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Research on Optimized Design Methods of Computational Modeling and Artificial Intelligence in Talent Cultivation of Art and Design Majors in the Interdisciplinary Background of Digital Intelligence Era

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Abstract The development of digital intelligence technology is a powerful driving force for breaking down professional barriers and cross-fertilization among multiple disciplines. This paper takes the talent cultivation of art and design majors as the research objective, and explores the optimization and improvement of students' learning methods as well as instructional design respectively. In the recommendation of learning resources, a feature matrix of art education information technology assessment resources is established to realize the cluster analysis of assessment art resource themes. And the four common problems of learners in personalized e-learning are constructed as multi-objective optimization problems to build a personalized e-learning resource recommendation problem model. Combined with the multi-objective particle swarm optimization algorithm (NEMOPSO), the recommendation model of art and design professional learning resources is constructed. With the assistance of the proposed recommendation model and the professional course design method, the performance of students in the experimental group reaches 4.00 and above in 10 creative force indicators, which verifies the high feasibility and reliability of the designed talent cultivation program.

Index Terms art and design talent cultivation, multi-objective particle swarm optimization, learning resource recommendation model, cluster analysis

I. Introduction

With the progress of science and technology and economic development, the new culture industry characterized by “Internet +” is closely linked with content creation and production, creative design services, cultural communication channels, cultural investment and operation [1]-[3]. This shows that the art and design profession has a closer and closer relationship with the market, industry, science and technology, and the demand for comprehensive talents is getting stronger and stronger, which requires practitioners to have a broad international vision, excellent professional technology, flexible industrial adaptability and strong overall management ability [4]-[7]. In this context, the cultivation of high-quality cross-border talents has become an urgent problem to be solved.

Art and design is a highly open, comprehensive and free application discipline, which should be inherited and developed as well as pushed forward [8]. Humanities and social disciplines represented by communication and psychology can provide a humanistic foundation for art and design, management and economics provide the perspective of industry and management, and the cultivation of music, painting and other literacy will be a plus for art composite talents [9]-[11]. In addition, the development of big data, artificial intelligence and other technologies make the integration of art and design with engineering and science possible [12]. For the cross-border cultivation of modern art talents, information technology as well as modern classroom is a necessary form to enhance students' knowledge of cross-border and improve their comprehensive ability in all aspects [13], [14]. Combining big data and artificial intelligence technology, understanding students' strengths and advantages, analyzing students' characteristics, ensuring the effectiveness of the classroom, and ensuring that art and design students can be able to work deeply in a cross-border field [15], [16]. Only by integrating the diversified elements of different related disciplines can we adapt to the employment needs of the industry “seeking newness and change” [17].

In this paper, we first elaborate the mathematical methods as well as the steps for constructing the feature matrices of many different assessment resources in art and design education informatization. Then it explains the process of constructing four common problems in personalized e-learning into corresponding fitness functions, so as to propose a personalized e-learning resource recommendation problem model. Subsequently, within the framework of multi-objective optimization strategy, the main contents of MOPSO framework, NEMOPSO parameter initialization, Chebyshev decomposition method and optimization update method are discussed respectively to form the model of learning resources recommendation for art and design majors. Finally, the convergence performance and overall performance of the model are analyzed, and the practical application effect of the designed talent training program is evaluated.

II. Art and Design Professional Learning Resources Recommendation Model

II. A. Characteristics Matrix Construction of Art Education Informatization Evaluation Resources

Constructing the matrix of the features of the assessment resources of art education informatization is a necessary step for the clustering analysis of course topics, and the feature matrix corresponding to the vector representation of each document is calculated, and the construction of the matrix is mainly divided into the following steps:

First of all, if you need to deal with M assessment resources document collection as in equation (1):

$$D=\{Doc_1,Doc_2,\cdots,Doc_m\} \tag{1}$$

After processing using the word-splitting tool cut can be obtained containing N different word-splitting results as in equation (2):

$$W=\{Word_1,Word_2,\cdots,Word_n\} \tag{2}$$

Documents are denoted using Doc_m, and clauses are denoted using $Word_n$, with subscripts n corresponding to different clauses. The two-dimensional statistical matrix of document-subtraction, $(Doc,Word)_{M\times N}$, constitutes the word vector space, denoted as $DW_{m\times n}$ as in equation (3):

$$DW_{m\times n}=\begin{bmatrix} dw_{11} & dw_{12} & \cdots & dw_{1n} \\ dw_{21} & dw_{22} & \cdots & dw_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ dw_{m1} & dw_{m2} & \cdots & dw_{mn} \end{bmatrix} \tag{3}$$

The corresponding matrix $DW_{m\times n}$ is two-dimensional and sparse, in which each row represents the number of times that $\{Word_1,Word_2,\cdots,Word_n\}$ different participles appear in the document Doc_{1-m}, at this time, we can only see the performance of the word vector space with different participle statistical dimensions.

After verification, we found that the words “digital campus” and “university” appear twice in Doc_m and Doc_2 documents, which is not enough to represent the theme of the document, at this time, we need to add a certain weight, and select a more distinguishable word as the theme of the document. General word assignment methods are TextRank, TF-IDF, Importance, DIMP, etc., and here the most common TF-IDF is chosen as the weighting calculation.

TF-IDF mainly consists of two parts “word frequency (TF)”, “inverse document frequency (IDF)” together, word frequency TF and two-dimensional matrix value is the same, represents the number of times the word appears in the document $times$, word frequency is expressed as equation (4):

$$Word_{tf}=times \tag{4}$$

When the length of the document affects the number of occurrences of keywords, it is also commonly used as the relative frequency of word frequency calculation, the relative word frequency for the number of occurrences of the word $times$ and the total number of times $totalTimes$ ratio, there is a formula (5):

$$Word_{tf}=\frac{times}{totalTimes} \tag{5}$$

Relative importance exists between comparisons, in order to compare the importance of all occurrences of words, it is necessary to first count the words occurring in all resource documents, and the sum of all resource documents is denoted as Docs, then the inverse document frequency IDF can be expressed as equation (6):

$$Word_{idf}=\log\left(\frac{totalDocs}{indocs+1}\right) \tag{6}$$

where $totalDocs$ is the current number of all evaluation resources document library, $indocs$ indicates the number of documents containing the word, the more frequently the word to be calculated appears, i.e., $indocs$ the greater the number of documents containing $word$, the inverse document frequency IDF will be smaller, when the number of times the occurrence of a low frequency close to 0, it will not be able to calculate, so in order to avoid such a situation, assuming that, no matter what, the word to be calculated will always appear once to give the denominator contains $word$ the number of documents + 1, which ensures that the calculation will run even if it is really zero.

The TF and IDF values of the word in the corpus documents can be calculated using Eqs. (4) and (5), and the document statistics results $DW_{m\times n}$, respectively, to obtain Eq. (7):

$$Word_{tf-idf} = Word_{tf} * Word_{idf} \tag{7}$$

Then use IF-IDF value to replace the word in the original document in the matrix of the number of statistics value, obtained with the right value of the two-dimensional feature matrix, as shown in the table below where each line of IF-IDF value together to form the distribution of the document's sub-word, that is, we get each line that is each document in each sub-word synthesized vector representation.

For example, document Doc_1 can be characterized by the keyword vector $\overline{DW_1}$ [digital campus, primary and secondary school, education cloud platform, ...], which corresponds to the weighted values of [0.037986, 0.204211, 0.759874, ..., ..., respectively. 0.306321].

Generally, the band weights of the documents are compared and result in the first N bits (or greater than a certain threshold), which is the keyword ranking of the document. Since the use of tf-idf value calculation considered in the use of the document in the document appears more frequently in the subject word to characterize the document, and the actual obtained is in the dictionary intervention, multi-semantic division under the existence of a list of sub-parameters, and the result will be subject to numerical computational constraints, in order to achieve the similarity comparison of the resources, it is still necessary to algorithms for further extraction of the current construction of the text-type features.

II. B.Personalized e-learning resource recommendation problem model

In the problem of personalized e-learning resource recommendation, some scholars believe that there are some important factors that need to be considered to improve the efficiency and accuracy of personalized e-learning resource recommendation. First, whether the learning concepts covered by the recommended personalized e-learning resources meet the learner's learning expectations, which depend on the learner's past learning experiences. Second, whether the difficulty of the e-learning resources matches the learner's ability, which depends on age, education level, and subject of study. Third, the limitation of individual learning time, because a learner's ability and attention affect the individual learning time, so the learning time of each learner is different. Fourth, the weights of e-learning resources in personalized e-learning resource recommendation need to be considered to balance each e-learning resource in personalized e-learning resource recommendation. The above problems are the core of the recommendation problem, and the process of modeling the personalized e-learning resource recommendation problem is to construct the above four aspects into four fitness functions.

(1) The subfunction F_1 represents the average difference between the learning concepts covered by the e-learning resources and the learning concepts expected by the learner L_k, which is used to evaluate which e-learning resources satisfy the learner's learning needs, as in equation (8):

$$F_1 = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} X_{nk}\left|r_{nm} - h_{km}\right|}{\sum_{n=1}^{N} X_{nk}}, 1 \le k \le K \tag{8}$$

(2) The subfunction F_2 represents the average difference between the difficulty level of an e-learning resource and the learner's ability level, which is used to help identify which e-learning resources are suitable for the learner L_k, as in equation (9):

$$F_2 = \frac{\sum_{n=1}^{N} X_{nk}\left|D_n - A_k\right|}{\sum_{n=1}^{N} X_{nk}}, 1 \le k \le K \tag{9}$$

(3) The subfunction F_3 represents the difference between the time required by the e-learning resource and the upper and lower bounds of the learner's L_k desired learning time, which is used to ensure that the full time required by the e-learning resource recommended to the learner is within the learner's desired learning time, as in equation (10):

$$F_3 = \left(\max\left(t_k - \sum_{n=1}^{N} t_n X_{nk}, 0\right)\right) + \left(\max\left(0, \sum_{n=1}^{N} t_n X_{nk} - t_{uk}\right)\right) \tag{10}$$

(4) The subfunction F_4 is used to balance the weights of learning concepts to avoid unbalanced learning concepts covered by e-learning resource recommendations, as in equation (11):

$$F_4 = \sum_{m=1}^{M} h_{km}\left|\sum_{n=1}^{N} X_{nm} r_{nm} - \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} X_{nk} r_{nm}}{\sum_{m=1}^{M} h_{km}}\right|, 1 \le k \le K \tag{11}$$

The above four subfunctions match the parameterized representation of learner characteristics and the parameterized representation of e-learning resource characteristics from four perspectives, which together constitute the personalized e-learning resource recommendation problem. The smaller values of the four objective functions mean that the personalized e-learning resource recommendation is closer to the learner's requirements, therefore, the personalized e-learning resource recommendation problem is the optimal solution that satisfies the four objective functions at the same time. In terms of how to use intelligent optimization algorithms to solve the personalized network recommendation problem, there are two methods in existing research. Some scholars construct the four sub-functions as a combinatorial optimization problem, combining the four sub-functions into a single-objective function through four weight values ($w1$, $w2$, $w3$ and $w4$), such as Eq. (12), and then optimize it using a single-objective evolutionary algorithm, which is used more in the existing literature.

$$\min F(x)=\sum_{j=1}^{4} w_j F_j \tag{12}$$

The personalized network learning resources recommendation problem is to satisfy four sub-objectives at the same time, it is a multi-objective optimization problem, should be constructed as a multi-objective optimization problem model and optimized by using the multi-objective particle swarm optimization algorithm, the optimal solution is expressed through the as in Equation (13):

$$\min f(x)=\left\{f_1(x), f_2(x), f_3(x), f_4(x)\right\} \tag{13}$$

When the personalized e-learning resources recommendation problem is constructed as a single-objective problem, each sub-objective needs to be assigned the corresponding weight, and the assignment method relies on the experience of the researcher and lacks scientific basis. When the personalized e-learning resources recommendation problem is constructed as a multi-objective optimization problem, the weight problem is no longer considered, each objective can maintain better independence, and the recommended content is more in line with the results of the recommendation problem model matching.

II. C.Multi-objective particle swarm optimization algorithm (NEMOPSO)

II. C. 1) MOPSO framework

The velocity update formulation and position update formulation of the multi-objective particle swarm optimization algorithm are shown in Eqs. (14)-(15):

$$\begin{aligned} v_i(t+1) &= \omega v_i(t)+c_1 r_1(pBest_{i_k}(t)-x_i(t)) \\ &\quad +c_2 r_2(gBest_k(t)-x_i(t)) \end{aligned} \tag{14}$$

$$x_i(t+1)=x_i(t)+v_i(t+1) \tag{15}$$

where $x_i(t)$ is the velocity vector of the i th particle, c_1 is the self-learning factor coefficient, c_2 is the social learning factor coefficient, r_1, r_2 take the values in the range $[0,1]$, and $gBest_k$ is the global optimal solution found in the population. Particle i learns from the population optimum and is used for its own position update.

II. C. 2) NEMOPSO parameter initialization

Initialize the number of particle populations and the number of weight vectors, specify the number of particle neighbors, in this paper, we set the number of particle neighbors to 3, and initialize the maximum capacity of the external archive $AR=60$.

II. C. 3) Chebyshev decomposition methods

The Chebyshev decomposition method is used to decompose the multi-objective optimization problem of online learning resources into numerous single-objective subproblems, which are assigned unique weight vectors corresponding to them.

(1) Calculate the weight vector of online learning resources. To solve the online learning resource recommendation model based on multi-objective optimization strategy, first decompose the online learning resource problem so that each online learning resource subproblem corresponds to a λ vector, and compute the weight vector of the online learning resource subproblem as in equation (16):

$$\lambda_i^j=\left(\frac{rand(N,1)}{norm\left(rand(N,1)\right)}\right) \tag{16}$$

(2) Online learning resources subproblem vector sorting. Because the neighborhood strategy in the evolutionary algorithm is to optimize the current vector using similar vectors, the distance between each weight vector needs to be calculated and sorted according to the distance to find the neighborhood of the current particle. Utilizing equation (17):

$$D_{ij}=pdist2\left(\lambda_i,\lambda_j\right) \tag{17}$$

The distance between the weight vectors in the online learning resource, i.e., the distance between the subproblems, is found and ranked using equation (18):

$$S = sort(D) \tag{18}$$

(3) Determine the current learning resource neighborhood. According to the above S value and $Neighbors = S(1:T)$ obtain the particle neighborhood, i.e., a number of learning resources that are similar to the current learning resource. T is the number of learning resources randomly selected among the number of several learning resources, and let $T = 2$.

(4) Solve for the learning resource neighborhood fitness mean. If the 2 learning resources randomly selected from the neighborhood are $x_{p1}(t)$, $x_{p2}(t)$, the neighborhood mean is equation (19):

$$c_2 r_2 \frac{1}{2}\left(x_{p1}(t) + x_{p2}(t)\right) \tag{19}$$

(5) Empowering particles to explore new regions. The algorithm can easily fall into the local optimum at the late stage of the optimization search and it is difficult to find the global optimum solution, therefore, the algorithm used in the online learning resources recommendation method is given the ability to explore new regions E, which is aimed at increasing the ability of the algorithm to explore other regions in the solution space and improving the convergence performance of the algorithm. The exploring new region capability is shown in equation (20):

$$E = \omega c_3 \cdot r \cdot \left(r - x_i(t)\right) \tag{20}$$

$c_3 = 0.002$ of them.

II. C. 4) Optimization update formula

According to the diversity-enhanced multi-objective particle swarm optimization algorithm, it is known that the social learning factor has the ability to handle both diversity and convergence, in satisfying the condition Eq. (21):

$$\frac{1}{2}\left(c_1 + c_2\right) > 2\left(1 + \omega\right) \tag{21}$$

When the population never converges, therefore the optimization is performed in the MOPSO updating process, i.e., the self-learning factor is omitted, $c_1 = 0$, which results in the particle velocity updating formula as in Eq. (22):

$$v_i(t+1) = \omega v_i(t) + c_2 r_2 \left(\frac{1}{2}(x_{p1}(t) + x_{p2}(t)) - x_i(t)\right) \tag{22}$$

The way of updating the new position of the particle is affected by Eq. (19) and Eq. (20), and the updating formula is Eq. (23):

$$x_i(t+1) = x_i(t) + \sum_{k=1}^{N} c_2 r_2 \left(\frac{1}{2}(x_{p1}(t) + x_{p2}(t)) - x_i(t)\right) + E + v_i(t+1) \tag{23}$$

III. Curriculum design for art and design majors in the context of disciplinary intersections

Art and design majors focus on cultivating students' professional innovation ability, and there is no uniform standard and answer for design works. As a professional discipline focusing on cultivating students' divergent thinking, the single teaching mode of traditional teaching can easily make students feel burned out, which leads to students' negative and resistance to professional knowledge. The use of online cross-curricular and offline professional courses in the form of a combination of modes, can expand the knowledge dimension of students at the same time, strengthen the students' knowledge of professional knowledge, the formation of diversified learning modes, so that students are interested in professional courses, and to further enhance the students' learning motivation.

Network cross-curricular relative to the traditional classroom mode, not only is the relevant supplement to the classroom content, but also allows students to learn independently of the teaching mode. Both network cross-curriculum and traditional curriculum need to develop the curriculum, “in a broad sense, curriculum development mainly includes curriculum planning, curriculum implementation, curriculum evaluation and adjustment of the three stages of program development”, the curriculum planning needs to be harmonized with the offline classroom planning, the integration of learning objectives and related materials, network teaching can use the corresponding platform to integrate the traditional offline mode of teaching. The corresponding platform can turn the traditional offline mode into a diversified course form integrating theory, practice, sharing, discussion and mutual evaluation, which can better diffuse students' thinking and significantly improve their innovation ability.

The online cross-curricular platform for art design majors should focus on five aspects of teaching design: course lectures, online discussions, case studies, competition sharing, and students' mutual evaluation, in order to better utilize the advantages of the online classroom and strengthen the necessary knowledge mastered by students in the professional courses.

IV. Evaluation and Application of Talent Training Programs for Art and Design Majors

In this paper, we use the art design professional learning resources recommendation model to assist students' learning and teachers' lesson preparation, synthesize the art design professional curriculum design methods in the interdisciplinary context, and form a new art design professional talent cultivation program in the era of digital intelligence. In this chapter, the performance test of the technical model and the evaluation of the application effect of the talent cultivation program will be carried out successively.

IV. A. Performance of the model

IV. A. 1) Loss parameters

The loss parameter of the model training is shown in Fig. 1, which can be seen that with the training, the loss parameter gradually decreases and stabilizes below 0.1, indicating that the performance of the model is continuously improving. And it tends to converge at 30 times, showing superior stability performance.

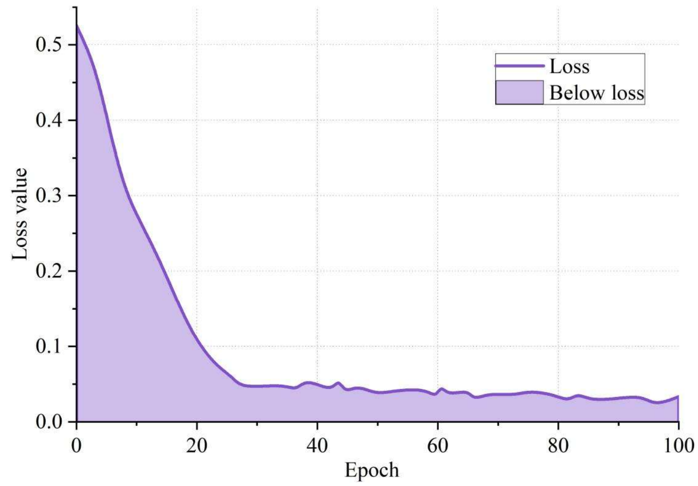


Figure 1: Predict the parameters of the network loss

IV. A. 2) Overall performance

This subsection briefly divides art and design students into 3 types according to their grades: (A) good foundation, (B) moderate foundation, and (C) poor foundation, and selects a total of 4 similar models of (M1) Random, (M2) DT, (M3) IRT, and (M4) MDT&CD -LSTM as a comparison method to unfold the prediction of the model algorithm of this paper with (M5) on the 3 types of students. The comparison of metrics data. The index data of class A student prediction is shown in Table 1, class B student prediction is shown in Table 2, and class C student prediction is shown in Table 3.

Table 1: The indicator data predicted by Type A students

Model	M1	M2	M3	M4	M5
Precision	0.6419	0.7067	0.7345	0.9234	0.9329
Recall	0.8602	0.8602	0.7024	0.9655	0.9584
F1	0.7321	0.7746	0.718	0.9439	0.9733
MAE	0.0574	0.0402	0.0677	0.0328	0.0227
CRR SD.	0.0325	0.0135	0.0428	0.0141	0.0137

Table 2: The indicator data predicted by Type B students

Model	M1	M2	M3	M4	M5
Precision	0.7598	0.7901	0.8602	0.9129	0.9567
Recall	0.8602	0.8602	0.9469	0.9946	0.9946
F1	0.8064	0.8233	0.9011	0.9456	0.969

MAE	0.0347	0.0333	0.0294	0.0226	0.0244
CRR SD.	0.0299	0.023	0.0249	0.0142	0.014

Table 3: The indicator data predicted by Type C students

Model	M1	M2	M3	M4	M5
Precision	0.6948	0.8076	0.7734	0.8602	0.9012
Recall	0.8734	0.9359	0.9359	0.9984	0.9984
F1	0.7721	0.8663	0.8456	0.9234	0.9469
MAE	0.0381	0.035	0.0322	0.0292	0.0259
CRR SD.	0.017	0.0238	0.0264	0.0162	0.0155

Comprehensively observing Tables 1-3, among the five modeling algorithms, only (M5) this paper modeling algorithm consistently maintains a precision rate of 90.00% and above, and reaches a maximum of 95.67% on Class B students. In terms of recall for class A students, (M5) modeling algorithm in this paper is slightly lower than (M4) MDT&CD -LSTM modeling algorithm by 0.0018. In terms of MAE, (M5) modeling algorithm in this paper reaches a maximum of only 0.0259, which is much lower than the remaining four similar modeling algorithms. In addition, on F1 value, (M5) this paper modeling algorithm still maintains the optimal performance, up to 0.9733 on Class A students.

IV. B. Assessment of the application of the model

Two classes in the first year of art majors in a university were selected as experimental subjects, with a total of 30 students in the two classes. One of the classes is assisted by the method of this paper to carry out the learning of art courses, and is set as (E) experimental group. The other class adopts the general teaching method to carry out the learning of art major courses, and is set as (C) control group.

IV. B. 1) Overall performance

The mean and standard deviation of the scores obtained by the students of the (E) experimental group and the students of the (C) control group on the learning effectiveness of the art major course are shown in Fig. 2 for the (EB) pre-test experimental group, the (EA) post-test experimental group, the (CB) pre-test control group, and the (CA) post-test control group. It is easy to see that the students in the (E) experimental group and the students in the (C) control group differed from each other in the mean values on the pre-test and post-test of the experiment, but the difference between the mean values of the students in the (E) experimental group was 39.54, which was greater than the difference between the mean values of the students in the (C) control group.

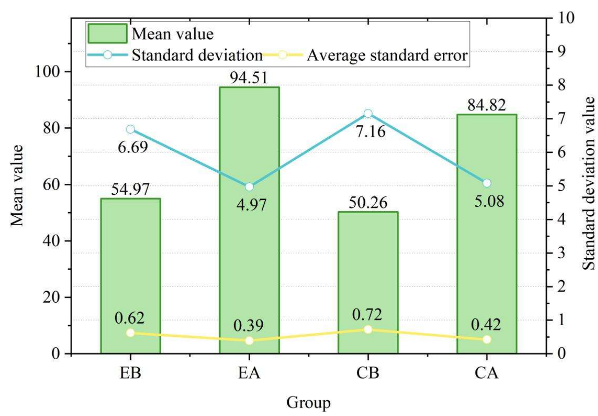


Figure 2: A comparison of learning outcomes

In order to explore more deeply the differences between the two groups of students in the effectiveness of their professional courses, the paired-samples t-test of the pre- and post-test data of the effectiveness of the professional courses of the two groups of students is shown in Table 4.

Table 4: Paired-samples t test

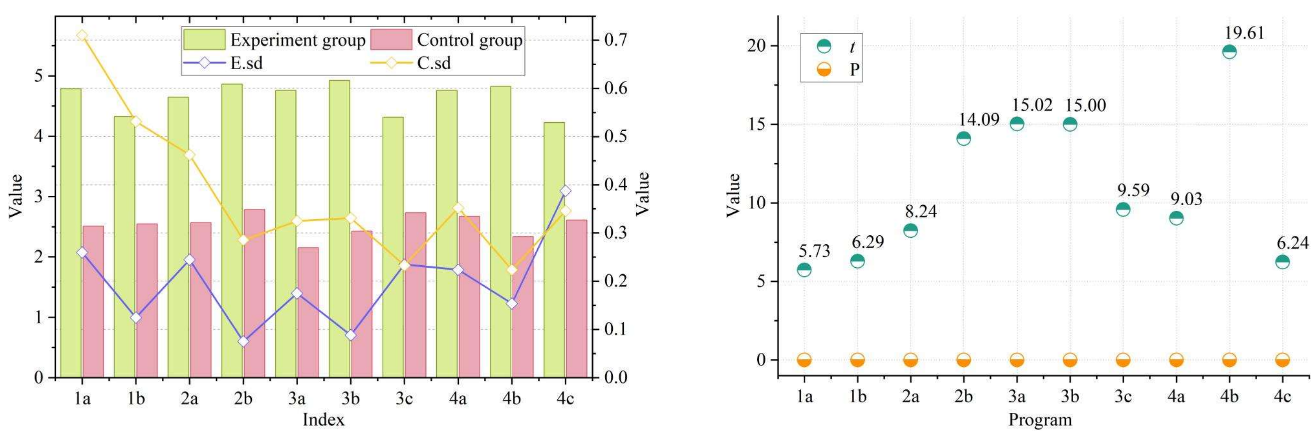
Group		E	C
Average value		-39.54	-34.56
Standard deviation		6.51	6.642
The difference is 95% confidence interval	Upper limit	0.887	1.0454
	Lower limit	-43.252	-37.253
t		-39.792	-36.09
Degree of freedom		30	30
Significance (double tail)		0.000	0.000

From the analysis results in Table 4, it is known that the results of (E) experimental group and (C) control group examined with paired samples t. The t-value of (E) experimental group measured before and after was -39.792, and the P=0.000 was significantly different. It indicates that after the experimental treatment, there is a significant difference in the course learning effectiveness of the (E) experimental group. The t-value of the pre- and post-test of the (C) control group is -36.09, P=0.000 reaching a significant difference. It means that after the experimental treatment, there is a significant difference between the control group in the course learning effectiveness scale. So there is a difference in the learning effectiveness of both groups of students for the cognitive domain of art and design after receiving specialized course instruction.

However, in terms of the posttest mean of the two groups, the mean of (E) experimental group is 94.51 higher than that of (C) control group is 84.82, which means that the students of the course under the methodological teaching mode of this paper are more likely to improve their learning effectiveness for the art professional course than those who learn under the traditional teaching mode. In other words, students in the art and design program under the teaching mode of this paper's methodology will improve their learning effectiveness more than students in the traditional teaching mode.

IV. B. 2) Expression of creativity

This subsection presents a comparative analysis of the performance of the students in the (E) experimental group and the (C) control group on the following 10 indicators of design creativity: (1a) originality, (1b) surprise, (2a) creative ideas, (2b) hands-on, (3a) logic, (3b) adaptability, (3c) challenge, (4a) sophistication, (4b) skill, and (4c) value-based. The performance of the two groups of students on mean as well as standard deviation is shown in Fig. 3(a) and t-value and significance results are shown in Fig. 3(b).



(a) Average value and standard deviation

(b) t and P

Figure 3: The comparison results of performance in terms of creativity indicators

Observing Fig. 3(a), it can be seen that the performance of the students in the (E) experimental group on the 10 indicators of creativity is 4.00 and above, while the students in the (C) control group are below 3.00, and the comparison of all the indicators are P<0.005. It shows that the level of creativity of the students can be significantly improved under the talent cultivation program of the art and design majors in this paper.

V. Conclusion

In terms of learning resource recommendation for art and design students, this paper designs a personalized network learning resource recommendation problem model and combines it with a multi-objective particle swarm optimization algorithm to propose a learning resource recommendation model for art and design majors. The model not only has excellent convergence performance, but also excellent overall performance. In the training, not only the loss parameter gradually decreases and stabilizes below 0.1, but also begins to converge at 30 times. In the prediction of different types of students, compared with similar modeling algorithms, the accuracy rate is always maintained at 90.00 and above and can reach up to 95.67%, the MAE is only 0.0259, and the F1 value can reach 0.9733.

Meanwhile, with the technical support of the designed learning resource recommendation model, this paper integrates the cross-disciplinary characteristics, puts forward the design method of art design professional courses, and forms the art design professional training program. The program in practical application, showing a more ideal auxiliary enhancement effect. The t-value of the experimental group students before and after the test is -39.792, P=0.000 has a significant difference, and assisted the students to improve their performance by 39.54. The experimental group students in the 10 indicators of creativity, the performance of the students reached 4.00 and above.

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