



## Generative AI Enhances Constructivist Learning: A Framework for Brand Design Education

Nan Ding<sup>1,2,\*</sup> and Jiu Wang<sup>3</sup>

<sup>1</sup> Art Design College, Chongqing Jiaotong University, Chongqing, 400074, China

<sup>2</sup> Center for European Studies, Chongqing Jiaotong University, Chongqing, 400074, China

<sup>3</sup> Sichuan Fine Arts Institute, Chongqing, 400053, China

**SUMMARY:** *In the context of the AIGC era, the traditional art and design field is undergoing profound changes, and the rationality and scientificity of the design professional curriculum system directly affects the quality of its talent cultivation. This paper explains the characteristics of contextualized teaching of art design under the theory of constructivism, and under its guidance, constructs the contextualized teaching mode of art design based on AIGC to cultivate students' design ability. Taking the application of color matching in the cultivation of design ability as an example, the DCGAN network is chosen to design the automatic color matching algorithm. Two classes of art design majors in a university are selected as experimental samples to complete the practical application of art design contextualized teaching mode. The experimental analysis proves the superiority of the proposed color matching algorithm, which can be used to assist students in improving their color perception and matching ability. After applying the proposed teaching mode, the students' professional performance and design ability improved by 23.84% and 8.64% respectively compared with those of the control group, and there was a significant difference at the 5% level, indicating that the contextualized teaching based on AIGC helps to promote the development of students' design ability.*

**KEYWORDS:** *AIGC; DCGAN; color matching algorithm; contextualized teaching; design ability development*

## 1 Introduction

In the current era of rapid development of informationization and globalization, the traditional teaching mode of design majors has been difficult to adapt to the needs of modern education [1, 2]. The rote memorization and boring lectures in the classroom have long been unable to satisfy the students' thirst for knowledge, but may cause their aversion to learning and avoidance of psychology [3, 4]. In this context, contextualized teaching came into being. Contextualized teaching emphasizes that by creating a context close to reality and rich in emotion, students can perceive knowledge in practice and take the initiative to explore and understand [5-7]. The traditional teaching mode is difficult to realize the students' sense of classroom participation, and the constructivist contextualized teaching takes this as the starting point to advocate that students actively construct their own knowledge system in the context [8-10]. With the development of artificial intelligence, artificial intelligence-generated content (AIGC) technology in the design professional field breaks through the shackles of the development of

\*13678406625@163.com

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complete dependence on the creation of designers, forming a new pattern of industry development of automated design, which further improves the training of design ability in the contextualized teaching of constructivism [11-14].

AIGC technology can improve the accuracy and information arrival rate of teaching with the help of arithmetic power and algorithms in data processing and deep learning [15, 16]. As a result, AIGC brings reconstruction and change in teaching mode, teaching method, learning paradigm and other aspects in design ability cultivation [17]. Design students can use the AI data model to quickly generate high-quality sketches of their solutions, reducing repetitive labor and improving learning efficiency [18, 19]; AIGC can provide students with design solutions in a variety of artistic styles and different visual language expressions, which expands the students' design horizons to a certain extent and improves their design ability [20, 21]. Teachers can also use AIGC to manage teaching plans, teaching design, etc. At the same time, teachers can use the virtual digital person in teaching to carry out "split" teaching, to enhance the interest of the teaching process, and can also create virtual scenes to enrich the teaching experience [22, 23]. In addition, AIGC can optimize all aspects of teaching and continuously pay attention to and accurately evaluate the learning status, learning situation and learning effect of students in the teaching process [24, 25].

The study analyzes around students' design ability cultivation, discusses the connection between Vygotsky's social constructivism theory and contextualized teaching, as well as the main features of social constructivism in the design ability cultivation of art and design education. On this basis, AIGC technology is empowered in art design teaching to construct the art design contextualized teaching mode. In order to enhance the students' color matching design ability, the automatic color matching algorithm based on deep convolutional generative adversarial network is designed, and quantitative and qualitative experimental analyses are carried out to explore the effect of its generating color matching scheme. Then take two classes of students majoring in art design in a university as samples to carry out contextualized teaching experiments, and compare the art design knowledge scores and design ability cultivation effects of the two classes before and after the experiments, so as to validate the role of the teaching mode constructed in this study on the cultivation of students' design ability.

## 2 Design capacity development in the context of AIGC

The rise of AIGC (Artificial Intelligence Generated Content) has affected the design industry, the employing demand of the design industry has changed, and the nurturing strategy of the art and design profession needs to be updated accordingly. In this context, this paper introduces contextualized teaching based on constructivism in the education of art and design majors, and constructs a contextualized teaching mode of art and design based on AIGC.

### 2.1 Contextualized teaching based on constructivism

Contextualized teaching is rooted in the theory and practice of constructivism. Vygotsky's theory of social constructivism holds that the individual and society are interconnected and inseparable, and that knowledge derives from social construction. There are many schools of constructivist doctrine, but one common view is that the learning process (the process of acquiring knowledge) is not based on external indoctrination, but rather on the process of constructing new experiences based on the student's own experiences.

Constructivists advocate the active participation of learners in the construction of knowledge through the creation and use of complex learning environments. Such learning environments should be authentic activities that are specific to the knowledge or subject matter

being studied, where learners can collaborate with each other, test the validity of each other's ideas, and are encouraged to formulate or apply multiple perspectives and to reflect on the results and processes of learning. The concept of “learning environment” here includes the ‘context’ in contextualized teaching, and it can also be said that the “context” is the learning environment designed and led by the teacher in the teaching process. It can also be said that “context” is the learning environment designed and implemented by teachers in the teaching process. In a certain sense, contextualized teaching is a practice of constructivist theory.

When Vygotsky's social constructivism theory is introduced into art and design education, its main features in the cultivation of art and design education ability are as follows:

(1) Organize teaching with cooperative learning as the center and develop teaching with community activities as the center.

(2) Shift from “teaching” to “dialogic teaching” and from ‘indoctrination’ to “reflection”.

(3) Blurring the boundaries between disciplines, mobilizing the enthusiasm, knowledge reserves and resources of all learners for a specific project, thus forming a vertical and horizontal knowledge network with full interaction between disciplines, focusing on dynamic and temporal constructive teaching content, and ultimately completing the problems to be solved by the teaching content.

## **2.2 Situationalized teaching mode of art and design based on AIGC**

Through the above analysis, it can be concluded that in the art design education that integrates constructivism with plotting and teaching, it is necessary to stimulate, guide and regulate students' autonomous activities through cooperation. Under the guidance of constructivism-based contextualized teaching, for the cultivation of students' design ability, AIGC is integrated into the construction of art design professional curriculum system in colleges and universities, and the art design contextualized teaching mode based on AIGC is proposed, which mainly includes the following points.

### **2.2.1 Assisted design capacity development**

In graphic drawing courses, teachers can use intelligent image generation tools such as StableDiffusion and Midjourney to complete classroom teaching and enrich the course content. Teachers can guide students to use AI image generation tools correctly, instruct students to enter keywords according to a specific theme, and then obtain a variety of image examples. Through careful observation of these different styles of images, students can more intuitively feel the creative changes and combinations of graphics, and then deepen their understanding of graphic language. In the color composition course, teachers can use AIGC's intelligent analysis and rapid generation function to carry out teaching, quickly generate a series of color combinations that meet the requirements, and simultaneously provide the color emotion analysis of each scheme and the data indicators of color contrast and harmony, helping students to deeply understand the diverse visual effects formed by different color combinations, and effectively improve their color perception and application skills.

### **2.2.2 Optimizing design quality and efficiency**

In the poster design course, students can input the design theme, publicity focus and emotional tone in the intelligent design software. Through studying a large number of excellent poster cases, AIGC can quickly generate a poster design framework with reasonable layout and visual impact. Students can optimize the details on the basis of this, which will significantly enhance the uniqueness and innovation of the design while improving the design efficiency and quality.

AIGC can also be effectively applied in other non-graphic design core courses. For example,

in the design of three-dimensional ornaments or costumes, teachers can use computer vision technology to analyze the trend of ornaments and historical costume styles, and generate various design style diagrams based on students' input of design themes, wearing scenarios, and target groups to help students quickly obtain design inspiration. In addition, with the help of 3D generation technology, students can preview the matching effect of materials and patterns in real time and make adjustments and optimizations, which improves the accuracy and efficiency of design and meets the needs of the rapid development of the design industry at the same time.

### 2.2.3 Constructing contextualized and interactive instruction

AIGC provides brand-new technical support for art and design education, but its effective implementation still needs to be based on the core of teaching design, take ability cultivation as the goal, actively optimize the traditional teaching mode, and realize contextualized interactive teaching. With the help of generative AIGC drawing tools, students can independently and quickly generate design sketches or conceptual drawings, and communicate and discuss with teachers and other students in the classroom to further come up with optimized solutions. This immediate feedback mechanism not only improves classroom participation, but also strengthens students' design thinking and collaboration skills. At the same time, the use of AI-driven virtual reality (VR) and augmented reality (AR) technology can simulate real design scenarios, such as physical scenes, painting modeling, etc., so that students can more intuitively understand the connection between the design space and the material effect, which greatly enhances their subjectivity and practical feasibility in learning and art design. Applying AIGC to the teaching practice of art design majors in colleges and universities helps to promote the formation of contextualized interactive teaching mode.

## 3 DCGAN-based color matching methods

In the cultivation of students' design ability, color perception and color matching is an important skill. In the above analysis of the situational teaching mode of art design, AIGC can build a multi-layer neural network model, so that the computer can simulate the information processing mechanism of biological neurons, complete the learning and analysis of massive data, and quickly generate a series of color matching schemes that meet the requirements. Based on this, this chapter takes the color matching in the cultivation of students' design ability as an entry point, proposes the color matching method based on DCGAN and carries out experimental analysis.

### 3.1 Generating Adversarial Networks

Generative Adversarial Network (GAN) model consists of two parts: generator and discriminator. In a GAN network, any differentiable function can represent the generator and discriminator, which are denoted by  $G$  and  $D$ , respectively. The function of the generator is to generate a pseudo-sample data  $G(Z)$  similar to the real sample by utilizing random noise  $Z$  (sampled from the prior distribution  $PZ(Z)$ ). The function of the discriminator is to receive the data from the true sample  $X$  as well as the pseudo-sample data generated by the generator to determine whether these data are true samples or pseudo-samples generated by the generator. The discriminative model that determines the result to be true outputs 1, i.e.,  $D(X) = 1$ , and vice versa 0. The two fight against each other, and iteratively optimize each other over and over again, so that the performance of the generator and the discriminative model improves continuously until the judge is unable to discriminate between the true and false data.

The GAN model adopts the concept of game theory, so that the generator  $G$  and the discriminator  $D$  against each other, and its optimization process is the process of great and great minimization. Its objective optimization function is represented by equation (1):

$$\begin{aligned} \min_G \max_D F(D, G) = & E_{x \sim P_{data}(x)} [\log D(x)] \\ & + E_{z \sim P_z(z)} [\log(1 - \log D(G(Z)))] \end{aligned} \quad (1)$$

In the above equation (1),  $Z$  is random noise obeying Gaussian distribution,  $G$  denotes the generator,  $D$  denotes the discriminator,  $P_{data}(x)$  denotes the probability distribution of the real samples,  $P_z(Z)$  denotes the probability distribution of the random noise,  $x \sim P_{data}(x)$  is the sample randomly drawn from the distribution of the real data,  $Z \sim P_z(Z)$  denotes the sample drawn from random noise,  $D(x)$  is the output vector generated after the discriminator receives the real data, and  $G(Z)$  denotes the output vector generated after the random noise is received. The training process of the GAN can be roughly divided into three stages. The first stage is to fix the discriminator  $D$  and train the generator  $G$ , and the second stage is to fix the generator  $G$  and train the discriminator  $D$ . The third phase is to loop the first two phases and optimize until the two reach a balance.

When the discriminator  $D$  is fixed and the generator  $G$  is trained, according to equation (1) above, it can be taken that the maximum value of  $F(D, G)$  can be taken, denoted as  $D^{\max}$ .  $F(D, G)$  can be written in the following form:

$$\begin{aligned} F(D, G) = & \int_x P_{data}(x) \log(D(x)) d_x + \int_z P_z(z) \log(1 - D(Z)) d_z \\ = & \int_x [P_{data}(x) \log(D(x)) d_x + P_g(x) \log(1 - D(g(Z))) d_x] \end{aligned} \quad (2)$$

For any nonzero real numbers  $h$ ,  $k$  and real numbers  $i \in [0, 1]$ , the following equation (3):

$$h \log(i) + k \log(1 - i) \quad (3)$$

The maximum value is obtained at  $\frac{h}{h+k}$ , so the optimal discriminator formula  $D^{\max}$  for the discriminator  $D$ , is shown in equation (3):

$$D^{\max}_G = \frac{P_{data}(x)}{(P_{data}(x) + P_g(x))} \quad (4)$$

When  $P_{data}(x)$  and the distribution of data generated by the generator  $P_g(x)$  are equal, the Nash equilibrium is reached, i.e.,  $P_{data}(x) = P_g(x)$ , and the GAN model reaches the optimal state. The discriminator determines the correctness of the samples to remain at 1/2, and cannot determine whether the data originates from real samples or false samples.

### 3.2 Improved GAN model

Deep Convolutional Generative Adversarial Network (DCGAN) is an improvement of Generative Adversarial Network. Because of the unstable and uncontrollable reasons during the training of generative adversarial network, it is improved on the basis of generative adversarial network by combining the powerful convolutional neural network CNN, and at the same time, in order to make the whole network microminiaturizable, the pooling layer in the convolutional neural network is taken away, and in addition, the fully-connected layer is replaced by the global pooling layer in order to alleviate the amount of computation. This stabilizes the state during the training process and can effectively improve the quality of the samples and the speed of convergence as well as the associated generative modeling applications.

The generative model of the Deep Convolutional Generative Adversarial Network is a convolutional neural network-like network based on a convolutional neural network, where the first layer of the model is a fully-connected layer containing multiple neural network units with a one-dimensional random noise vector as input, followed by connecting multiple inverse-convolutional layers on demand to generate the desired data size. Each layer of the model (except the last one) is connected to a normalization layer, which renormalizes the activation values of the previous layer at each batch so that the mean of the output data is close to 0 and the standard deviation of the output data is close to 1. Each layer (except the last one) is connected to an activation layer (LeakyReLU function), which is a variant of the ReLU activation function, and which is effective in generating the required size of data. LeakyReLU effectively solves the case of silent neurons when the ReLU input value is negative, and the sparse implementation of the model can better mine relevant features and fit the training data.

Deep convolutional generative adversarial network discriminative model construction is relatively simple, in fact, it is the continuous convolution of the data and extract features, and finally turned into a one-dimensional vector to get the results. It is mainly composed of convolutional layer, activation function, pooling layer and fully connected layer, and the pooling layer in the model of this paper is replaced by a convolutional layer with a step size larger than 1, because a convolutional layer with a step size larger than 1 can also play the role of pooling layer. Like the generative model of deep convolutional generative adversarial networks, each layer of the discriminative model is connected to a specification layer (excluding the first layer), and each layer is connected to an activation layer.

In summary, the deep convolutional generative adversarial network improves on the generative adversarial network as follows:

- (1) The pooling layer is replaced with a convolutional layer, the generator mainly replaces the pooling layer with an inverse convolutional layer, and the discriminator mainly replaces the pooling layer with a convolutional layer with a step size greater than one;
- (2) A specification layer is added to both the generator model and the discriminant model, which solves the problem of poor data initialization, and at the same time the layer renormalizes the activation values of the previous layer on each batch, which is also an effective solution for the generator to converge all the samples to the same point;
- (3) An activation layer (LeakyReLU function) is added to all layers of the discriminative model and the generative model removing the first layer.

### 3.3 Automatic color matching algorithm

According to the DCGAN algorithm idea introduced in the previous section to establish an automatic color matching algorithm model, to achieve the function of generating diversified excellent color matching schemes, to provide more personalized color matching schemes for

the cultivation of students' design ability in college teaching, to greatly shorten the time of their data collection, and to substantially improve the design efficiency.

Given that the generative adversarial network in the training process there are problems such as collapse, instability, difficult to converge, the depth convolutional generative adversarial network is used and transformed on its basis. Deep convolutional generative adversarial network uses convolutional neural network to replace the generator and discriminator of the multilayer perceptual machine model, respectively, and removes the pooling layer in the convolutional neural network to achieve the purpose of the network can be microscopic, and at the same time, in order to alleviate the computational amount of the network with a fully pooled layer instead of a fully connected layer.

The overall basic flow of the algorithm is as follows:

First of all, the real data of training is standardized into the  $[-1,1]$  interval, which is convenient for the subsequent use of cross-entropy to measure for optimizing the network parameters. In this paper, the network generator is constructed from the beginning layer for a fully connected layer containing  $5*3*8$  neural network units to the model, and specify the dimensionality of the input data as 100, after which the data is transformed into  $5*3*8$ , and after that the data size that meets a set of coloring is composed of 5 colors and each color is composed of the 3 primary colors of R, G, and B is generated by 2 convolution of  $5*3*1$ . Each layer of the model (excluding the last layer) is connected to a canonical layer, which is connected to a canonical layer and an activation layer (LeakyReLU function) in each layer of the model excluding the last layer. The specification layer renormalizes the activation values of the previous layer on each batch, even if the mean of its output data is close to 0 and its standard deviation is close to 1. The activation layer consists of the LeakyReLU activation function, which effectively solves the situation of silent neurons when the ReLU input value is negative, and the sparsity achieved on the model enables better mining of the relevant features and fitting of the training data.

The network discriminator constructed in this paper is mainly to discriminate the authenticity of the input data, by continuously convolving the data and extracting the features, and finally converting them into one-dimensional vectors to get the results. It is mainly composed of convolution layer, activation layer, Dropout layer and Flatten layer. The role of the dropout layer is in the network training process, the neural network units in accordance with a certain probability will be temporarily discarded from the network, can be used to prevent overfitting. Flatten layer as a convolutional layer to the full connectivity layer of the transition, used to the input data “flatten”, so as to achieve the effect of multi-dimensional input one-dimensionalization.

### **3.4 Experimental analysis**

#### **3.4.1 Experimental samples**

A total of 1500 sample images were obtained by manual collection and random sampling of the Kanas dataset. The sample set is mainly used to train and test the DGGAN backbone network. The main color is extracted from the sample set to obtain the main color palette, and the main color palette is mutilated to construct the paired palettes, in order to ensure the consistency of the size of the paired palettes, black is used to replace the mutilated color blocks, and the mutilated color blocks are the colors that need to be matched. The palette samples are divided into training set and test set according to the ratio of 8:2, of which, the total number of training samples is 1200 and the total number of test samples is 300.

### 3.4.2 Quantitative analysis

In order to scientifically analyze the results of the comparison experiments, CNN neural network and GAN neural network are selected as the comparison methods to evaluate the color matching effect of the three methods. The results of the palette similarity analysis and quantitative analysis are shown in Table 1, and it should be pointed out that, due to the difference between the quantitative unit and the order of magnitude, except for the Peak Signal-to-Noise Ratio (PSNR) index, which retains two decimal places, the rest of the indexes are retained to three decimal places. The test results of the methods in this chapter possess high palette similarity with the source palette, and the normalized minimum color difference average and palette similarity results are 0.213 and 0.771, respectively, and both evaluation indexes are better than the comparison methods. Specifically, compared with CNN neural network and GAN neural network, the improvement in the integrated evaluation index (SIM) and peak signal-to-noise ratio are 0.107 and 0.024, 5.78dB and 3.80dB, respectively.

*Table 1: Results of palette similarity analysis and quantitative analysis*

Evaluation index	CNN	GAN	DGGAN
Palette similarity analysis			
The average of the minimum color difference	0.343	0.256	<b>0.213</b>
Palette similarity	0.683	0.744	<b>0.771</b>
Quantitative analysis			
SSIM	0.725	0.747	<b>0.785</b>
SIM	0.652	0.735	<b>0.759</b>
PSNR/dB	22.83	24.81	<b>28.61</b>

### 3.4.3 Qualitative analysis

The above quantitative analysis represents the overall similarity between the experimental results and the source palette under visual perception, while in practical application, the user's subjective evaluation is the gold standard in this field, and this paper carries out a psychophysical experimental analysis of the color matching effect on the basis of the quantitative analysis. The test set is randomly and equally divided into four groups, each group contains 75 sets of samples, and each set of samples contains three sets of comparison experiments in addition to the source color palette. Twenty-five subjects were invited to subjectively evaluate the test results, and each subject chose at least 1 test set for the subjective scoring experiment, and each sample set would receive no fewer than 5 subjective scores. The subjective scoring method in this chapter is based on perceptual engineering, i.e., subjects rated the aesthetics of the generated color palettes according to the Likert five-point similarity scale, and the higher the aesthetics, the higher the rating, with a total score of 5 points. The results of the average ratings of all subjects on the four sets of color palettes are shown in Fig. 1. The mean subjective ratings of the CNN neural network, GAN neural network, and the DGGAN algorithm in this paper are 3.776, 3.794, and 3.885 points, respectively, which are all higher than the mean ratings of the source color palettes (3.767 points). Compared with the CNN and GAN methods, the color palette generated by the method in this chapter is improved by 2.89% and 2.40% in subjective preference, and the method in this chapter is closer to the effect of the matching scheme designed by designers majoring in art and design and the effect of the color matching of the source palette in the subjective scoring results, which indicates that the DGGAN color matching method proposed in this paper also has a better effect in the subjective evaluation. Through this color matching method, it can stimulate students' inspiration and creativity,

improve their color perception and matching application ability, and thus promote the development of their design ability.

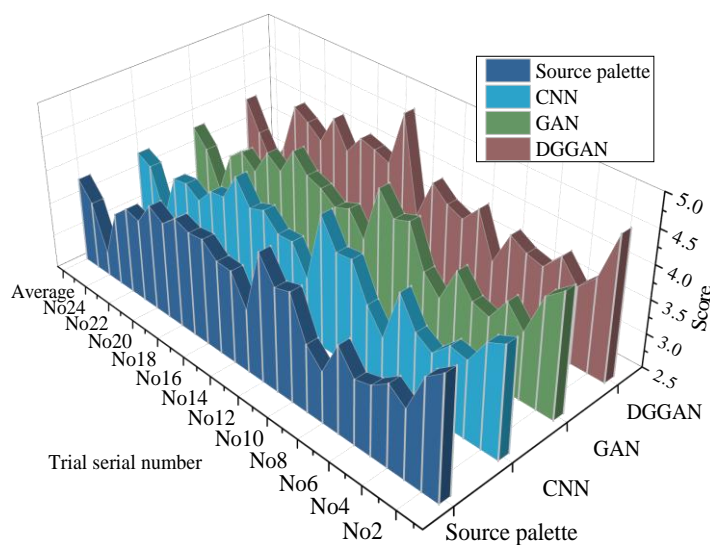


Figure 1: Palette subjective scoring results

## 4 Experiments in contextualized teaching and analysis

### 4.1 Purpose of the experiment

The purpose of implementing this experiment is to apply the AIGC-based contextualized teaching model of art design constructed in this study to actual teaching, and to verify whether the teaching model constructed in this study can strongly enhance students' design ability through the comparison of teaching experiments between experimental classes and control classes.

### 4.2 Subjects

The research subjects of this experiment are students in two classes of art design majors in a university. Among them, the experimental group (Group A), with a total of 45 students, used the AIGC-based art design contextualized teaching mode to implement teaching, supplemented by the DCFAN color matching model. The control group (Group B), with 44 students, continued to use the traditional teaching process in the experiment. Through the comparison of the final grades of the two classes in the last semester, the midterm grades of this semester, and the relevant pre-test data statistics of this experiment, the two classes' performance level and the students' design level are similar.

### 4.3 Experimental tools

This experiment uses the art and design knowledge test paper and the design ability development effect questionnaire as research tools.

#### (1) Art and design knowledge test paper

In order to prove that the AIGC-based contextualized art and design teaching model can help students' understanding of art and design knowledge, the study designed two sets of test papers with the same level of difficulty, a pre-test to determine the starting point of knowledge level of Group A and Group B, and a post-test to test the difference in knowledge level of Group

A and Group B after controlling for the influence of the “teaching model”. The study designed two sets of test papers with the same level of difficulty to determine the starting point of knowledge of Group A and Group B, and a post-test to control the effect of “teaching mode”.

#### (2) Designing a questionnaire on the effect of competency development

The questionnaire on the effect of design ability cultivation mainly investigates whether there is any change or improvement in students' design ability before and after the experimental teaching from the seven dimensions of “Color perception and application ability X1, Aesthetic ability X2, Layout and composition ability X3, Morphological perception ability X4, Practical ability X5, Requirement comprehension ability X6, and Creative narration ability X7”. The survey was conducted to investigate whether there was any change or improvement in the students' design ability before and after the experimental teaching. The results of the survey were also totaled using a five-point Likert scale. In order to ensure the scientific validity of the questionnaire, the reliability of the questionnaire was also tested to a certain extent before it was formally put into the survey. The reliability coefficient value of the questionnaire is 0.926, which is greater than 0.9, and the reliability coefficients of the six dimensions of the questionnaire are also greater than 0.7, so the reliability of the data allows for the next step in the analysis.

## 4.4 Analysis of experimental results

### 4.4.1 Pre-experimental testing and data analysis

#### (1) Analysis of the results of the pre-test

In order to understand the mastery of art and design knowledge of the two classes before the implementation of teaching and learning, the prepared test paper was pre-tested for the two classes. After determining that the data have the qualities of normality and have the chi-square, and further completing the t-test of the data, the results of the pre-test results of the two classes are shown in Figure 2, and it is found that there is no significant difference in the understanding of art and design knowledge between the two classes ( $p > 0.05$ ), and the level of the two classes is extremely similar, and the test scores of the test paper are all in the range of 40 points.

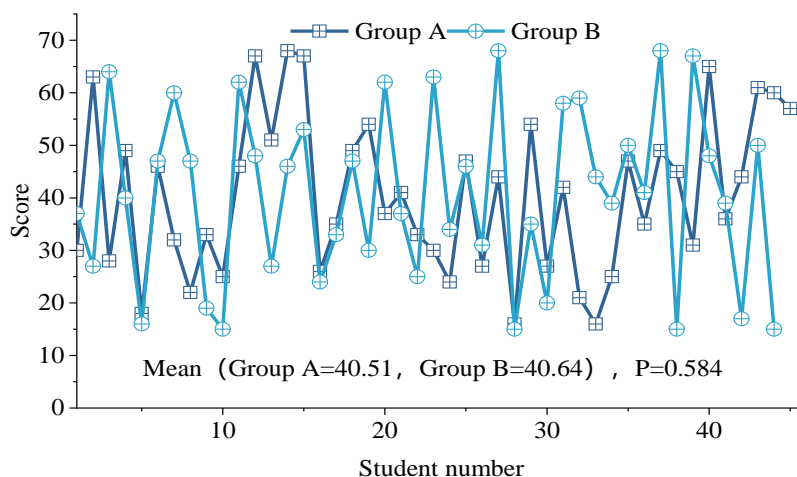


Figure 2: The previous grade results of the two classes

#### (2) Analysis of the pre-test of design ability

The results of the statistical analysis of the pre-test of design ability of the students in the two classes are shown in Figures 3 and 4, and the statistical results of the independent samples t-test of the pre-test data of the seven dimensions are shown in Table 2.

The two groups of experimental subjects for the seven dimensions do not show significant differences ( $p>0.05$ ), representing Group A and Group B for the color perception and application ability X1, aesthetic ability X2, layout and composition ability X3, morphology perception ability X4, practical ability X5, demand comprehension ability X6, and creative narrative ability X7 all show consistency, and there is no difference. According to the data analysis, it can be seen that Group A and Group B have almost the same level of design ability, with the scores of each dimension of design ability around 6.5, and the overall scores of design ability are 45.91 and 45.96.

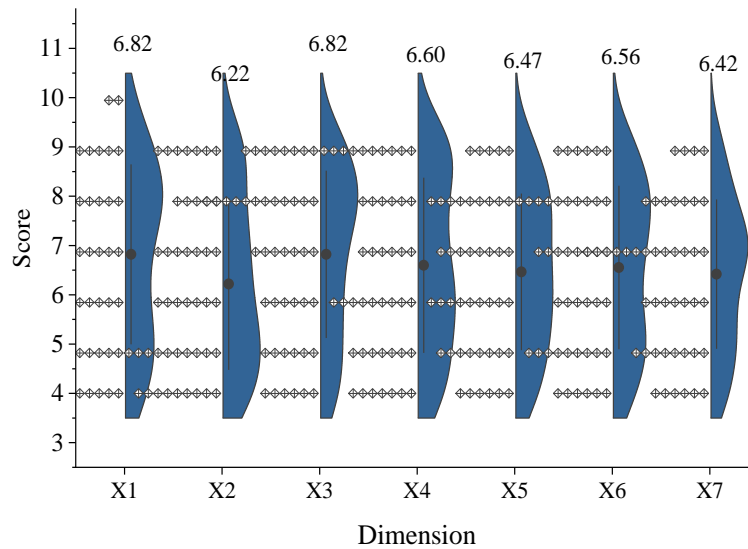


Figure 3: The previous results of the students' design ability(Group A)

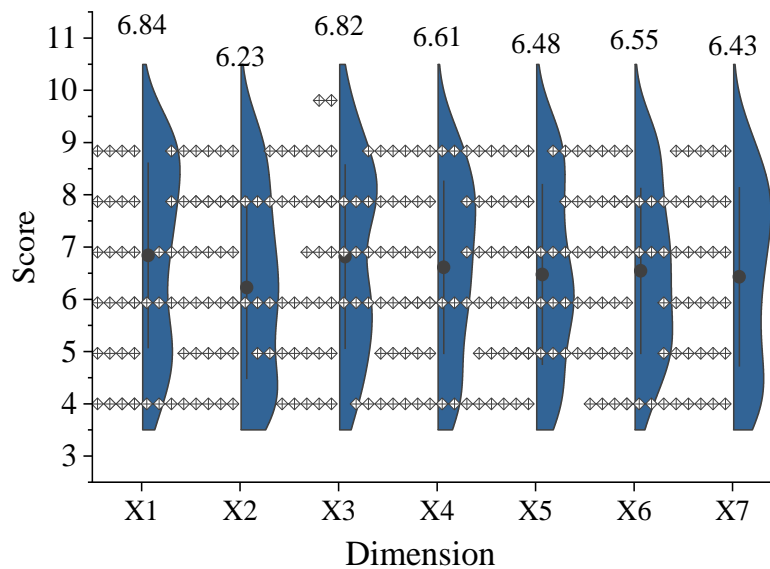


Figure 4: The previous results of the students' design ability(Group B)

Table 2: Analysis of the significant differences in the previous survey

Dimension	<i>t</i>	<i>p</i>
X1	-0.192	0.788
X2	0.102	0.827
X3	0.291	0.611
X4	-0.539	0.659
X5	0.509	0.396
X6	0.203	0.232
X7	0.391	0.192

#### 4.4.2 Post-experimental tests and data analysis

##### (1) Post-test score analysis

At the end of the experimental teaching, a post-test was conducted on the students' mastery of art and design knowledge, and the prepared post-test papers were distributed to Group A and Group B at the same time, and the data statistics were completed after correction. The comparison of art and design knowledge post-test scores is shown in Figure 5. After experiencing classroom learning in different teaching modes, there was a significant difference in the comparison of the scores of art and design knowledge between the two classes ( $p=0.028<0.05$ ), with Group A's scores being much higher than Group B's, by 23.84% overall. From the results, it can be seen that the contextualized teaching mode of art and design based on AIGC is better than the traditional teaching process to help students absorb and master design knowledge.

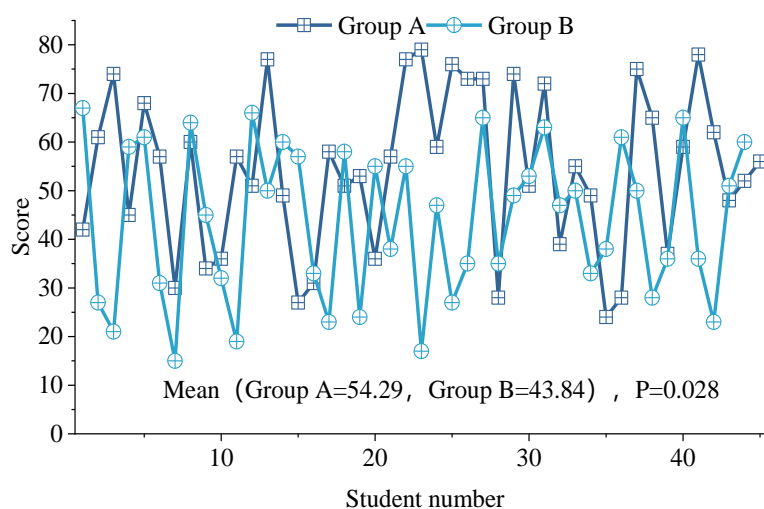


Figure 5: The aftertest grade results of the two classes

##### (2) Post-test analysis of design ability

The results of the statistical analysis of the students' design ability posttest in the two classes are shown in Figures 6 and 7, and the statistical results of the independent samples t-test for the posttest data of the seven dimensions and the total score of design ability are shown in Table 3. The design ability of students in both classes improved after the teaching experiment, and the overall scores of design ability of students in Group A and Group B were 51.91 and 47.78 respectively, which were 13.07% and 3.96% higher than that before the teaching experiment. The improvement of design ability of students in Group A was significantly higher than that of Group B and the design ability of students in Group A was 8.64% higher than that

of Group B by 8.64%. Among them, there was a 9.45% improvement in color perception and application ability X1, indicating that the DCGAN color matching model optimizes students' color perception and application ability. The two groups showed a significant difference ( $p < 0.05$ ) in the seven dimensions of design ability development, and the overall difference between the pre- and post-tests of design ability showed a significant difference ( $p = 0.026 < 0.05$ ). It indicates that the contextualized teaching mode of art design based on AIGC is more conducive to improving students' design ability than the traditional teaching process.

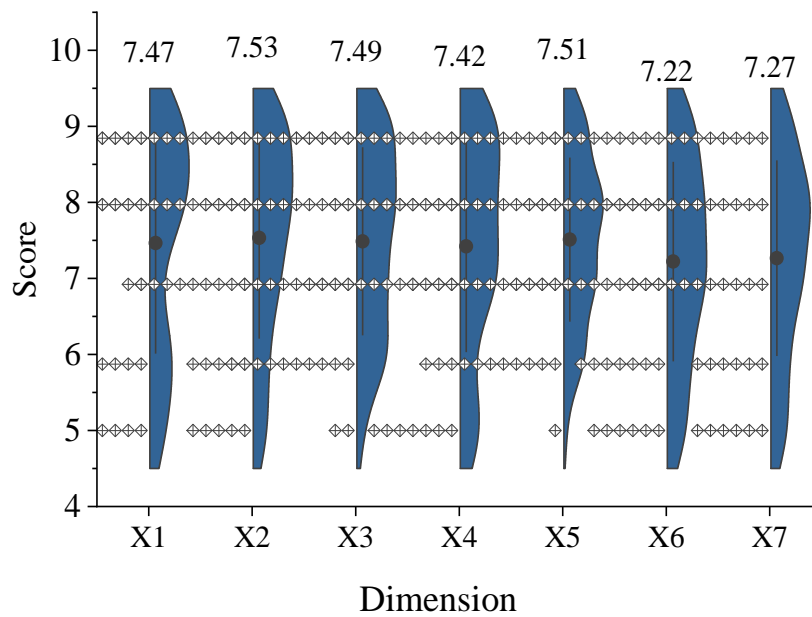


Figure 6: The aftertest results of the students' design ability(Group A)

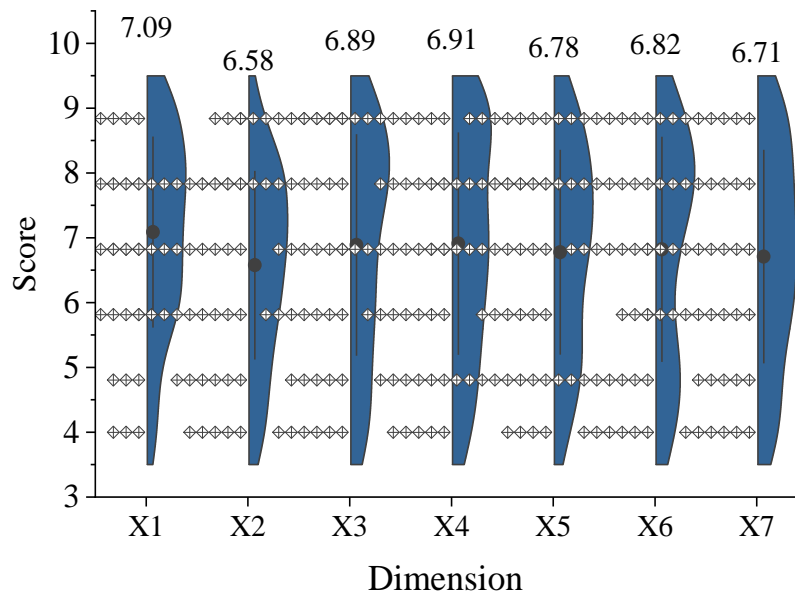


Figure 7: The aftertest results of the students' design ability(Group B)

*Table 3: Analysis of the significant differences in the after survey*

Dimension	<i>t</i>	<i>p</i>
X1	-1.977	0.006
X2	-2.543	0.035
X3	-2.213	0.008
X4	-2.812	0.016
X5	-2.156	0.028
X6	-1.817	0.008
X7	-2.367	0.015
Total score	-2.872	0.026

## 5 Conclusion

AIGC in the era of artificial intelligence brings opportunities and challenges to the design industry and design education. Based on constructivism theory, this study constructs an AIGC-enabled art design contextualized teaching model, and at the same time proposes a color matching model using the DCGAN algorithm. Then we take two classes of students majoring in art design in a university as an example to carry out teaching experiments and analyze the effect of the proposed contextualized teaching model of art design on the cultivation of students' design ability. The conclusions are as follows:

On the one hand, through comparative experiments, the DCGAN model improves 0.107 and 0.024 in the comprehensive evaluation index, 5.78dB and 3.80dB in the peak signal-to-noise ratio, and 2.89% and 2.40% in the subjective degree of liking, which verifies the quantitative color matching effect of the model, and it can realize the intelligent recommendation of color matching in students' design learning. On the other hand, after adopting the AIGC-based contextualized teaching model of art design, the design knowledge scores and design abilities of Group A students were enhanced, which were 23.84% and 8.64% higher than those of Group B, respectively, and both of them were significantly different ( $p < 0.05$ ). Specifically, the two groups showed significant differences ( $p < 0.05$ ) in color perception and application ability, aesthetic ability, layout and composition ability, morphology perception ability, practical ability, demand comprehension ability, and creative narrative ability, indicating that after the application of the contextualized teaching mode, the students' design ability was better cultivated in these seven dimensions, and that the teaching and implementation of the contextualized teaching mode of art design based on AIGC was helpful to cultivate students' design knowledge and design ability. The implementation of AIGC-based art design contextualized teaching mode has a certain role in promoting the cultivation of students' design ability.

In the art design teaching to strengthen the process, experiential goals, combined with AIGC technology, to guide students to active participation, hands-on practice, independent thinking, cooperative inquiry, so as to realize the transformation of the students' learning mode and the continuous improvement of design ability.

## About the Author

Nan Ding was born in Chongqing, China in 1986. Having graduated from the Sichuan Fine Arts Institute with a Master's degree, he is currently employed at Chongqing Jiaotong University. His research encompasses digital translation of cultural heritage and interactive narrative design;

digital twins and contextualised adaptation of industrial heritage; alongside pioneering applications and practical pathways for artificial intelligence, immersive experiences and interactive design within cultural shaping, heritage revitalisation and educational transformation.

Jiu Wang was born in 1985 in Xuchang City, Henan Province, China. He graduated from the Sichuan Fine Arts Institute with a Master's degree and is currently employed at the same institution. His research encompasses the contemporary reinterpretation and technological reconstruction of object-based sculpture; technological intervention and social interaction within public art; and innovative practices in technological art for the revitalisation of cultural heritage.

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