

## Research Article

# Deep Learning-Based Analysis of the Influence of Illustration Design on Emotions in Immersive Art

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With the rapid development of information technology, art has become the most widely used form of visual art in the media. It is not only expressive but also closely related to the traditional art of painting. Excellent hand-drawn illustrations not only have stronger image expression and effect but also have an impact on people's emotions. Therefore, this paper first examines immersive art in contemporary art, including the research on the concept of "immersion art," the "immersion" embodied in art, and the "projection mechanism" in "immersion art," and second, the research is based on deep learning. However, in view of the limitation of personal professional direction and the lack of understanding of the contents of psychology, semiotics, anthropology, and other multidisciplinary fields, the research direction of this paper mainly focuses on the preliminary identification and selection of material semantics, focusing on planning, selection, and construction. The atmosphere of illustration, the interpretation of psychology, and the study of semiotics are shallow. In addition, teachers conduct teaching evaluation when the concept of teaching evaluation is not clear; there are defects in teaching evaluation objectives; there are many problems in the relationship between ability evaluation and knowledge evaluation; in the process of illustration teaching evaluation, summative evaluation is used instead of procedural evaluation. The phenomenon is serious. Finally, based on deep learning illustration design and emotional research, analyze the "healing" illustration cognitive visual case and compare deep learning and shallow learning illustrations. It is concluded that the assessment of in-depth teaching can provide students with more learning opportunities, access to more learning-related materials, and more transparency and freedom in questions. Interpret illustrations from a semiotic perspective, extract emotional semantic symbols from illustrations, compare them with emotional semantic maps of extended materials, locate and quickly create desired materials and colors. The emotional semantic symbols expressed in the works confirm the accuracy of the Guangcai emotional semantic map and also show that "healing" illustrations can effectively alleviate people's negative emotions.

## 1. Introduction

This paper examines the effect of words and illustrations on children's learning of school science subjects, a test that distinguishes the effect of the pictures themselves, the text itself, the general effect of pictures added to the text, and the specific effects of pictures in relation to partial text redundancy. The results show that pictures have no general motivational effect on text learning, but for illustrations at higher ability levels, the effect of specific pictures is beneficial [1]. Learning ability and picture type had a significant interaction effect on multiple-choice question scoring. In the case of multimedia interactive graphics, the high learning

ability group scored significantly higher than the multimedia static graphics group. In the picture manipulation test, the variables of learning ability and picture type had significant main effects [2]. Illustration as a means of visual expression, which explores the history of the discipline and how it relates to art, design and photography; it investigates how illustrated illustrations are read and understood, and how today's illustrators and illustrators create personal visions language [3]. This paper discusses a framework that is demonstrated with interactive illustrated examples. Based on specific requirements, the design process is derived, and appropriate techniques are identified from multimedia and GUI designs, which are then applied to illustrated examples [4].

Conceptual illustrations have a vocabulary function. Designers develop design vocabulary arrows, dots, and other symbols to help designers express their implied meaning through illustrations. This process of communication and analysis through diagrams is either a process of thinking through illustrations or through the design thinking process [5]. This article provides an overview of deep learning in neural networks, including popular architectural models and training algorithms. Deep learning is the part of machine learning that attempts to model high-level knowledge abstractions using multiple layers of neurons consisting of complex structures or nonlinear transformations [6]. Deep learning is the ability to learn a computer model that consists of multiple layers of processing based on representations of data at multiple levels of abstraction. These methods include visual object recognition, object, and domain recognition [7]. This article reviews the factors that influence deep learning and discusses some of the ways that environmental educators can encourage students to use deep learning strategies. These strategies are believed to be necessary to maximize environmental curriculum benefits and may foster creative interdisciplinary approaches to sustainability beyond institutions [8]. In this paper, we describe a software system for building interactive virtual environments, especially for virtual reality artworks. It is an object-oriented framework that builds on top of existing VR, real-time graphics, and audio toolkits. Many common application functions and tools are provided to simplify world creation [9]. This article discusses multiple modes of teaching and learning, a constructed virtual world in which the user's creative imagination transports them to the "other side" of the computer screen. These constructed environments support interaction between the learner community and enable multiple simultaneous participants to access a graphically constructed 3D environment, interact with digital artifacts and various functional tools, and represent themselves through avatars to other participants. Communicate and participate in collaborative art learning [10]. This article explores the emergence of immersive experiential art and its coupling to new-age digital technologies, as well as the deep relationship between immersive art and virtual reality. The essence of immersive art in the era of technological fusion and its aesthetic turn and laws. It can enhance people's immersive artistic creation, expression, and audience experience in the era of 5G technology; virtual reality technology, and intelligent technology are interconnected [11]. Designed to improve public understanding of the subjective experience of auditory hallucinations and to increase empathy for individuals who hear sounds and have other unusual sensory experiences. The pilot study developed a new immersive art exhibition, "Changes in Consciousness," which provides the public with a personalized voice-audio simulation experience in two real-world environments, an art gallery and the London Underground. Results after the exhibition, the feeling of hearing the sound, the empathy for the sound listener, and the comfort of talking about these experiences increased significantly [12]. This article attempts to showcase the fourth generation of immersive art forms, an interactive art platform through

which artists and designers serve audiences to make their art. Therefore, we introduced the art form "sound clay" on the boundary of immersive art. Viewers can simultaneously deform the clay and refine the transformed sound in an immersive environment [13]. This article explores audience engagement in immersive, headphone, and headset performances, with a particular focus on the audience's experience with their own interoceptive processing. Interception, the assessment of one's internal systems, is a key way in which these works of art are performed, and through the use of binaural recordings, headphones, and three-dimensional film, as well as the inherent dramatization of sound, text, illustration, and narrative techniques, the artist is able to target the audience awareness of interoceptive feelings [14]. Current AR technology has moved away from this attempt at sensory suspension of skepticism in favor of a new form of immersive society. In the context of this new mobile form of augmented reality based on social interactivity, artists are now beginning to explore the cultural potential that this new medium can offer. We will view socially immersive artwork and collaboratively positioned media as a consequence of this new medium based on social immersion rather than sensory immersion [15].

## 2. A Review of Research on Immersive Art in Contemporary Art

*2.1. The Concept of "Immersive Art".* Immersive art is a large-scale form of media art created by artists and presented in a specific space. It is human-centred achieved by combining augmented reality interactive media and nondigital media, allowing people to focus and produce an immersive sensory art experience. The ideal artistic effect achieved in this way is to allow people to communicate and interact with the artistic environment, focusing on the experience of being present, so as to generate the most direct perceptual relationship, allowing people to make artistic contact in a short period of time. The distance in the perception process and the reflection of the audience are also part of the artistic creation, realizing the two-way communication between the art and the audience. This definition has several meanings, namely: (1) "sunk art" is an art form that first appeared in the art world, expressing artistic concepts through the artist's thinking and creating the relationship between art and the world; (2) in a specific In space, done in a space or environment, also used as "immersive art" is one of the means to complete a work, including things, smells, temperature, color of light, and human body, these nondigital immersive media increase the diversity and sensitivity of immersive art; (3) "Immersive art" for the public, the human body is surrounded by the artistic environment, which is the main element of the art form. The human body changes from an objective body to a "phenomenal body." The "body" and the opposite state of the environment also become the "space" where people and the environment are integrated phenomenon rather than people facing each other in a specific environment; (4) the art installation does not clearly distinguish between reality and projection (virtual) but creates an immersive environment through the projection of

illustrations, solving the problem of isolation between art and the public; (5) “immersive art” keeps pace with the times, a new art form emerges, and the proliferation of media forms blurs the boundaries between virtual and reality and integrates people, media, and environment into a whole. The most advanced form of material experience. Using the fusion of multimedia and cross-art cross-border collaboration, immersive art realizes the “presence experience” of virtual interpersonal relationships. The connection on the field shortens the distance between art and the public, and the public Instead of using rude words or “hanging a diary” (referring to painting) to understand the relationship between art and time, you can directly intervene and immerse in it, and create different relationships in the process of aesthetic experience. “Immersive art” subverts traditional art presentation and communication.

2.2. “*Immersion*” Embodied in Art. Tamara Joad, Lecturer in Art History at the University of Edinburgh, UK, elaborated: “The catalogues predicted in the 1960s and 1970s were self-criticism, isolation and illusions of reality, while augmented reality (AR) art helps to shape the aesthetics it is immersive, Associative and truly virtual.” In this article, the author begins to associate “immersion” with an aesthetic phenomenon. The audience is immersed in the environment of the work, a conscious and thoughtful immersion. This is an improvement on the previous projection installations. The venue is transformed into a venue, and nondigital projection forms such as light, fog, sound, and smell are added to the projection of the image, so that the audience can actively participate in the art work. This is the first-time researchers have used the term “immersion” to describe large-scale installation art. The artistic practice and art form of “immersive art” discussed in this article is an art field in which reality and projection (virtual) interact and change public status. From the perspective of form and research content, it creates an immersive environment from art and conference or collective, installation, and other project illustrations. When the audience enters the installation art environment designed by the artist, due to the large scale, effect simulation, visual feast, and sensory experience of the installation, the audience actively blocks the environment, brings information and distraction and focuses on interaction.

2.3. “*Projection Mechanism*” in “*Immersive Art*”. There is no doubt that immersive art requires a projection mechanism. In immersive art, such a projection mechanism is mainly manifested in second-degree experience. The second experience is essentially a fusion of the artist’s aesthetic orientation and the audience’s aesthetic orientation. In the process of the second experience, the aesthetic orientation of the artist and the audience’s aesthetic orientation play different roles. On the other hand, the audience’s aesthetic orientation is a certain state of psychological preparation for appreciation, mainly manifested in specific psychological expectations, which determines how the evaluator actively discovers and accepts works; on the other hand, when the

artist’s aesthetic orientation is reflected in the artistic form of the work, it is mainly an aesthetic activity of a fascinating structure. This call determines what the work can bring to the audience and what kind of different experiences it can bring to the audience. It is the result of the mutual selection, coordination, and fusion of the artist’s aesthetic goals and the audience’s aesthetic goals. First of all, it is the external expression of the artist’s emotional appeal, aesthetic purpose, and conceptual thinking. Frames set by the artist. And strive to align their aesthetic understanding with the original intention of the artist, while in immersive art, the artist uses new technologies and media to create new forms of thinking and expression. For artists, they are more interested in how to stimulate the public to actively participate in art works and build new forms and meanings in the works. The public has more contact with artists and art works and can communicate directly. It can shape the concept from the perspective of aesthetic projection and make the aesthetic subject and object interact.

### 3. Illustration Style Conversion Algorithm Based on Deep Learning

3.1. *Style Transfer Algorithm Based on Gram Matrix*. Aiming at the problems of poor performance and strong limitations of traditional methods, the characteristics of different layers of convolutional neural network to extract image features are discussed, and an image style transfer algorithm based on Gram matrix is proposed. A variety of artistic style transfer experiments were carried out. Finally, it was verified by experiments that the proposed algorithm can better realize the style transfer of artistic images in a shorter time than the traditional algorithm, which shows that the algorithm is more effective in image feature extraction and image style transfer tasks. The whole process of the method is as follows: first, the noise illustrations are randomly formatted, and the target illustrations and separable texture noise illustrations are input into the prelearned VGG convolutional neural network to extract attribute information. The network is used here because it has been shown to have good illustration perception, perform well in classification tasks, and be able to extract more descriptive features. After extracting the target and noise attributes, the corresponding Gram matrices  $G^L$  and  $G^L$  are created using the attribute activation values, where  $G^L$  is an array formula consisting of trigger values describing the attributes in object terms:

$$G_{ij}^L = \sum_k F_{ik}^L F_{jk}^L. \quad (1)$$

$G$  is a matrix consisting of the activation values of the noise illustration properties, the formula is as follows:

$$G_{ij}^L = \sum_k F_{ik}^L F_{jk}^L. \quad (2)$$

When the Gram matrices  $G^L$  and  $G^L$  of the target style illustration and the noise illustration are obtained, the style representation of the two illustrations is actually understood,

and then the difference between the two Gram matrices is minimized as the loss function, namely:

$$E_L = \sum (G^L - G^I)^2. \quad (3)$$

Like the texture synthesis process, in the style transfer task, the noise insets are first randomized and then the noise insets, target style additions, and content additions are simultaneously fed into the VGG network to extract attributes. In the texture synthesis part, the noise illustration is reduced by constructing a Gram matrix between the noise illustration and the target style illustration, so as to approximate the texture of the target style illustration. Limiting the increase in noise minimizes the distance between the feature inset  $F$  of the  $L$ -th layer of the VGG network and the content inset  $P$  of the  $L$ -th layer of the VGG network, i.e., minimizing the two differences between the features of the spatial structure. In this way, the texture properties and state structure properties of the noise illustrations are simultaneously optimized to form the style loss function and the content loss function, respectively, and the weighted sum of the two is passed as the loss function to the algorithm. The formula is as follows:

$$L_{\text{total}} = \alpha L_{\text{content}} + \beta L_{\text{style}}, \quad (4)$$

where  $L$  is the texture synthesis algorithm caused by the style loss function and the content loss function:

$$L_{\text{content}} = \sum (\sum F^l - F^I)^2. \quad (5)$$

**3.2. Adaptive Instance Normalization Network.** Another algorithm described in this paper allows transferring random styles and was proposed by Huang and Belongie et al., whose ideas were based on that of Dumoulin et al. The method proposed by CIN (Conditiona Instance Normalization) has been previously developed by Dumoulin et al. to solve the translation problem of illustrations in multiple styles. The formula for this method can be expressed as follows:

$$\text{CIN}(F(I_c, s)) = \gamma^s \left( \frac{F(I_c - \mu F(I_c))}{\sigma F(I_c)} \right) + \beta^s, \quad (6)$$

where  $F$  is the activation value of the input illustration attribute after passing through the convolutional network,  $c$  and  $s$  are the content illustration and style illustration, respectively, and  $\mu$  and  $\sigma$  are the mean and standard deviation.

Since the network adopts an encoder and decoder structure, since the decoder is responsible for combining the rendered feature maps back into the pixel space, high-quality, style-transferred illustrations can be obtained after learning the network parameters of the decoder. The loss function used in decoder training consists of two parts, content loss and style loss:

$$L_c = \|f(g(t)) - t\|_2, \quad (7)$$

where  $t$  is the output of the adaptive expression normalization layer: the fusion function map, and  $g$  is the decoder. The content loss function combines the difference between

the VGG function of the illustration and the merge function, which is a new content loss planning idea, which can lead to faster convergence. The style loss function is as follows:

$$L_c = \sum_{i=1}^L \|u((\emptyset_i g(t)) - u\emptyset_i(s))\|_2, \quad (8)$$

where  $s$  is an illustration in object style. The style loss function compares the difference between the mean and standard deviation of the feature maps of the VGG network that created the illustrations and the style illustrations. The total loss function consists of the addition of content loss and style loss:

$$L = L_c + L_s. \quad (9)$$

**3.3. Design of Dual-Core Compression Activation Module.** The DKSE module proposed in this paper combines the characteristics of SE module and SK module, which can better extract general modeling functions and local details of artistic illustrations. The DKSE module consists of the following four parts, and the expression formula is as follows:

$$V = \sum_{i=1}^N U_i \bullet F_{ex}(F_{sq}(F_{gp}(U))). \quad (10)$$

**Split:**  $U$  is the function graph combined with the DKSE module branches,  $F_{gp}(\cdot)$  is the global mean pooling operation,  $F_{sq}(\cdot)$  is the channel compression processing,  $F_{ex}(\cdot)$  is the channel function activation function,  $N$  is the number of DKSE module branches, and the value is 2 in this paper.

Two convolutional filters of different sizes are used to extract the overall features and local details of the artwork.  $E$  and  $F$  are the mapping process of convolution mapping, batch normalization and ReLU wake-up function processing, respectively. In the  $i$ -th branch, the convolutional mapping formula of each filter to the intermediate map  $X$  is as follows:

$$u_{ic}^i = w_{ic} \times X = \sum_{k=1}^c w_{ic}^k \times X^k + b_{ic}. \quad (11)$$

There is no saturation area, and there is no gradient disappearance problem; there is no complex exponential operation, the calculation is simple, and the efficiency is improved; the actual convergence speed is faster, much faster than Sigmoid/tanh; it is more in line with the biological neural activation mechanism than Sigmoid.

$$u_{ic} = \delta\left(\wp\left(u_{ic}^i\right)\right), i = 1, \dots, N. \quad (12)$$

**Squeeze:** after the Split operation, we get two new feature maps  $U_1$  and  $U_2$ , and combine the attribute data of the two feature maps by summing the corresponding elements:

$$U = U_1 + U_2. \quad (13)$$

Combined with the global average, the data of each feature layer of the feature map  $U$  are compressed into a

single channel feature value. The feature map  $U$  has  $C$  feature layers. Combined with the global mean, the eigenvalues of the  $C$  channels represented by the SeR statistic can be obtained. The  $c$ th element in the statistic  $S$  is computed by compressing the spatial data of the  $c$ th layer of the feature map  $U$ :

$$S_c = F_{gp}(U_c) = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W U_c(i, j). \quad (14)$$

**Excitation:** To improve the stylistic properties extracted from each art type and reduce the influence of low-impact feature data, we use a  $1 \times 1$  convolution function to reduce the number of output channels of the feature map in the compression step to  $1/r$  of the original number of channels then do a  $1 \times 1$  convolution. After batch normalization and activation of the ReLU function, the number of channels is expanded by  $1 * 1$  convolution operation, and finally, the weight is normalized by the Sigmoid gate mechanism to obtain the style characteristics of various artistic illustrations.

$$Z = F_{ex}(S) = \sigma(W_2 \delta(\wp(W_1 S))). \quad (15)$$

**Scale:** The  $Z$  weight obtained by the squeeze and excitation operations is the artwork attribute information filtered by the primary attribute and suppressed by the secondary attribute.  $Z$  is weighted with feature maps  $U_1$  and  $U_2$ , respectively, and the relevant channel feature fusion operation is performed. The expression is as follows:

$$V_c = u_{1c} \cdot Z_c + u_{2c} \cdot Z_c. \quad (16)$$

**3.4. Get the Art Illustration Sample Library.** This paper performs data augmentation processing on existing art illustrations. Data augmentation is the process of increasing illustration data by creating deformed illustrations that belong to the same category as the original illustrations using specific methods. Because the style information of each art illustration is evenly distributed, we extract art illustrations with high resolution and rich style information and cut them to a size of  $299 \times 299$  pixels, so as to obtain multiple data illustrations of such art styles. In this way, while increasing the illustration data, the detailed information of the illustration is more fully displayed, and the loss of local detail information is minimized. The specific algorithm is as follows: for an illustration,  $W$  represents the width of the illustration,  $H$  represents the height of the illustration, and  $D$  is the channel of the illustration. Use 299 to round down the length and width of the illustration to get  $n$  segments with a length of 299 in the length direction,  $n$  segments with a width of 299 in the width direction, and finally get  $n$  pieces of size  $299 \times 299 \times D$  from an illustration Artistic illustration, the expression formula is as follows:

$$\begin{aligned} n_h &= \left\lfloor \frac{H}{299} \right\rfloor, \\ n_w &= \left\lfloor \frac{W}{299} \right\rfloor, \\ n &= n_h \times n_w. \end{aligned} \quad (17)$$

Slight changes in horizontal and vertical or size of artistic illustrations have little effect on their overall artistic style characteristics. Therefore, data enhancement processing is performed not only on the illustration sample library but also on the training set in the process of training the network. During the training process, the training set is randomly rotated in the range of  $0^\circ$  to  $20^\circ$ , and the horizontal and vertical directions are translated by  $0 \sim 0.1$  times the length and width of the inset, respectively. During the experiment, we divided the validation set and the training set according to the ratio of 82 to the number of each type of art illustrations.

### 3.5. Data Enhancement Processing Results

**3.5.1. Depth-Wise Separable Convolution.** The prototype of depth-wise separable convolution can be considered to come from the Inception module in the convolutional neural network. The convolution calculation is divided into two parts. First, the channel (depth) is subjected to spatial convolution (depth-wise convolution), and the output is spliced and then perform pointwise convolution with a unit convolution kernel to obtain the feature map. In terms of applications, depth-wise separable convolutions are used in the construction of microneural networks and in the structure optimization of large-scale convolutional neural networks. Deep learning algorithms that use depth-wise separable convolutions include exception and mobilities the traditional convolution process; all channels corresponding to the image region are considered simultaneously. The process of depth separation convolution is to look at the spatial region and channel of the corresponding image separately. The convolution process can be divided into depth-wise convolution and point convolution operations. In the traditional convolution process, the number of convolution kernel parameters and the amount of calculation are as follows:

$$\begin{aligned} S_c &= h \times w \times C \times C', \\ C_s &= M \times N \times S_c. \end{aligned} \quad (18)$$

For the depth-wise separable convolution operation, the number of convolution kernel parameters is mainly obtained by summing the number of convolution kernel parameters in the depth-wise convolution and point-by-point convolution operations. The number of parameters of the convolution kernel and the depth resolution the calculation formula of the rate convolution operation is given by:

$$\begin{aligned} S_d &= h \times w \times C + 1 \times 1 \times C \times C', \\ C_d &= M \times N \times S_d. \end{aligned} \quad (19)$$

According to the above formula, the ratio of ordinary convolution and depth-wise separable convolution on the number of convolution kernel parameters can be calculated as follows:

$$\frac{S_d}{S_c} = \frac{C_d}{C_c} = \frac{1}{hw} + \frac{1}{C}. \quad (20)$$

From the above analysis, it can be concluded that the depth-wise separable convolution function can effectively reduce the amount of network computation and the number of network model parameters. Because the network adopts the structure of encoder and decoder, the encoder part must distinguish between content pictures and target style pictures, and the decoder section network must be trained. The loss function used in decoder training consists of two parts, content loss and style loss. The content loss function is as follows:

$$Y(X) = [Y_1 \cdot Y_2 \cdot Y_3](X). \quad (21)$$

## 4. Research on Emotional Semantics Based on Deep Learning Illustration Design

### 4.1. Deep Learning Illustration Design

*4.1.1. Experimental Data Collection.* Illustration is a universal language in the world, so more and more students have studied illustration design. Now, two classes of questionnaires are used. Students in both classes have passed the exam. Content is accurately tested. The data of the illustration paper and the test data are analyzed by EXCEL and SPSS22, and most of the data of the conversation are compressed by the secondary code analysis. It describes the results of a class-wide survey of students before problem-oriented learning begins, and it can be seen that students in this class vary greatly in their use of deep learning methods among individuals, and the use of shallow learning methods is the same. Also, deep learning scores higher than superficial ones, so it is prudent to conclude that students are more likely to use deep learning methods in illustration classes.

*4.1.2. Statistics and Analysis of Questionnaire Results.* The results of the questionnaire showed that there are two parameter tables for deep learning and shallow learning illustration. Descriptive analysis of the collected data shows that the density of students who choose the method before learning the illustration intensive course varies greatly; in the shallow learning illustration method, the frequency of selection also varies greatly. So far, it can be concluded that a group of students is before the start of the illustration course. In an illustration course, you may want to use a deep learning approach to descriptive analysis through deep learning, shallow learning, and effective learning to compare numerical values, as can be seen in Figure 1 and Table 1.

It is worth noting that it cannot be judged from the descriptive values whether there is a big gap between students before and after the course between deep learning illustration and shallow learning illustration, so it is necessary to take the next step. A total of 56 students who participated in the two surveys were selected from the roster of students who obtained useful data from the previous two surveys, and paired *T* tests were performed on the data from the deep learning and surface learning scales. The results are shown in Figures 2–4: the *t* value, also known as Student's *t*

test, is mainly used for normal distribution with small sample size (for example,  $n < 30$ ), and the population standard deviation  $\sigma$  is unknown. The *t*-test uses the *t*-distribution theory to infer the probability of the difference, so as to compare whether the difference between two means is significant.

Through the data in Figures 2 and 3, the differences between the two samples before and after deep learning and shallow learning can be compared, as shown in Figure 4.

*4.2. Research on Emotional Semantic Vocabulary Extraction from Surface Features of Illustrations.* The diversified development of illustration has greatly enriched its own artistic language. For the emotional semantic knowledge and analysis of illustrations, we can start from the physical characteristics of illustrations, divide them according to hardness to meet different visual needs, and divide emotional degrees according to psychological characteristics, so as to classify and study illustrations more effectively to obtain the emotions in illustrations. It can show the emotional semantics of illustrations more clearly, and provide reference and evaluation for the creation of illustrations. The integrity of illustration is reflected not only in the diversity of illustration uses but also in the richness of the techniques used in illustration. Generalized illustration is not only a physical illustration but also a creative method and creative process. The experimental nature of generalized illustrations not only brings us unlimited exploration power but also brings the drawbacks of blindly pursuing illustrations. In order to obtain the emotional symbols of the meaning in the illustrations and guide the artistic creation of the illustrations, this research stage will use a combination of interviews and questionnaires to extract and analyze the emotional and semantic vocabulary of the illustrations. First of all, through interviews with art teachers, students, and design practitioners around, to understand the advantages and disadvantages of comprehensive illustration in the application, at the same time, conduct basic research on the emotional influence factors in illustration and analyze the emotional influence factors of illustration. Illustration from the interview: according to the survey results, a total of 35 people were interviewed, of which nine people believed that the color of the illustration had a greater impact on the emotion of the illustration, followed by eight people who believed that the texture of the illustration was a bigger factor, and the texture of the illustration and the image in the illustration creation. The following eight people and six people have a greater influence on the emotional factors of photos, and the other four people think that it is related to the illustration components, and the following conclusions are drawn.

Based on the above findings on emotional factors in unfolded stock photos, it can be tentatively hypothesized that while the abundance and uses of illustrations are constantly changing, the feelings of unfolding illustrations are not unpredictable and unattainable. When using fine artwork to create illustrations, intuition is often used to choose images that are combined and overlapped to create an image effect. Research was used to find out the

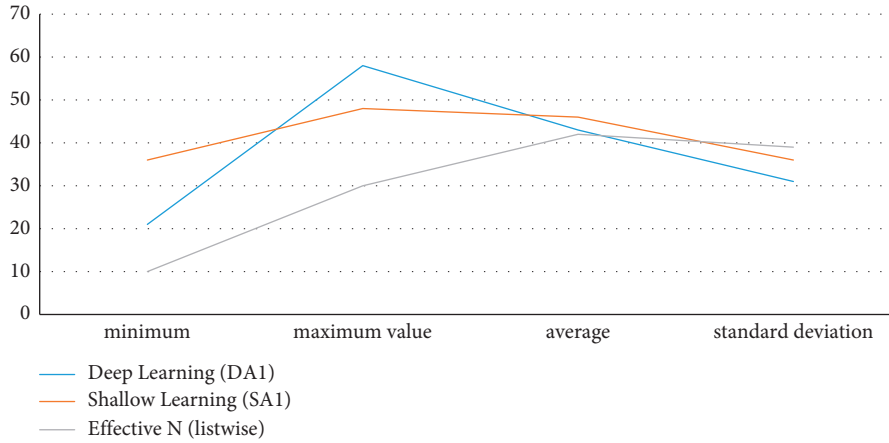


FIGURE 1: Descriptive statistics of questionnaire test results.

TABLE 1: Illustrated picture emotional influence factors.

Color (%)	Quality of a material (%)	Texture (%)	Area (%)
26.67	23.34	23.34	16.63

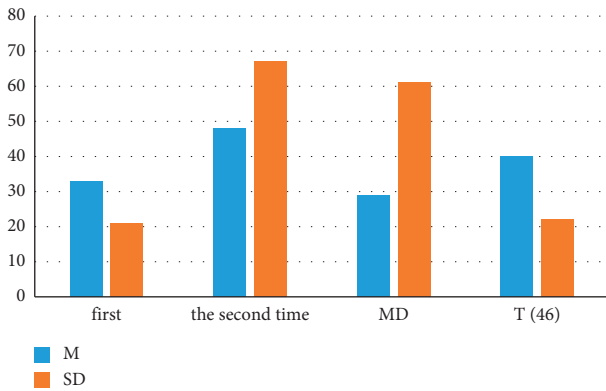


FIGURE 2: Paired sample test for deep learning illustration.

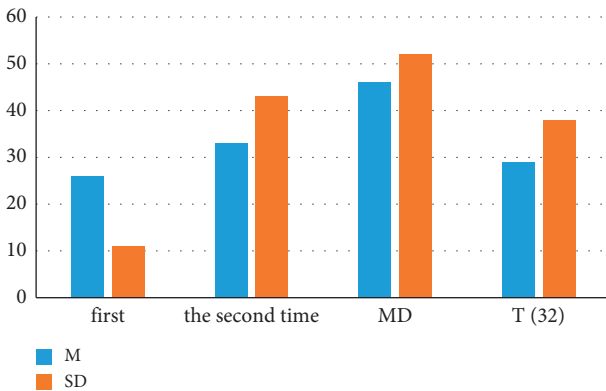


FIGURE 3: Paired sample test for shallow learning illustration.

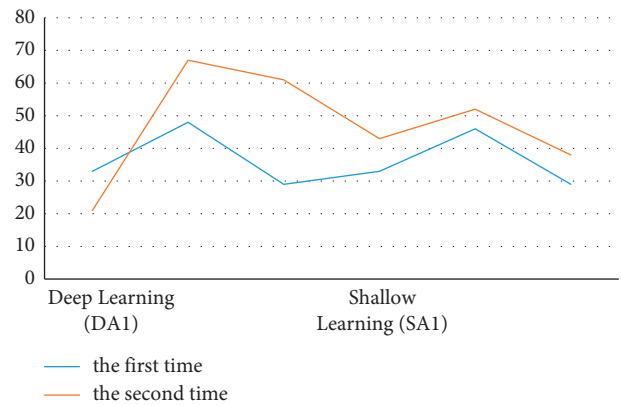


FIGURE 4: Comparison of samples before and after deep learning and shallow learning illustration.

TABLE 2: Restrictions on selected illustrations.

Material surface features	Felt	Linen	Jam	Board	Ceramics
Fineness	5.89	6.9	7.89	8.9	9.23
Softness	8.21	9.67	5.98	3.12	1
Roughness	6.2	3.5	2.62	5.9	0.1
Warmth	9.4	5.67	2.53	5.5	0.73

TABLE 3: Different types of comprehensive material color research.

Material type	Comprehensive color type
Same material	Different colors
Different materials	Different colors
Different materials	Same color

relationship between the characteristics of the illustration and the perception of the illustration, and the effect of the different characteristics described on the perception of the illustration and the overall picture mood. This study of the sentiment of synthetic illustrations is based on the analysis

and study of the emotional elements that make up the illustrations of each image. The final feel of the combined image is determined by examining the ratio of a single image to a combination of multiple images on the screen, etc.

TABLE 4: Trend chart of texture and emotion change of felt illustration

Texture change trend	Rough → fine	Loose → flat
Emotional trends	wild → gentle	Lazy → neat

TABLE 5: Trend chart of texture and emotion change of linen illustration.

Texture change trend	Rough texture → fine texture	
Emotional trends	Rustic → Elegant	Original Fun → Delicate and delicate

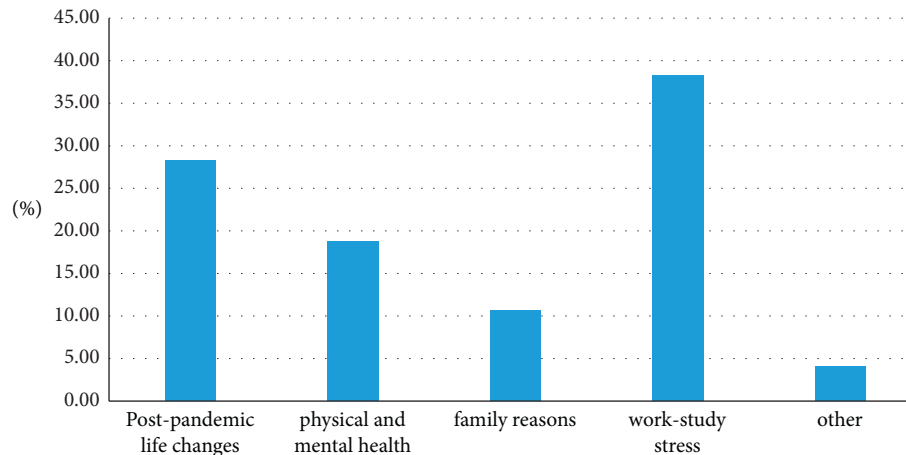


FIGURE 5: Question: What is the main source of your psychological stress?

Therefore, interviews were used to formulate respondents' perceptions of illustrator sentiment and to select the main factors they believed to influence and relate to illustrator sentiment. The Observation Glossary has been compressed with the illustration design research as a tool for overall illustration, and the following research work has been done. The five selected are the surface properties of various images such as felt, linen, cardboard, wood, and ceramics. It is shown in Table 2.

#### 4.3. Research on Color Emotion Semantics of Illustrations.

When creating a comprehensive illustration, the color of the illustration should be included in the scope of thinking. The study of illustration color, including the combination of the material and color of the illustration itself, is a compound language. To study the color of illustrations, it is necessary to extract the colors of the illustrations and interpret the semantic symbols contained in the colors of the pictures. It is shown in Table 3.

#### 4.4. Emotional Semantic Analysis Contained in Comprehensive Illustration Texture.

In order to analyze the texture language of the image, it is necessary to clarify the classification method of the image texture language and use the structure of the different texture languages of the image to extract the emotional semantic symbols of the extended image texture. As an example of felt painting, the texture of the felt illustration ranges from delicate to rough, and the texture language ranges from soft to wild, all of which reflect

the rich expressiveness of this illustration and the infinite possibilities of language expression. The structural language of his illustration's changes with the texture of the images and his emotional nature shows the same tendency. Felt art has changed from rough to delicate, showing extreme emotional changes from wild to gentle, and the texture effect from loose to flat also shows a change from lazy to neat. It is shown in Table 4.

When using linen illustrations, the color of linen conveys a strong artistic atmosphere and nostalgic charm, reflecting the original, simple, and sincere feelings of linen. Linen is used as the utensil in the illustrations. The texture of coarse linen is more primitive and retro, while the finely woven linen reflects delicate and subtle emotional changes, which is more modern and artistic. It is shown in Table 5.

#### 4.5. Visual Representation and Design Method of "Healing Department" Illustration.

According to a feedback analysis of a survey on the psychological attractiveness of young people, 53.89% of the respondents are currently emotionally anxious, followed by depression and boredom. Work and study, most people think they need to be healed, and the main reason for healing is to gain psychological comfort. Most people choose "healing" pictures and pictures to calm their emotions. It is shown in Figures 5 and 6.

The survey analyzed the psychological needs of the target audience. The survey showed that young people have a high demand for "healing" and are willing to choose a beautiful and relaxing way to "heal" illustrations to ease their



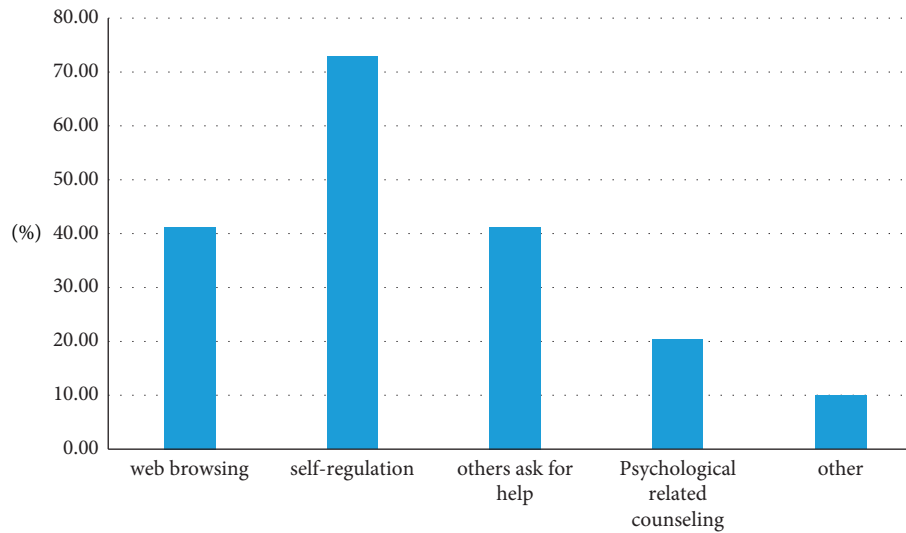


FIGURE 6: Question: In what ways do you usually adjust your emotions?

emotions. In terms of self-discipline. Based on the findings, the authors then analyzed color, composition, shape, and texture and concluded which visual effects can alleviate and enhance negative emotions such as anxiety and depression, and applied them to scents.

*4.5.1. Visual Performance of Illustrations of "Healing Department".* The visual expressions of Healing's illustrations can evoke conscious and unconscious emotional needs, such as poetry and music. From the perspective of visual cognition, the color, composition, shape, and texture of a "healing" illustration give people different psychological feelings, the readers' psychological states are also different, and the interpretations produced by seeing the same visual effects are also different. Bring your own feelings. deep learning of illustration can provide students with more learning opportunities, access to more learning-related materials, and more transparency and freedom in questions. It also plays the role of art appreciation or supplementary explanation to the content of the text. The meaning is to make the idea of the text clearer and clearer. Illustration is an art form, which has been widely used in many fields of modern design with its real sense of life, intuitive image and aesthetic appeal. Interpret illustration learning from a semiotics perspective, extract emotional semantic symbols from illustrations, compare them with emotional semantic maps of extended materials, locate and quickly create required materials and colors. The visual expression of illustration can evoke people's conscious and unconscious emotional needs.

## 5. Conclusion

Through the analysis of the questionnaires the enlightenment obtained in this study is to use information technology to optimize the teaching content. Finally, the effect of deep learning and shallow learning is compared, and the conclusion is that the evaluation of deep illustration teaching can provide more learning opportunities for

students, exposure to more learning-related materials, the problem is more transparent and freer, which is difficult to speculate easily. The purpose of this problem is to facilitate the use of deep learning methods to find meaning types. Starting from semiotics, interpreting illustrations, extracting emotional semantic symbols from images, and drawing extensive illustrative semantic symbol maps. Illustration of the process of creating an illustration: he also studies "healing" illustrations, defines the concept of "healing" illustrations from the perspective of art therapy, describes its developmental origins, analyzes the healing principles of illustrations, and uses questionnaires to analyze "healing" illustrations. A group of 30-year-olds are researching the call for healing. Their target audience is work, study, and life. Most people need healing. Then condensed the analysis of the psychological changes and needs of the target group, the image of "improvement" had a significant impact. Finally, we analyze a visual case of a "healing" illustration that can effectively alleviate people's negative emotions. The teaching purpose is not clear. Objectively speaking, the course of illustration expression technique is mainly attached to animation design, art design, and other majors, which makes the course of illustration expression technique not paid much attention by teachers and students. Over time, the problems of perfunctory teaching in the course of illustration expression techniques are serious, the course assessment is loose, the teaching content is outdated, and other problems are prominent, and the teaching objectives are not clear, which has brought serious obstacles to the teaching of illustration expression techniques course. The teaching methods are old, and the enthusiasm for learning is low, which makes it difficult to stimulate students' creative desire.

## Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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