and the actual output.

The essence of the BP algorithm is a series of equations in mathematics as follows: x is supposed to be a real number. Assuming $y = g(x)$ and $t = f(g(x)) = f(y)$, the chain rule is shown in Formula 1:

$$\frac{dt}{dx} = \frac{dt}{dy}\frac{dy}{dx} \tag{1}$$

This scalar case can be extended. Supposing that $x \in R^p, y \in R^q$, g is the mapping from R^p to R^q and f is the mapping from R^q to R. If $y = g(x)$ and $t = f(y)$, Formula 2 can be obtained:

$$\frac{\partial t}{\partial x_i} = \sum_j \frac{\partial t}{\partial y_i}\frac{\partial y_i}{\partial x_i} \tag{2}$$

Using vector notation, it can be equivalently written as Formula 3:

$$\nabla xt = (\partial y / \partial x)^T \nabla yz \tag{3}$$

In Formula 3, $\partial y / \partial x$ is the n×m Jacobian matrix of g. The BP algorithm can consist of the product of each such Jacobian gradient.

The loss function is determined: For the sample (x_k, y_k), it is assumed that the output of the neural network is $\hat{y}_k = (\hat{y}_1^k, \hat{y}_2^k, ...\hat{y}_n^k)$, which is as Formula 4 and Formula 5:

$$\hat{y}_m^n = f(\beta_m - \theta_m) \tag{4}$$

$$\beta_m = \sum_d^q \omega_{hm} b_h \tag{5}$$

In Formula 4 and Formula 5, θ_m is the gateway of the m[th] node of the output layer. β_m is the input of the m[th] node of the output layer, and ω_{hm} is the connection density between the hidden layer node and the obtained m[th] node. b_h is the result of part h of the hidden layer. q is the number of hidden layer nodes. d is the number of layer input nodes, and then the root mean square grid error in example (x_k, y_k).

$$\sum_k \frac{1}{2}\sum_{m=1}^{l}(\hat{y}_m^k - y_m^k)^2 \tag{6}$$

In Formula 6, l is the number of output layer nodes.

The BP algorithm adjusts the parameters according to the gradient descent method as Formula 7 and Formula 8:

$$w = w + \Delta w \tag{7}$$

$$\Delta v = -\eta \frac{\partial E_k}{\partial w} \tag{8}$$

The gradient $\frac{\partial E_k}{\partial \theta}$ of the output layer threshold θ_m is calculated. $\hat{y}_m^k$ directly affects E_k. θ_m directly affects $\hat{y}_m^k$, and the chain rule can be used to obtain Formula 9:

$$\frac{\partial E_k}{\partial \theta_m} = \frac{\partial E_k}{\partial \hat{y}_m^k}\frac{\partial \hat{y}_m^k}{\partial \theta_m} \tag{9}$$

That is:

$$\frac{\partial E_k}{\partial \theta_m} = \hat{y}_m^k - y_m^k \tag{10}$$

The activation function is the sigmoid function. Formula 11 can be obtained by Formula 4:

$$\frac{\partial \hat{y}_m^k}{\partial \theta_m} = \hat{y}_m^k(1-\hat{y}_m^k) \tag{11}$$

$$\frac{\partial E_k}{\partial \theta_m} = \frac{\partial E_k}{\partial \hat{y}_m^k}\frac{\partial \hat{y}_m^k}{\partial \theta_m} = \hat{y}_m^k(1-\hat{y}_m^k)(y_m^k - \hat{y}_m^k) \tag{12}$$

b) Student learning interest sub-model LIFSM

In this section, a vector field model will be used to represent a model of learning interest to test the behavioral traits of other behaviors to define educational resources. The format is:

$$R = \{(x_1, y_1, z_1), (x_2, y_2, z_2), \ldots.(x_n, y_n, z_n)\} \tag{13}$$

x_i is the feature that can represent the source of education and y_i is the density of the feature x_i in R, z_i is a function of the elements x_i. The difference in interest length is noted to improve feature development, and a useful training model is created and defined as:

$$LIFSM = \{(x_1, y_1^S, y_1^L, d_1, z_1, parent_1), \ldots.,(x_n, y_n^S, y_n^L, d_n, z_n, parent_n)\} \tag{14}$$

Among them, x_i is the feature item, y_i^S represents the short-term interest weight of x_i, y_i^L represents the long-term interest weight of x_i, d_i is the update time of the long-term interest weight, and z_i is the x_i category to which it belongs. Parenti is the parent feature item of z_i, parenti will be 0 when there is no parent feature.

Short-term interest represents the interest of students in a relatively short period of time, and its calculation formula is:

$$Y_i^S = \frac{1}{N}\sum_{m=1}^{N}\frac{1}{S_m}\sum_{k=1}^{S_m} y(x_i, p_k) \tag{15}$$

N is the statistical time size (usually in days), and s_m is the number of system pages that students browse on the mth day. k is the weight of ti in the current page feature vector Pk, and the calculation formula is shown in Formula 16.

$$y(x_i, p_k) = \frac{f(x_i, p_k) \times \log\left(\frac{m}{mt_i} + 0.0.1\right)}{\sqrt{\sum_{p_k \in P}^{x_i \in X} xf(x_i, p_k) \times \log\left(\frac{m}{mp_k} + 0.0.1\right)}} \tag{16}$$

$xf(x_i, p_k)$ is the number of times contained x_i in the page p_k, X is the set of feature items, P is the set of pages, m is the total number of pages, and m_{xi} is the number of pages containing x_i that appear, const(P_k) is the extra parameter of behavior in the P_k learner, and the value formula of const(P_k) is as shown in Formula 3 :

$$const(p_k) = \begin{cases} 0, \frac{timep_k}{wnp_k} \prec TH \\ 1, \frac{timep_k}{wnp_k} \geq TH \\ 2, save, download, pr\text{int}, mark \end{cases} \tag{17}$$

time P_k is the total time students take to complete pages P_k and P_k while reading P_k pages of text on pages P_k and wn P_k. All weights are taken simultaneously without summation [19].

Long-term interests are the needs of students in the long-term education system, which generally do not change easily, and are the main source of data for assessing students' learning needs. However, students' interests will change and forget with the time world and students' understanding. Of course, with the gradual increase of short-term interests, new long-term interests will also appear. Therefore, when calculating long-term returns, time and short-term returns are also combined, as shown in the formula:

$$Y_i^l = Y_i^{l-pre} \times e^{-\frac{\ln 2}{h \times l^{cur}}} (d - d_i) + Y_i^S \tag{18}$$

c) Knowledge mastering sub-model KMFSM

There is a lot of uncertainty in the judgment of students' learning, and it is more advantageous to use Bayesian network to deal with this situation, so this section will also use Bayesian network to build a teaching model [20].

In 1763, the English mathematician and theologian Reverend Thomas Bayes introduced the famous Bayesian theory and solutions. The math is described as:

$$P(H \mid E, c) = \frac{P(H \mid c) * P(E \mid H, c)}{p(E, c)} \tag{19}$$

Among them, c is the preliminary information, E is the additional element, H is the reliable predictor, and $P(H \mid E, C)$ is the probability factor. $P(H \mid C)$ is the precondition of c, and H is the probability of the previous function, $P(E \mid H, C)$ is the probability of proving E. Of course, when both H and c are assumed to be true, $P(H \mid C)$ is a factor, which has nothing to do with H.

G is a vertex formed by a random variable set X, and the function logic relationship is a directed acyclic graph of arcs. Assuming that the vertex of G is a subset variable set of random variables M_i, and P is the conditional probability of event M_i occurrence under the premise that the πi event occurs, the joint conditional probability distribution on the random variable set M is defined as:

$$p(M_1, M_2, M_3, ...) = \prod p(M_i \mid \pi_i) \tag{20}$$

Bayesian network probabilistic decision is made by considering probabilistic data distributions and computing probabilities to make optimal decisions.

A student's grade can be calculated according to Formula 21:

$$score = \frac{\sum_{m=1}^{Num}(\sum_{n=1}^{4}(QueTypeScore_{mn} * \omega_n))}{Num} \quad (21)$$

$QueTypeScore_{mn}$ is a function of the new query type numbered m. Given the status of the multiple-choice and spelling questions, the correct answer counts is calculated as 1, and the error counts is measured as 0. Wn is the score for the j - type question and Num is the number of words tested in the test.

III. Experimental Design of Language Teaching Evaluation Based on Multimodal Theory

(1) Experimental process

Three classes were randomly selected at a university to conduct the experiment, and the course selected for evaluation was English. In order to avoid experimental errors, sophomore students of the same major were selected to conduct the experimental test. Among them, 1 class is taught by single-modal learning method, 2 classes are taught by dual-modal learning method, and 3 classes are taught by multi-modal learning method. After 18 weeks of language teaching, students in the three classes were tested for class attention, teacher-student interaction, student achievement, student satisfaction and teacher satisfaction, and the benefits of multimodal teaching were analyzed.

(2) Experimental data

The three selected classes were of the same major. In order to avoid experimental errors, the teaching age of teachers was not much different. The specific data of students are shown in Table 1, and the specific data of teachers are shown in Table 2.

Table 1: student data sheet

	Class 1 students	Class 2 students	Class3 students
number of people	70	72	70
male to female ratio	4:3	4:5	3:4
average age	20	20	20
class time	45min	45min	45min

Table 2: Faculty data sheet

	Class 1 teacher	Class 2 teacher	Class3 teacher
number of people	10	10	10
male to female ratio	1:1	2:3	3:2
average age	41	35	40
class time	45min	45min	45min

(3) The purpose of the experiment

The experiment was conducted in order to test the impact of multimodal theory-based language teaching evaluation research on students and teachers in artificial intelligence scenarios, observe the difference between multimodal teaching and single-modality teaching, promote the development of multimodal language teaching, improve classroom efficiency and students' interest in learning.

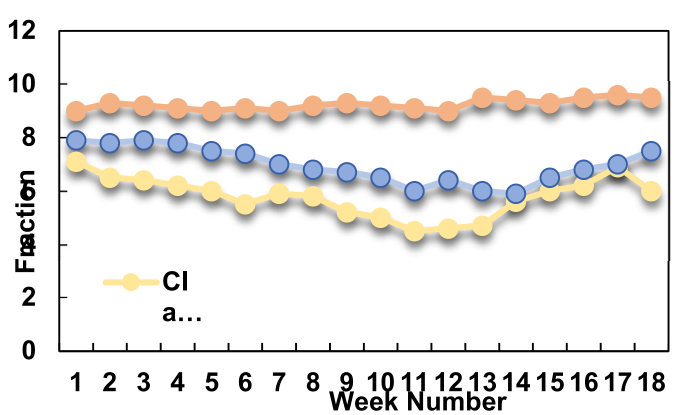


Figure 5: Student attention test

IV. Experiment Results of Language Teaching Evaluation Based on Multimodal Theory

(1) Student attention test

Class 1, class 2, class 3 conducted language teaching according to single-modal multi-modal, dual-modal and multi-modal respectively. After the weekly teaching, the teacher rated the students' attention in class with a full score of 10 points. The results are shown in Figure 5.

It can be seen from Figure 5 that the attention of class 3 students is higher than that of class 2 and class 1. The attention of students in class 3 is relatively stable, there is not much fluctuation effect, and the classroom efficiency is better. Compared with class 3, the attention of students in class 2 does not fluctuate significantly. Affected by the factors of the exam at the end of the month, it first decreases and then increases. The attention fluctuations of the students in class 1 are the most obvious, and after the attention drops, there is a clear upward trend. Compared with dual-modal teaching, students' attention increases by 32% in multi-modal teaching, and 59.6% in single-modal teaching. Compared with single-modal and dual-modal teaching, multi-modal teaching can attract students' interest in learning and improve students' attention.

(2) The degree of interaction between teachers and students

At the end of each week's teaching, the teacher counted the number of classes in class 1 of single-modal teaching, class 2 of dual-modal teaching, and class 3 of multi-modal teaching, and observed the degree of teacher-student interaction in the three classes. The results are shown in Figure 6.

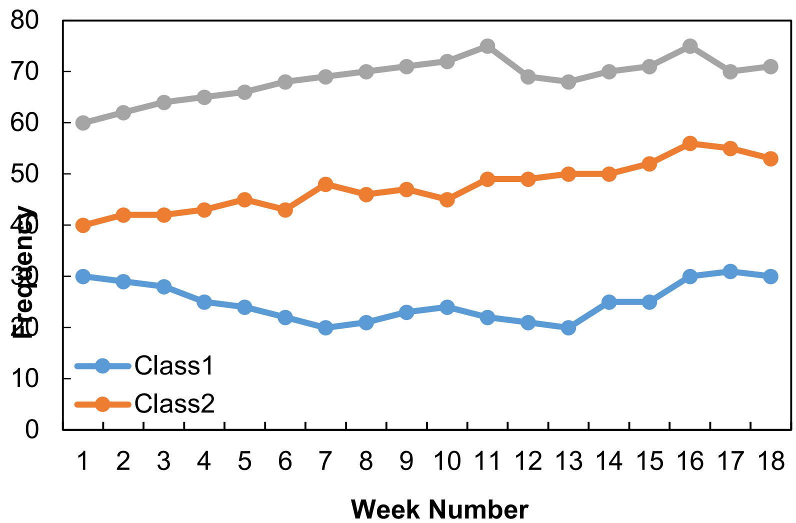


Figure 6: Degree of interaction between teachers and students

It can be seen from Figure 6 that the interaction between teachers and students in class 3 is much higher than that in class 2 and class 1. The average number of interactions between students in class 3 is 68.6, the number of interactions between students in class 2 is 47.5, and the number of interactions between students in class 1 is 47.5. The number of interactions between teachers and students in class 3 is 21.1 higher than that of class 2, and 43.6 higher than that of class 1. The degree of interaction between teachers and students in class 2 and 3 shows an overall upward trend, and class 1 shows a trend of first decreasing and then increasing. The level of interaction between teachers and students in the class is the most stable. Multimodal learning language teaching can promote the interaction between teachers and students, improve students' interest in learning and teachers' interest in teaching.

(3) Student achievement test

Three classes were tested every three weeks. In order to avoid experimental errors, the students' test papers and test time were the same. The full score of the papers was 100 points, and the average score of the class was taken to observe the impact of multimodal language teaching on students' performance. The results are shown in Figure 7.

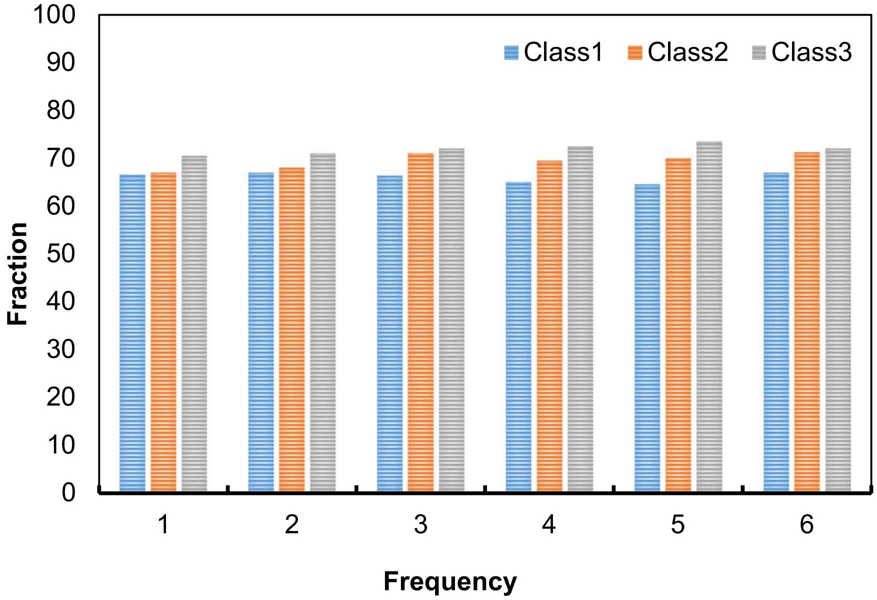
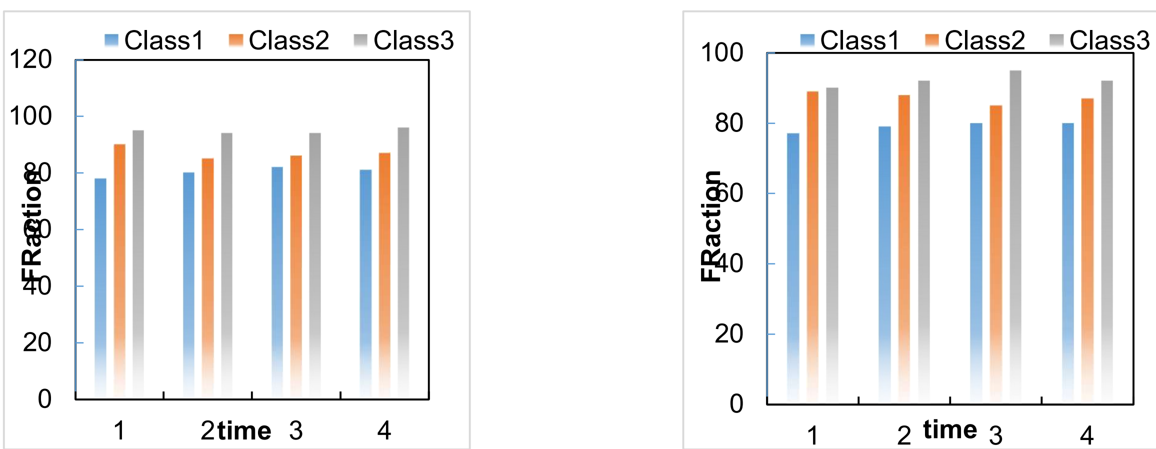


Figure 7: Student achievement test

As can be seen from Figure 7, the average grade of class 3 is higher than that of class 2 and class 1, and the grades of the three classes are very stable without much fluctuation. Among them, the average score of class 1 is 66.05, the average score of class 2 is 69.45, the average score of class 3 is 71.91. The average score of class 3 students is 3.5% higher than the average score of class 2, the average score of class 3 students is 8.8% higher than the average score of class 1. Students who are taught in multimodal have higher grades than those who study in dual mode and those who study in single mode, and multimodal learning can improve students' learning level.

(4) Student satisfaction and teacher satisfaction

After the experiment, students and teachers in 3 classes were asked to rate their satisfaction with the teaching method once a month, with a full score of 100 points, and the satisfaction of students and teachers in 3 classes was observed. The results are shown in Figures 8.



A: Student satisfaction

B: Teacher satisfaction

Figure 8: Student satisfaction and teacher satisfaction

It can be seen from Figure 8 that the satisfaction of teachers and students in class 3 is higher than that of class 1 and class 2. The average score of student satisfaction in class 3 is 94.75, the average score of student satisfaction in class 2 is 87, and the average score of student satisfaction in class 1 is 80.25. The average satisfaction score of class 3 has an increase of 13.75 compared with class 2, and an increase of 15.5 compared to class 1. The average score of teacher satisfaction in class 3 is 92.25, the average score of teacher satisfaction in class 2 is 87.25, and the average teacher satisfaction score in class 1 is 79. The average satisfaction score of teachers in class 3 is 5 higher than that in class 2, and 13.25 higher than that in class 1.

V. Discussion

This paper conducted multimodal teaching experiments in different classes, and proved the benefits of multimodal theoretical teaching. Although the multimodal theory has achieved remarkable results in language teaching, there are still some shortcomings in this teaching experiment: The teaching experiment was carried out for a short period of time, and only 18 weeks could not fully prove that the multimodal theory was suitable for long-term in teaching practice, and the drawbacks of applying multimodal theory to language teaching had not been fully revealed, the objects of teaching experiments were limited. The circumstances in which students attend classes also had an immeasurable impact on the experimental results.

VI. Conclusions

This paper studied the language teaching evaluation based on the multimodal theory in the artificial intelligence scenario, conducted experiments on different classes, and found the different effects of single-modality, dual-modality and multimodality on language teaching through experiments. The effect of multimodal teaching on improving students' attention in class and the degree of interaction between teachers and students is better than that of single mode. Students and teachers are also more satisfied with the language teaching method of multimodal theory. Multimodal theory teaching can stimulate students' interest in learning and motivation, the language teaching of multimodal theory is more suitable for the development of the times and has a role in promoting the education industry.

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