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Research on Multi-objective Optimization Algorithm for Optimal Design of Art Education Curriculum Based on Emotional Learning Model

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ABSTRACT

Teaching curriculum design is centered around the three dimensions of affective attitudes and values, processes and methods, and knowledge and skills, which fit with the affective learning model composed of emotion, learning and cognition. This paper brings affective analysis into art curriculum design and proposes a learner affective model for teaching art courses driven by multiple teaching objectives. Through multi-objective optimization, we give an interactive decision-making method based on a hierarchical affective cognitive model to simulate learners' affective decision-making under multi-objective-driven teaching. Analyze the teaching process of incorporating affective learning strategies in an art course, and examine the interrelationship between affective engagement and learners' knowledge construction in three rounds of learning activities. To analyze the impact of affective learning strategies on students' learning outcomes. The experimental group (affective learning strategy group) significantly outperformed the corresponding creativity abilities of students in the control group in the three components of surprise, originality and challenge after the teaching of the art course, and the affective learning strategy succeeded in stimulating students' creativity. The combination of affective learning model and curriculum design can enhance the effectiveness of art education.

Keywords: multi-objective optimization, affective learning model, interactive decision making, curriculum optimization

1. Introduction

Through art education, cultivating students' aesthetic quality and emotion, improving students' art knowledge and skills, developing students' intellect, helping students shape a healthy personality, and realizing students' overall development are the important goals of art education in colleges and universities [1-4]. However, for a long time, China's art education has been characterized by the

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misunderstanding of educational ideas, such as "light on applied art, light on pure art, light on art theory, and light on art skills", which has led to serious deviations and misalignments between educational practices and art curricula in art education [5-8], and resulted in the relatively low level of theoretical knowledge and practical application ability of art majors. As a result, the theoretical knowledge and practical application ability of art students are relatively low, and the applied characteristics of art education have not been fully demonstrated. With the development trend of diversification of social demand for art talents, it is crucial to strengthen the cultivation of art talents' quality [9-12]. Therefore, in the practice of art education, it should be combined with the reality, on the basis of a full understanding of the current situation of art education, the scientific positioning of art education, on the basis of establishing a correct concept of education, combined with the advantages of educational resources, as well as the objectives of art education, optimize the design of the curriculum system, and improve the comprehensive quality of students [13-16].

Multi-objective optimization algorithm is a class of algorithms used to solve optimization problems with multiple objective functions. In practical problems, there are often multiple conflicting objectives, which requires considering multiple objectives simultaneously and finding the best compromise between them [17-19]. The goal of multi-objective optimization algorithms is to find a set of solutions and make this set of solutions optimal or near-optimal in each objective function. Common multi-objective optimization algorithms include genetic algorithms, particle swarm optimization algorithms, simulated annealing algorithms, etc., which play an important role in the optimal design of art courses [20-23].

This paper proposes three major goals for the optimal design of art education curriculum from the three dimensions of teaching goals (emotion and values, process and method, knowledge and skills). An affective learning model is constructed to classify learners' affective factors into three categories: affirmative, negative and intrinsic hostility. Combined with the learner affective model, we propose a learner affective simulation decision-making method using multi-objective optimization evaluation for multi-objective-driven teaching. Step-by-step design of an art education program teaching experiment to integrate affective learning strategies into art curriculum teaching. Analyze the impact of affective engagement on learners' knowledge construction, and comparatively analyze the role of affective learning strategies in art education curriculum design.

2. Optimizing the design of art education curricula

2.1. Course Optimization Design Objectives

First, cultivate students' creative thinking. In the teaching process, help students establish a variety of creative thinking models, including horizontal thinking, vertical thinking, logical thinking and so on. Through the flexible use of different thinking models, they can better understand what they observe, generate richer thinking, and transform the thinking into the presentation of the design. Through a series of methods to help students better understand and apply the knowledge they have acquired, so as to help students get inspiration from daily experience and transform it into more concrete image expression.

Second, to improve students' comprehensive literacy. Through the teaching of the curriculum, students are helped to better understand design. However, the current art curriculum pays more attention to the comprehensive literacy of young people, a concept that is lacking in traditional teaching. Curriculum design that promotes comprehensive literacy requires students to explore, practice, and experience the process of deeply understanding and practicing life concepts that are beneficial to social and individual development.

Dewey's naturalism states that art not only enhances daily experiences, but also transforms those experiences into personalized actions. The study of art can help young people to obtain spiritual baptism, stimulate creativity, and make their minds more open, so that they can become more colorful.

In addition, the development of creative thinking in the design of the art curriculum can also help students to better understand the relationship between human beings and the world around them. Through this program, students can benefit from comprehensive practice, further understand the core content of the curriculum, and enhance their excellent personal qualities including exploratory, innovative, coordinated, perseverance, and the spirit of courage and challenge.

Thirdly, to enhance students' practical skills. The realization of design and art must make full use of resources in order to better reveal and explore students' unique personal attributes. Since art is essentially an open-minded discipline, art teaching does not depend solely on a solid and complete template, and students need to practice and think more about design. This teaching design guides students to utilize a variety of resources for design practice, with the aim of providing more opportunities to enhance students' practical skills, encouraging them to take on challenges, and boosting their self-confidence so as to cultivate a stronger sense of independence.

2.2. Emotional Learning Model of the Brain

2.2.1. Emotion, Learning and Cognition. Emotion is a special function of the human brain, which can reflect whether the individual's needs are satisfied or not, and can reflect the human body's attitude towards some external state of affairs. When the individual's needs to achieve a certain level of satisfaction, it will be brewed with its corresponding such as happy, happy good emotions. On the contrary, when the needs are not satisfied, it will produce more negative emotions such as hatred and anger. Positive emotions become a motivating factor that drives positive cognition and contributes to the accumulation of learning outcomes. Emotion and cognition cannot exist independently of each other in the learning process; they influence each other and complement each other.

2.2.2. Emotional Learning Model. Brain Emotional Learning model, which is a computational model based on the way of information transfer between the amygdala tissue and the orbitofrontal cortex tissue in the human brain, referred to as the A-O system model [24-25].

The structure of the BEL model is shown in Fig. 1. The BEL model is designed on the basis of an incomplete simulation of the way in which emotional information interacts between the amygdala and the orbitofrontal cortex, and is divided into two main components: the amygdala and the orbitofrontal cortex. The amygdala is an important part of the brain for processing and memory processing of emotion, while the orbitofrontal cortex mainly serves to laterally inhibit and regulate overall emotional learning. This part of the amygdala mainly processes stimuli from the thalamus, while the part of the prefrontal cortex is responsible for processing stimuli provided by both sources, the sensory cortex and the amygdala.

For each set of emotional signals, corresponding nodes are set up within the A-O system to process them. The sensory input signal SI is computed by the sensory input function (SIF) and the reward input signal is computed by the emotional cue function (ECF). The sources of input signals to the amygdala are mainly from the sensory input signal SI, the reward signal REW, and the signal Ath from the thalamus, and the stimulus signals received by the orbitofrontal cortex are mainly from the sensory cortical input signal SI and from the amygdala, and are not stimulated by signals from the thalamus.

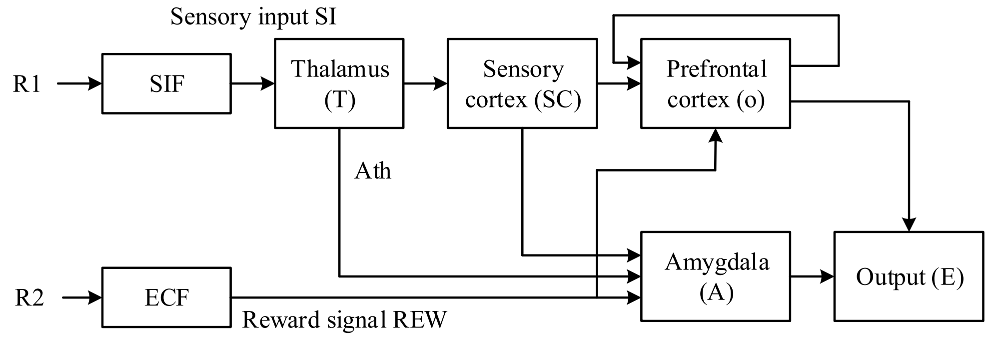


Fig. 1. BEL model structure

If we assume that the sensory input has m stimulus signal (i.e., SI is m -dimensional, $SI=[SI_1, SI_2 \cdots SI_m]$), the thalamus isolates the most salient value A_{th} of the sensory input signal SI and then delivers A_{th} to the amygdala, i.e.,:

$$A_{sh} = \max(SI) \tag{1}$$

Output values A_i for the amygdala and O_i for the orbitofrontal cortex, respectively:

$$A_i = SI_i \cdot V_i, i = 1, 2, \cdots m, A_{m+1} = A_{zh} \cdot V_{m+1} \tag{2}$$

$$O_i = SI_i \cdot W_i, i = 1, 2, \cdots m \tag{3}$$

where V_i in Eq. is the weight value of its corresponding node A_i and W_i is the weight value of its corresponding node O_i.

The BEL model of the A-O system has a special bionic weights learning approach, and the weight adjustment laws of the amygdala and orbitofrontal cortex are shown in Eqs. (4) and (5):

$$\Delta V_i = \lambda_v \left[SI_i \cdot \max(0, REW - \sum_{i=1}^{m+1} A_i) \right], \Delta V_{m+1} = \lambda_v \left[A_m \cdot \max(0, REW - \sum_{i=1}^{m+1} A_i) \right] \tag{4}$$

$$\Delta W_i = \lambda_w \left[SI_i \cdot (E' - REW) \right] \tag{5}$$

where Eq. λ_v, λ_w is the learning rate within the amygdala and orbitofrontal cortex, respectively, and E' is the BEL model output of the amygdala portion when it is not subject to stimulus signals from the thalamic tissue, denoted:

$$E' = \sum_{i=1}^{m+1} A_i - \sum_{i=1}^{m} O_i - A_{ih} \cdot V_{m+1} \tag{6}$$

As can be seen from the formula, the positive and negative of the weights regulation law ΔV_t within the amygdala is consistent with SI_i from beginning to end which also indicates that the emotional stimulus signals within the amygdala will be permanently memorized and the state always maintained as long as they have been learned. Then the weight regulation step ΔW_i in the frontal cortex can be positive or negative, indicating that the frontal cortex serves the function of inhibiting and correcting the amygdala during the learning process, and through the guidance of the reward signal REW, it reduces the error and guides the amygdala to the predefined expectation value for learning.

The output of the BEL model is:

$$E = \sum_{i=1}^{m+1} A_i - \sum_{i=1}^{m} O_i \tag{7}$$

2.3. Modeling Learner Emotions in Multi-Objective Driven Instruction

2.3.1. Classification of learners' affective factors. Psychology recognizes positive emotions (or positive emotions) as positive, force-enhancing emotions that satisfy a person's needs. For example, happy, proud, elated, proud ...... of these positive emotions can improve human activity. And can not meet the needs of people, negative, force-reducing emotions for negative emotions (or negative emotions), for example, shame, sadness, nervousness, fear of negative emotions to reduce people's activity ability. In the emotion model, the main purpose is to distinguish 14 common emotions according to 3 dimensions of pleasure, activation and dominance, and to divide them into positive and negative emotions.12 emotion classifications are shown in Table 1.

For the influence of learners' emotions, some scholars believe that it mainly focuses on several key points such as anxiety, motivation, and self-confidence (self-efficacy).

Table 1. 12 emotional categories

Positive emotion	Interest, Joy, Surprise, Be willing to
Negative emotion	Sad, Anxiety, Guilt, Be shy, Intrinsic antagonism
Hostility	Anger, Loathing, Belittle

2.3.2. Learner Affect Model. The dynamics of students' emotions during the learning process were demonstrated through the Learning Mate Model. The learner emotion model is shown in Figure 2, which consists of two coordinate axes and four quadrants, with the horizontal axis being the positive emotion-negative emotion axis and the vertical axis being the learning-non-learning axis. Students' learning begins in quadrant I, which shows the emotions of awe, satisfaction and curiosity about the new learning content. Then the student's affect transitions to Quadrant II, which manifests itself in the emotions of confusion and disorganization caused by the student's unanswered questions and doubts about the new issue. At this point students begin to develop certain negative emotions and the construction of new knowledge occurs. During the learning process, when difficulties or failures are encountered, the student's emotions then shift to Quadrant III. If the student's emotion can not get effective help emotionally and cognitively, the student's emotion will be even lower, resulting in more negative emotions, and ultimately hindering learning, resulting in learning activities can not be completed properly. And when students get help in time, students cognitively out of the misconceptions when they are low emotionally relieved, emotionally transferred to Ⅳ this time students have a new hope, a stronger new desire to explore and curiosity, to continue the new learning and from the Ⅰ quadrant of the week again and again.

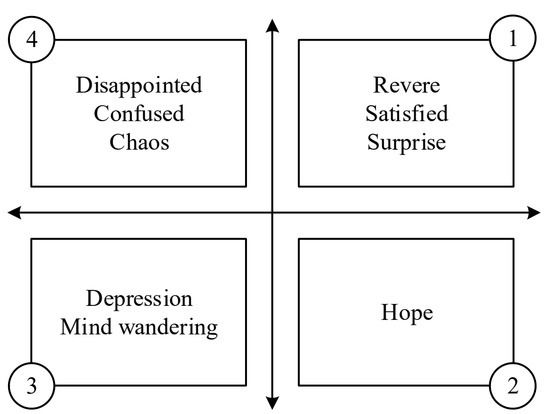


Fig. 2. The learner's emotional model

2.3.3. Emotionally interactive decision-making methods. Conventional multi-objective decision-making methods cannot fully reflect the subjective preferences of the decision maker, while interactive decision-making methods reflect the preferences of the decision maker through information interaction with the decision maker, but the solution process requires the participation of the decision maker in the whole process, which increases the workload and cognitive burden of the decision maker. For this reason, it can be considered to construct an emotional virtual man, which can replace the decision maker to complete the decision solving process through the emotional interactive decision-making method.

There are many kinds of solution methods for multi-objective optimization problems. When choosing a solution method, two aspects are considered:

1) Whether the optimal solution is a non-inferior solution to this multi-objective problem and the effectiveness of the method.

2) Whether the optimal solution can satisfy one's emotional preference.

The multi-objective optimization problem can be described as:

$$\max f(x) = \{f_1(x), f_2(x), \ldots, f_1(x)\} \tag{8}$$

$$s.t. \begin{cases} g_i(x) \le 0, i = 1, 2, \ldots, m \\ X = (x_1, x_2, \ldots, x_n)^T, x_* \in R \end{cases} \tag{9}$$

Two indicators, the degree of achievement of objectives and the degree of overall harmonization, are given below. The degree of objective attainment reflects the degree of satisfaction achieved by each objective function in comparison with the ideal value. The overall coordination degree is a bridge to achieve the transformation of multi-objective problems into single-objective problems, and measures the overall objective satisfaction of the optimization problem through the Euclidean distance.

According to the definition of evaluation indexes, the degree of achievement of objectives and the overall coordination degree are defined as follows. The achievement degree function of each objective function is:

$$\mu(f_i(x)) = \frac{f_i(x^*) - f_i^{\min}}{f_i^{\max} - f_i^{\min}}, i = 1, 2, \ldots, l \tag{10}$$

where x^* is a non-inferior solution to the optimization problem, it is clear that the larger the value of the objective attainment function $\mu(f_i(x))$, the closer the corresponding objective function takes to the ideal value.

Since distance can measure the proximity of two quantities in space, Euclidean distance is applied to define the overall coordination degree. Here, the Euclidean distance between the current decision value of the objective function and the ideal value is selected:

$$d_1 = \sqrt{\sum_{i=1}^{l} \left[f_i(x) - f_i^{\max} \right]^2} \tag{11}$$

The Euclidean distance between the current decision value and the lower bound value of the objective function:

$$d_2 = \sqrt{\sum_{i=1}^{l} \left[f_i(x) - f_i^{\min} \right]^2} \tag{12}$$

The Euclidean distance between the ideal and lower bound values of the objective function:

$$d_3 = \sqrt{\sum_{i=1}^{l} \left[f_i(x) - f_i^{\min} \right]^2} \tag{13}$$

Define the overall coordination degree function for a multi-objective optimization problem:

$$\lambda(d) = \frac{d_1 + d_2}{d_1 + d_3} \tag{14}$$

For a specific multi-objective optimization problem, the decision maker can determine the expected value of each objective function according to the actual conditions and their own subjective desire. The acceptable lower limit value of each objective function can also be obtained through mathematical planning methods, so when the problem is determined, $f^{\max}, f^{\min}$ can be determined, and the value of d_3 can be calculated directly at this time. As the objective function approaches to the ideal value, the value of d_1 decreases and the value of d_2 gradually becomes larger, so the overall coordination degree $\lambda(d)$ will gradually become larger.

The decision value of the affective interactive decision-making method is decided by the rational decision-making module and the affective decision-making module comprehensively, which gives the adjusted value of the achievement degree of each objective function respectively. The two parts of the goal attainment values represent the individual's rational and emotional choices, respectively. The rational decision module is a conventional mathematical planning solution process, i.e., to find the optimal solution that maximizes the overall coordination without considering the subjective desire of the decision maker. For the multi-objective decision-making problem, the rational decision-making process is:

$$\begin{cases} \max \lambda(d) \\ x \in X \end{cases} \tag{15}$$

Solving the above optimization problem yields the rational decision-making optimal solution $\tilde{x}^*, k = 1, 2, \ldots$. Calculate the current objective function value $\tilde{f}_i(\tilde{x}^*)$, as well as the goal attainment function $\tilde{\mu}(\tilde{f}_i(\tilde{x}^*))$ and the overall coordination function $\tilde{\lambda}(d)$.

The Rational Decision Making module takes the maximum overall coordination function as the only objective, and obtains the adjusted value of the goal attainment when the maximum overall coordination is satisfied:

$$_{\Delta}\mu_{1,k}^{i} = \tilde{\mu}(\tilde{f}_i(\tilde{x}^k)) - \mu(f_i(x^{k-1})) \tag{16}$$

On the basis of the hierarchical emotion cognition model, the emotion cognition decision-making module can be constructed. The purpose of the introduction of emotional factors is to fully reflect the subjective wishes of the decision maker in the process of solving multi-objective decision-making problems, thus eliminating the need for the direct involvement of the decision maker and reducing the burden on the decision maker. In the multi-objective decision-making problem, the subjective desire of the decision maker is mainly reflected in the priority of each objective function and the requirement of the satisfaction of each objective function.

Accordingly, the adjusted value of goal attainment given by the emotional decision-making module is obtained:

$$\Delta\mu_{2,k}^{'} = \begin{cases} -sign(\chi)^* q_i, M_{Pcur} \le 0 \\ -sign(M_{Acur}^* M_{I\lambda cur})^* q_i, M_{Pcur} > 0 \end{cases} \\ k = 1, 2, \ldots, i = 1, 2, \ldots, n \tag{17}$$

The emotional virtual man gives a combined adjusted value for goal attainment based on decision information from both the rational and emotional decision-making modules:

$$\Delta\mu_k^{'} = (1-\beta)\Delta\mu_{1,k}^{'} + \beta\Delta\mu_{2,k}^{'} \tag{18}$$

where, β is the coefficient of the degree of emotional assistance, and $\beta \in [0,1]$. The emotional assistance coefficient is usually chosen to be below 0.5.

After the virtual person makes a decision, the original multi-objective optimization problem is transformed according to the comprehensive adjusted value of the degree of goal attainment:

$$\max \lambda(d)$$
$$s.t.\begin{cases} \mu(f_i(x)) \geq \mu_{k-1}^i + \Delta\mu_k^i \\ \cdots \\ \mu(f_i(x)) \geq \mu_{k-1}^i + \Delta\mu_k^i \\ x \in X \end{cases} \tag{19}$$

The optimal solution for solving the planning problem is the decision-making solution with the involvement of an emotional avatar x_k^*. That is:

$$\begin{cases} \mu(f(x)) \Rightarrow \text{Decision makers attach importance to objective function} \\ \qquad s = \sqrt{\sum_{i=1}^{n}(\mu_k^{'} - \mu_{k-1}^{'})\hat{}2} \leq 0.1 \end{cases} \tag{20}$$

That is, when the optimal solution is found so that the ranking of the degree of goal attainment meets the conditions of the decision maker's attention to each objective function and the standard deviation of the change of the goal attainment index, the optimal solution found by the affective interactive decision-making method is considered to be the optimal solution of the multi-objective optimization problem. Otherwise, the next round of interactive decision-making process continues until the proposed solution meets the above conditions.

3. Design and Implementation of Emotional Learning Strategies into the Fine Arts Curriculum

First, the design strategy of collaborative knowledge construction activities driven by emotional engagement is proposed to guide the design and implementation of specific learning activities.

Next, an undergraduate course, Fine Arts, from a comprehensive institution was selected as the practice field, and the course objectives and content, course support platform, learner characteristics and teaching practice arrangements were analyzed.

Then, three rounds of knowledge construction learning activities were practiced using a design-based research methodology. By analyzing the knowledge construction and emotional engagement of each round of activities, problems were identified and improvement measures were proposed. Interventions were carried out in the next round of teaching practice, and the effectiveness of the interventions was assessed through effect analysis.

3.1. Experimental design

In order to ensure the accuracy and credibility of the experimental results of this study, the gender ratio of the students in the two classes and the basic situation of the relevant art abilities need to be ensured firstly before the formal implementation of the teaching practice activities. Therefore, in this study, the learning effectiveness test was divided into a pre-test and a post-test, and the content of the pre-test and post-test was the same for both classes, and both groups of students were tested before the experimental teaching, and the post-test was conducted immediately after the end of the experimental teaching activities.

The performance on the pre-test, i.e., the learning effectiveness test, before the start of the formal experimental teaching is denoted by S1 for the experimental group and S2 for the control group.

X1 and X2 denote the practical teaching activities related to the two groups of students under two different teaching modes, i.e., the experimental group that was taught using the affective teaching mode, and the control group that was taught using the traditional teaching method. The experimental period of both groups was six weeks.

The experimental group and the control group were given a post-test at the end of the experimental teaching, in which the second test of the performance on the learning effectiveness test was indicated by N1 for the experimental group and N2 for the control group, and K1 represented the performance of the experimental group's creativity at the end of the experimental teaching, and K2 represented the performance of the control group's creativity at the end of the experimental teaching. The test related to the situation of the students' attitude towards learning at the end of the experimental teaching in the two groups is denoted by Q, Q1 for the experimental group and Q2 for the control group.

3.2. Research Process and Structure

The specific process of this study is described in detail:
1) Determine the purpose of the study.
2) Collect relevant information: according to the theme of this research, summarize the required information by searching and collecting relevant contents on paper media as well as network resources.
3) Retrieve relevant literature: read and screen the collected relevant literature, and organize the relevant literature.
4) Define the experimental subjects: the school is a comprehensive institution and the relevant topic of this study. It was decided that two classes of first grade students in the school would be the experimental subjects.
5) Developing the research plan: According to the research purpose, the design of the teaching experiment of this study was carried out with a non-randomized experimental control group pre and post-test design in a quasi-experimental study.
6) Determine the teaching unit: establish the relevant teaching unit according to the difficulty of the students' learning situation.
7) Conducting pre-tests: Before the formal experimental teaching activities began, the quizzes were distributed to the students of the two classes.
8) Conducting teaching experiments: according to the design of teaching experiments to ensure the teaching progress, the experimental group was taught by the affective teaching method, and the control group was taught by the traditional teaching method.
9) Post-experiment: After the completion of the experimental teaching, two questionnaires, the Learning Effectiveness Measurement Form and the Learning Attitude Questionnaire, were distributed in the last class of the teaching, and the creativity scale was filled in for the students' creative works.
10) Implementation of questionnaire analysis and statistics: the collected questionnaires were analyzed and counted to draw conclusions.

3.3. Research variables

According to the different control subjects of the research variables, this study divides the research variables into three main categories, and the specifics of these three categories are as follows:

The first category is the self-variables. Different teaching methods are the self-variables of this study. Therefore, in the teaching experiment, the experimental group and the control group implemented the affective teaching method and the traditional teaching method respectively.

The second category is dependent variable items. They are learning effectiveness, learning attitude and creativity.

The third category is control variables. The control variables in this study mainly refer to the time and place of teaching, students' basic abilities and status, and even the environment in which the teaching takes place. In order to improve the credibility of experimental teaching, it is therefore important to try to control the many factors that can affect the actual teaching and learning outcomes.

3.4. Incorporating multi-objective affective instructional design

Instructional design is a process of constructing a framework for problem-solving approach, which in the art course mainly includes the identification of teaching objects, the setting of teaching objectives, the use of teaching methods and the development of learning evaluation.

Designed from intuitive exploration to analysis and summary, from design and thinking to creative practice, and finally evaluation and communication of the five-step emotional teaching model of art education courses, the specific content is as follows:

1) Intuitive exploration: Teachers play relevant videos before class, create relevant learning situations, create a learning atmosphere, and mobilize students' enthusiasm for learning.

2) Analysis and summary: Through teaching activities to trigger student discussion, the discussion consists of interactive discussion between teachers and students and students' cooperative teaching and learning. In this process, the teacher mainly plays a guiding role.

3) Design and Thinking: Through classroom teaching, students have a general understanding of the art course content through the teacher's guidance, group discussion and independent observation and investigation.

4) Creative Practice: Students will have a brief understanding through the video or pictures played by the multimedia. Through simple imitation, group discussion and teacher's guidance, students can complete their works.

5) Evaluation and communication: Teachers will let students show their art works in groups or on their own, analyzing the creative ideas and personal feelings behind the works as well as the cultural connotations that the students have given to the works.

4. Optimizing the effectiveness of fine arts curricula with multiple pedagogical objectives

4.1. Simulation Experiment Analysis of Emotional Learning Models

The brain emotion learning model has some discriminative ability, consider the following numerical model with inputs chosen as random inputs.

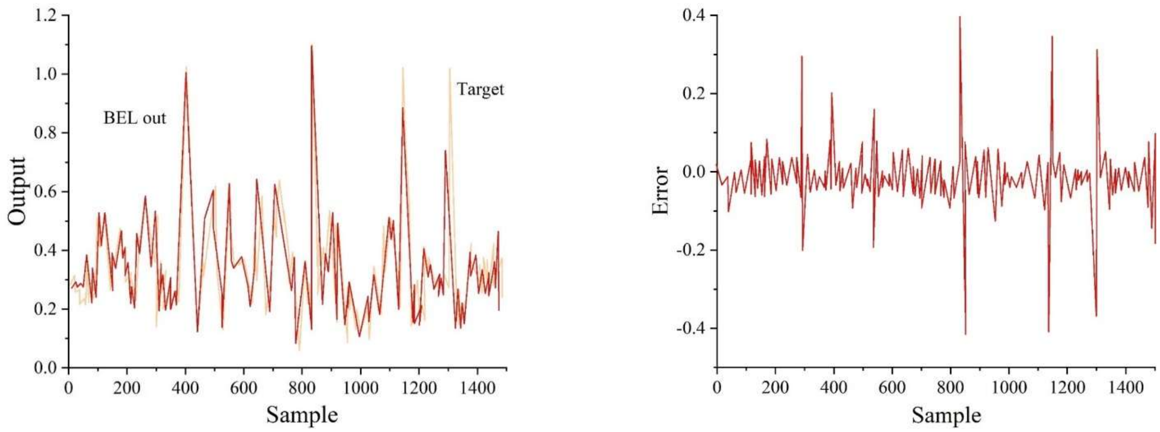
$$y(k) = u^2(k) + \frac{y(k-1)}{1 + y^2(k-1) + y^3(k-1)} \tag{21}$$

2000 sets of sample data are obtained from this numerical model, and the model is recognized using the algorithm of the brain emotion learning model described above.

1) Parameter setting. Parameters $\alpha = 0.7$, $\beta = 0.3$, $\gamma = 0.05$ are selected. While assigning initial values to the model weights, i.e., $v_1 = 0.9$, $v_2 = 0.2$, $v_3 = 0.7$, $v_4 = 0.3$, $v_{th} = 1.1$, $w_1 = 0.6$, $w_2 = 1.3$, $w_3 = 0.7$, $w_4 = 0.04$.

2) Simulation experiment results. The prediction output effect and prediction error of the brain emotion learning model are shown in Fig. 3.

It can be seen through the figure that as far as the prediction effect is concerned, the prediction effect of BEL is better when the data change trend is not big. However, when the data change trend changes greatly, especially in the spikes and troughs of the data, the BEL prediction effect is not satisfactory and the error is large. This indicates that there is a certain lag in the parameter adjustment process when BEL performs data prediction, which affects the prediction effect.



(a) Forecast output (b) Prediction error

Fig. 3. Forecast output effect and prediction error

4.2. Effectiveness of the Optimized Design of Fine Arts Education Curriculum

4.2.1. Correlation Analysis of Emotional Engagement and Knowledge Construction Perspectives. In order to further understand the interrelationship between affective input and collaborative knowledge construction, Pearson correlation analyses were conducted to focus on the correlations between seven types of affective input variables such as pleasantness, hopefulness, positive affective interactions (including gratitude, encouragement, and appreciation), disappointment, rejection, insight, and confusion, and three knowledge construction variables such as shared viewpoints, negotiated viewpoints, and elevated viewpoints in the three rounds of the learning activity, and the correlation analysis of the calculations are shown in Table 2.

In the first round of activities, positive affective interactions were significantly positively correlated with negotiated viewpoints (r=0.652), hope and shared viewpoints (r=0.503), and insight and negotiated viewpoints (r=0.415), and rejection and negotiated viewpoints (r=-0.725), disappointment and negotiated viewpoints (r=-0.512), and disillusionment and shared viewpoints (r=-0.503) were significant negative correlation. Willingness to participate influences the number of shares, and positive affective interactions and insight favor knowledge negotiation. Learners who feel rejection fade away from knowledge negotiation, and disappointment reduces the number of times they participate in knowledge sharing and negotiation.

In the second round of activities, the number of pairs of emotional engagement and constructed views that had a significant correlation was three: hope was significantly and positively correlated with negotiated views (r=0.869), pleasantness was significantly and positively correlated with negotiated views (r=0.594), and rejection was significantly and positively correlated with sublimated views (r=0.577). This indicates that hope is strongly correlated with knowledge negotiation (r>0.7) and pleasantness is also positively correlated with knowledge negotiation to some extent. Whereas the intervention taken in the second round of activities was the addition of affective communication scaffolding, which implies that affective communication scaffolding served to elevate learners' hope and pleasantness and facilitated knowledge negotiation.

In the third round of activities, hope showed a significant positive correlation with shared viewpoints, negotiated viewpoints and sublimated viewpoints. And hope was strongly correlated with negotiated views (r=0.789>0.7). Compared to the first two rounds, the correlation of hope, a positive emotion, with shared viewpoints was enhanced, and the correlation with sublimated viewpoints was significant. It suggests that teacher emotional support promotes learners' knowledge sharing and knowledge sublimation by enhancing their hope. Positive affective interactions also have strong correlations with both shared views (r = 0.736 > 0.7) and negotiated views (r = 0.805 > 0.7), which are significantly enhanced compared to the previous two rounds. It suggests that teacher emotional support promotes learners' knowledge sharing and knowledge negotiation by enhancing their positive emotional interactions. Meanwhile, the correlations of pleasantness and joking with shared and negotiated perspectives were also enhanced. It can be seen that teacher affective support plays a better role than learner affective interaction scaffolding in the teaching practice conducted in this study.

Table 2. Correlation analysis

Variable	Joy	Hope	Positive emotional interaction	Disappointed	Reject	Relax	Insight	Puzzle	Jest
First round									
Shared view	0.452	0.503	0.399	-0.503*	-0.424	0.347	0.135	0.396	0.425
Consultative view	0.241	0.437	0.652**	-0.512**	-0.725**	0.312	0.415	0.433	0.327
Sublimation view	-0.237	-0.136	-0.043	-0.142	-0.039	0.258	0.369	-0.299	-0.236
Second rotation									
Shared view	0.153	-0.072	-0.198	-0.205	0.153	-0.115	-0.198	-0.279	0.362
Consultative view	0.594	0.869**	0.425	-0.087	0.312	0.179	0.093	0.196	0.143
Sublimation view	0.165	0.452	0.053	0.362	0.577	0.058	0.067	0.176	-0.69
Third round									
Shared view	0.593*	0.688**	0.736**	-0.634**	-0.367	0.289	0.463	0.085	0.637*
Consultative view	0.711**	0.789**	0.805**	-0.679**	-0.293	0.526*	0.569*	-0.173	0.624*
Sublimation view	0.427	0.452*	0.364	-0.362	-0.055	0.235	0.152	-0.323	0.213

4.2.2. Impact of different pedagogical approaches on student learning outcomes. At the end of the teaching experiment, the collected data from the pre and post-tests of the students' learning effectiveness tests were statistically processed. The mean and standard deviation of the scores obtained by the two groups of students on learning effectiveness are shown in Table 3. The experimental group's posttest 112.364 was significantly higher than the control group's posttest score.

Table 3. The average and standard deviation of the study results before and after the test

Group	Cross-survey	Sample size	Mean value	Standard deviation
Experimental group	Premeasurement	46	69.5312	15.9682
	Posttest	46	112.364	8.0071
Control group	Premeasurement	47	67.619	13.9037
	Posttest	47	99.708	12.7856

A paired-sample t-test was conducted for the scores of the experimental and control groups of students on the pre- and post-tests of the Art Teaching Effectiveness Quiz. The results of the sample test of the two groups' scores are shown in Table 4.

The information from the results of the study in the table shows that the t-value of the experimental group's pre- and post-test is -20.153, $p<0.05$, reaching a significant difference. This means that after the experimental treatment, there is a significant difference between the experimental group in the pre- and post-test situation of the students' learning effectiveness test. The paired samples t-tests of the pre and post-test scores of the two groups of students reached a significant level, which means that there is a difference in the learning effectiveness of the two groups of students in the art course after accepting the teaching program of the affective learning strategy method and the traditional teaching method.

However, if we look at the mean of the post-tests of the two groups, the mean of the experimental group is 112.364 which is higher than the mean of the control group which is 99.708, which means that receiving the ELS program is more helpful to improve the learning effectiveness of the students than the traditional teaching.

Table 4. Two results of the sample test result

Group	Mean value	SD	Standard error mean	95% confidence interval of the difference		t	Freedom	Sig (double tail)
				Lower limit	Upper limit			
Before and after the experimental group	-45.869	16.209	3.264	-50.236	-39.245	-20.153	52	0.000
Check the control group before and after	-32.007	18.033	3.499	-34.859	-25.397	-13.896	53	0.000

4.2.3. Effectiveness of Fine Arts Teaching. First of all the researcher assessed the consistency of the raters, spearman rank correlation coefficient is applied to both variables are ordinal scales in order to calculate the degree of consistency between the ranks of the two groups.

The rank correlation coefficients for the experimental group are shown in Table 5.

Table 5. The correlation coefficient of the experimental group

Experimental group			Scorer A	Scorer B	Scorer C	Scorer D
Spearman	Scorer A	Correlation coefficient	1.000	0.865**	0.911**	0.937**
		Significance (double tail)	/	0.004	0.000	0.000
		Case number	46	46	46	46
	Scorer B	Correlation coefficient	0.865**	1.000	0.787**	0.855**
		Significance (double tail)	0.004	/	0.009	0.003
		Case number	46	46	46	46
	Scorer C	Correlation coefficient	0.911**	0.787**	1.000	0.891**
		Significance (double tail)	0.000	0.009	/	0.003
		Case number	46	46	46	46
	Scorer D	Correlation coefficient	0.937**	0.855**	0.891**	1.000
		Significance (double tail)	0.000	0.003	0.003	/
		Case number	46	46	46	46

The rating correlation coefficients for the control group are shown in Table 6. The rating coefficients were significantly correlated among the raters.

Table 6. The correlation coefficient of the control group

Control group			Scorer A	Scorer B	Scorer C	Scorer D
Spearman	Scorer A	Correlation coefficient	1.000	0.952**	0.923**	0.974**
		Significance (double tail)		0.000	0.000	0.000
		Case number	47	47	47	47
	Scorer B	Correlation coefficient	0.952**	1.000	0.977**	0.941**
		Significance (double tail)	0.000	/	0.000	0.000
		Case number	47	47	47	47
	Scorer C	Correlation coefficient	0.923**	0.977**	1.000	0.947**
		Significance (double tail)	0.000	0.000	/	0.000
		Case number	47	47	47	47
	Scorer D	Correlation coefficient	0.958**	0.922**	0.947**	1.000
		Significance (double tail)	0.000	0.000	0.000	/
		Case number	47	47	47	47

The correlation coefficients of the ratings of the experimental and control groups are shown in Table 7. The results of the ratings of the four raters in the experimental and control groups are correlated at the 0.01 level of significance.

Table 7. The correlation coefficient of the experimental group and the control group

The experimental group and the control group						
			Scorer A	Scorer B	Scorer C	Scorer D
Spearman	Scorer A	Correlation coefficient	1.000	0.964**	0.915**	0.973**
		Significance (double tail)	/	0.000	0.000	0.000
		Case number	93	93	93	93
	Scorer B	Correlation coefficient	0.952**	1.000	0.966**	0.964**
		Significance (double tail)	0.000	/	0.000	0.000
		Case number	93	93	93	93
	Scorer C	Correlation coefficient	0.963**	0.976**	1.000	0.978**
		Significance (double tail)	0.000	0.000	/	0.000
		Case number	93	93	93	93
	Scorer D	Correlation coefficient	0.958**	0.936**	0.977**	1.000
		Significance (double tail)	0.000	0.000	0.000	/
		Case number	93	93	93	93

The average of the scores obtained by the two groups of students on each item of the Creativity Practice Scale was analyzed in an independent samples t-test. A summary of the t-tests of the experimental and control groups on the creativity scale is shown in Table 8.

The average scores of the students in the experimental group were better than those in the control group, and the differences between the two groups in the three aspects of "surprise", "originality" and "challenge" were significantly greater than the differences in "flexibility", "logic", "refinement", "value" and "good technique". This indicates that after the experimental treatment, the students in the experimental group significantly outperformed the students in the control group in this part of creativity in the three components of creativity, namely, surprise, originality, and challenge, which also indicates that the integration of affective learning strategy pedagogy into the art curriculum is helpful in enhancing the part of creativity of the students.

Table 8. The experimental group and the control group are the test of the test of creativity

Project	Group	Number	Average	Standard deviation	t value	Significant p
1-a wonder	Experimental group	46	4.522	0.1524	17.632	0.000
	Control group	47	3.016	0.0893		
1-b originality	Experimental group	46	4.635	0.2036	8.071	0.000
	Control group	47	3.716	0.0985		
2-a flexibility	Experimental group	46	4.299	0.1032	9.362	0.000
	Control group	47	3.168	0.2147		
2-b logicality	Experimental group	46	4.593	0.1328	6.754	0.000
	Control group	47	3.326	0.3609		
2-c challenge	Experimental group	46	4.498	0.2156	11.24	0.000
	Control group	47	3.693	0.1277		
3-a delicacy	Experimental group	46	4.693	0.0992	7.809	0.000
	Control group	47	3.787	0.1254		
3-b valuability	Experimental group	46	4.771	0.1563	10.441	0.000
	Control group	47	3.265	0.1834		
3-c Good technique	Experimental group	46	4.891	0.1337	11.655	0.000
	Control group	47	3.362	0.1911		

5. Conclusion

In this paper, we introduce the triple transformation model of emotion, learning and cognition (the brain emotional learning model), categorize the emotional factors of art learners, and propose a learner emotion model based on art teaching objectives. And the multi-objective optimization evaluation is used to simulate the emotional interaction decision-making.

Simulation experiments are conducted on the brain emotional learning model to test the prediction results of emotional input on cognitive export and the prediction error. Based on the prediction error, the effectiveness of the art curriculum was predicted, which was used as the basis for the optimization of the art education curriculum. Emotional learning strategies can effectively enhance students' learning and creativity when put into the design of art courses. The t-test of the pre and post-test scores of the experimental group shows that there is a significant difference between the pre and post-tests of the experimental group in the students' learning effectiveness test. And the mean score of the post-test of the experimental group is 112.364, which is significantly higher than the mean score of the post-test of the control group. It shows that in the teaching of art education courses, the implementation of emotional learning strategy program teaching is more helpful to improve students' learning effectiveness than traditional teaching, and the emotional learning model is reasonable as a method for the optimal design of art education courses.

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